Rating-based CDS curves

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Abstract

This paper explores the extent to which term structure of individual CDS spreads can be explained by the firm's rating. Using the Nelson-Siegel model, we construct, for each day, CDS curves from a cross-section of CDS spreads for each rating class. We find that individual CDS deviations from the curve tend to diminish over time and CDS spreads converge towards the fitted curves. The likelihood of convergence increases with the absolute size of the deviation. The convergence is especially stable if CDS spreads are lower relative to the rating-based curve. Trading strategies exploiting the convergence generate an average return of 3.7% (5-day holding period) and 9% (20-day holding period).

Key Words: Credit Default Swap (CDS), Trading Strategy, CDS Term Structure, Credit Rating.

JEL: G11, G17, G24

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1 Introduction

The outstanding notional value of CDS (credit default swap) contracts is multi-trillion dollars, and identifying the determinants of CDS spreads has been a central question in CDS studies. Recently, the CDS market has become active again after the market shrunk during the financial turbulence in 2007–2009. $15.7 billion notional positions of single-name CDSs was cleared in the Intercontinental Exchange in January 2017.[1]

The pricing for CDSs, conventionally, is based on evaluating individual firms' credit/default risk, as the contract is meant as a protection against a firm's default. In theory, the price of a CDS should be driven only by a firm's default probability and the recovery rate.[2] Empirically, however, other non-credit factors also affect CDS spreads. Hull and White (2001) include counterparty default risk in pricing CDS spreads. The CDS illiquidity affects CDS spreads profoundly (see Corò, Dufour, and Varotto (2013), Qiu and Yu (2012), and Tang and Yan (2007)). Several studies find that CDS spreads co-move systematically (see Anderson (2017) and Galil, Shapir, Amiram, and Ben-Zion (2014)).

One way to look at a systematic component of an individual firm's credit risk is to consider its credit rating, provided by one of the rating agencies (e.g., S&P and Moody's). The rating can be linked to the average historical default probability of firms with similar credit conditions. Several studies, for example, Chava, Ganduri, and Ornthanalai (2016) and Hart and Zingales (2011), argue, however, that ratings are not very informative in terms of credit quality of a firm because they reflect past information. Others, such as Loeffler (2007) and Loeffler (2013), on the contrary, show that credit ratings can "look through the cycle" and influence the short-term risk estimates. At the same time, a firm's default risk is relatively stable (Bai and Wu 2016), and it is still very common for market participants to use rating information to gauge the default risk.[3]

[1] "Credit default swaps activity heats up", *Financial Times*, `https://www.ft.com/content/c47dce8e-ca9f-11e5-be0b-b7ece4e953a0`.

[2] The accuracy of the default probability estimate is important here. The potential models span the classical structural models such as Merton (1974), and it's extensions including, a flexible corporate debt structure and default date in Leland and Toft (1996), or creditor-shareholder bargaining at firm's default (Fan and Sundaresan 2000; Ericsson and Renault 2006), as well as the reduced-form models including, for example, Altman (1968), Jarrow, Lando, and Turnbull (1997), Duffie and Singleton (1999), and Campbell, Hilscher, and Szilagyi (2008) among others.

[3] For example, firms' ratings still can be used to determine the capital requirements in banks under the Basel III framework `https://www.bis.org/bcbs/publ/d424.htm`.

In this paper we show that a firm's rating also plays a role in determining CDS spreads. In particular, we provide a novel insight into the dynamics of individual CDS spreads. Our findings suggest that CDS market participants anchor a firm's CDS spread to other peer firms' CDS spreads with the same rating. Such anchoring affects not only the actual levels of CDS spreads but also their dynamics over time.

Methodologically, we group CDSs cross-sectionally by their underlying firm rating, and use a model of Nelson and Siegel (1987) to construct rating-based hazard rate curves. The use of a credit or rating curve is a common industrial practice[4], and the application of the Nelson-Siegel model is widely used in Treasury bond pricing. We are the first, to the best of our knowledge, to study the information content and time-series properties of rating-based CDS curves. Using panel regressions in the spirit of the error correction model, we find that deviations of individual CDS-implied hazard rates from the rating curves move in the opposite direction to the time-series changes of the CDS-implied hazard rates, showing that the hazard rates (and, thus, CDS spreads themselves) converge to the rating-based fitted curves over time. Our findings suggest that the residuals are transient, while the fitted curves reflect market consensus on the fundamental non-diversifiable CDS risks.

Further analysis reveals that the convergence speed of CDS-implied hazard rates to the fitted curves is related to the magnitude of the deviation between them. We sort the CDSs into five portfolios based on the relative size of the deviations, and find evidence that larger deviations make convergence more likely. A trading strategy that consists of a long position in the portfolio of CDSs with the *largest negative* deviations and a short position in the portfolio of CDSs with the *largest positive* deviations produces statistically significant positive returns for 5 and 20 days holding periods. These results further confirm the time-series convergence of the CDS spreads to the rating-based CDS curves. Notably, the convergence speed of the portfolio containing strongly underpriced CDSs is less volatile over time and across ratings, CDS maturities, and industries than the convergence speed of the portfolio of overprices CDSs. This suggests that investors, in particular protection sellers, are more concerned about underestimating default

[4]For instance, GFI/FENICS constructs single-name CDS spreads using Hull-White methodology; Markit also provides various smoothed credit curves (such as single-name CDS curves and sector credit curves) by pair-wise interpolating individual CDS spreads. See the Markit (2012) user manual for more information. In practice, credit curves are often used by clients to analyze the delta risk of the CDS spreads (CV01) or to assess the CDS spreads for other tenors. Credit curve providers might not consider the term structure of the CDS spreads, or provide the accuracy test for these curves.

risk than about being too conservative in their estimates, and almost always adjust relatively low CDS spreads towards a higher rating-implied level. Consequently, betting on the spread increase of relatively underpriced CDS contracts consistently deliveries positive and significant average returns, even after adjusting for transaction costs. Our results are robust across different years, industries, rating classes and CDS maturities, highlighting the overall importance of the rating classification for investors' decisions in the CDS market.

2 Related literature

Our study is related to several strands of literature: the first one illustrates the links between credit ratings and individual CDS spreads, the second one highlights the importance of systematic drivers of CDS spreads, in addition to individual credit-risk related variables, and the last one links through-the-cycle and point-in-time default risk estimation.[5]

Most of studies agree that there is a strong link between CDS spreads and credit ratings. The existing evidence on the direction of that link is, however, rather mixed. Some scholars suggest that CDS spread changes lead the announcements of rating changes, thus, ratings are less informative in the presence of traded CDSs (Hart and Zingales 2011; Finnerty, Miller, and Chen 2013; Chava, Ganduri, and Ornthanalai 2016). Others, on the contrary, document that rating announcements do impact CDS spreads. For example, Hull, Predescu, and White (2004) find that 'Review on Downgrade' announcements affect CDS spreads, and Norden and Weber (2004) and Micu, Remolona, and Wooldridge (2006) conclude that all types of rating announcements have a significant impact on CDS spreads.

As far as systematic factors are concerned, Longstaff, Pan, Pedersen, and Singleton (2011) find that global factors are more important than individual country factors in driving sovereign CDS spreads. Doshi, Ericsson, Jacobs, and Turnbull (2013) show that variables reflecting market conditions, such as the 6-month Treasury yield and the difference between the 10-year and 6-month yields, can explain the cross-sectional CDS variations. Similarly, Tang and Yan

[5]Empirical literature suggests multiple individual CDS factors that impact the spreads. Das, Hanouna, and Sarin (2009) find that both accounting-based and market-based credit information are important drivers of CDS spreads. Several studies find that CDS illiquidity increases CDS spreads. See, for example, Tang and Yan (2007), Corò, Dufour, and Varotto (2013), and Das and Hanouna (2009) among others.

(2013) study CDS transaction data and find both firm and market fundamental variables, such as VIX, are significant drivers of CDS spreads. The importance of macro variables also increases during the crisis period. Conrad, Dittmar, and Hameed (2011) show that changes of CDS spreads of systematically important financial institutions lead changes of CDS spreads of the other firms. Galil, Shapir, Amiram, and Ben-Zion (2014) find that median CDS spreads of mixed credit quality have a cross-sectional explanatory power for individual CDS spreads. Lin, Kolokolova, and Poon (2016) construct various CDS-based systematic factors, and show that these factors have a higher explanatory power for quarterly changes of 1-year CDS spreads than firm-specific factors.

Our study is linked to the strand of literature discussing differences and co-dependencies between the through-the-cycle and point-in-time default risk measures. Through-the-cycle approach captures "permanent" credit risk; and the ratings reported by the rating agencies are the examples of such measures. The point-in-time approach also evaluates the current conditions and "temporary" credit risk. A typical example here is Expected Default Frequencies (EDFs) used by Moody's KMV, which are based on firms' current firm market values and can timely capture the changes in credit quality. Although point-in-time methodology provides timely estimates for firm's credit risk, for practical purposes investors often need to have a more "stable" version of credit risk estimation to trigger adjustments in their portfolios, in order to avoid unnecessary transaction costs (Altman and Rijken 2004, Loeffler 2004). In Loeffler (2004), Loeffler (2007), and Loeffler (2013), the author conducts a series of studies for predictability on the default risk using ratings, and finds that the reported rating predicts the trends in the EDFs, estimated from various models such as Hodrick-Prescott filter and moving average. The author also argues that rating information is of the same level of importance as other market-based information for predicting firm's credit risk.

Our study suggests that credit ratings and rating-based hazard rate curves can be viewed as systematic determinants of individual CDS spreads, capturing the through-the-cycle credit risk of underlying bonds. Individual CDS spreads are influenced in addition by current conditions and the point-in-time creditworthiness of the underlying, which is reflected in their pricing. We provide empirical evidence that deviations from the rating-based curves disappear over time and CDS spreads converge towards the rating-based curves.

3 Constructing rating-based CDS curves

In this section, we first explain how the CDS-implied hazard rate is calculated from CDS spread. Then, we detail the Nelson-Siegel model and explain how it is used to produce the rating-based CDS curves.

CDS represents an insurance to protect CDS buyers against a loss due to the firm's default. In a CDS contract, protection sellers compensate protection buyers the amount lost due to a credit event (e.g. default). In return, protection buyers pay periodic premiums to protection sellers during the protection periods up to the credit event. Hence, the pricing of a CDS contract has two components: the protection part and the premium part.

Assume that there are N payments in a CDS contract and the N payment periods are $[t, t_1], [t_1, t_2], ..., [t_{N-1}, t_N]$. A premium is paid at the end of each period, and default takes place only immediately after the premium is paid such that there is no accrual at default. If the market discount rate (r) and the firm's hazard rate (h) are time-varying, then the expected present values of the protection and premium legs at time t can be expressed as[6]:

$$PV_{\text{Protection}} = \mathbb{E}\left[\sum_{i=1}^{N} \exp\left(-\int_t^{t_i} r_u du\right) \exp\left(-\int_t^{t_i} h_u du\right) (1-R)\, h_{t_i}\, \Delta t_i \middle| \mathcal{F}_t\right] \quad (1)$$

$$PV_{\text{Premium}} = \mathbb{E}\left[\sum_{i=1}^{N} \exp\left(-\int_t^{t_i} r_u du\right) \exp\left(-\int_t^{t_i} h_u du\right) k\, \Delta t_i \middle| \mathcal{F}_t\right] \quad (2)$$

where Δt_i is the time period between payments, R is the recovery rate of the underlying CDS, k is the premium (i.e. CDS spreads) paid by the protection buyer to the protection seller, and $\mathcal{F}$ is the information filtration. The fair price of the CDS spread (k) is determined when the two expected present values are the same. Our aim is to obtain h_u implied by the observed CDS spread.

Following Carr and Wu (2011), for each CDS spread of a particular maturity τ we assume a flat term structure for the market discount rate and the hazard rate such that $r_u = r$ and

[6] See Longstaff, Mithal, and Neis (2005)

$h_u = h$. Then, under no-arbitrage,

$$e^{-r(t_i-t)}\, e^{-h(t_i-t)}\, (1-R)\, h\, \Delta t_i = e^{-r(t_i-t)}\, e^{-h(t_i-t)}\, k\, \Delta t_i,\ \forall t_i. \tag{3}$$

Given the recovery rate (R) and the CDS spread (k), the hazard rate h implied by a CDS spread is

$$h = \frac{k}{1-R}. \tag{4}$$

The resulting hazard rates are different for CDSs with different maturities; thus the CDS-implied hazard rate of firm i at time t with CDS maturity τ is expressed by $h_{i,t,\tau} = \frac{k_{i,t,\tau}}{1-R_{i,t}}$, where $R_{i,t}$ is the reported recovery rate in Markit.[7] Thus, such hazard rates capture average default risk of the underlying bond over the lifetime of the CDS analogous to the yields to maturity of corporate bonds.[8]

We assign to each hazard rate the corresponding firm's average credit rating, which is also provided by Markit. Markit calculates a firm's average rating as the average of the Moody's and S&P ratings adjusted to the seniority of the CDS and rounded to eliminate the '+' and '–' levels. The rating provides information about the comparative default risk across rating classes, assuming that all entities in the same rating class will have the same default rate. We then decompose the implied hazard rate $h_{i,t,\tau}$ into:

$$h_{i,t,\tau} = y_{r,t,\tau} + e_{i,t,\tau}, \tag{5}$$

where $y_{r,t,\tau}$ is the hazard rate specific to rating class r on day t for maturity τ, and e is the firm-specific residual. $y_{r,t,\tau}$ is time-varying and maturity dependent, but the same for all firms in the same rating class; y captures the systematic rating class information, while e represents the firm's idiosyncratic information and noise.

[7] Markit requires the data providers to report the quote for CDS spreads and the corresponding recovery rate at the individual entity level.

[8] One alternative to our implied hazard rate would be be the forward hazard rate, such that each CDS of the same underlying is priced using different forward hazard rates at different periods. The empirical challenge is that such forward hazard rates are inherently "unsmooth", subject to a very high level of noise and estimation errors.

The crucial question is then how to estimate the systematic rating class component. One may consider a simple approach of taking a mean or median across the implied hazard rates for each rating class. Such an approach, however, is likely to produce unstable results for ratings and tenors with low number of observations and to be extremely sensitive to outliers, which are often observed in the relatively illiquid CDS market due to its OTC nature. Thus, the resulting hazard rate curves are not likely to be smooth, and will be extremely volatile over time. Also, this simple approach does not account for the term structure of CDS tenors.

In order to overcome these issues, we use the information of the implied hazard rates for CDSs of different maturities jointly, when recovering the rating curves. In particular, we use the Nelson-Siegel model to estimate $y(\tau)$ for each rating class r on day t:[9]

$$y(\tau|\beta_0,\beta_1,\beta_2,m) = \beta_0 + \beta_1\left(\frac{1-\exp\left(-\tau/m\right)}{\tau/m}\right) + \beta_2\left(\frac{1-\exp\left(-\tau/m\right)}{\tau/m} - \exp\left(-\tau/m\right)\right) \tag{6}$$

where β_0 and β_1 are the long-term and short-term hazard rates, β_2 captures a possible hump at the medium term, and m determines the shape and the timing of the hump. Following Hu, Pan, and Wang (2013), among many others, we set $\beta_0 > 0$, $\beta_0 + \beta_1 > 0$, and $m > 0$ to avoid negative $y(\tau)$.

The estimation is performed for each observation date t, using all CDSs of the same rating r on that day. Since $y(\tau)$ is fitted to a group of CDSs with the same rating, $y(\tau)$ will be the same for all CDSs that have the same maturity and the same rating. We do not impose any restrictions on the relation between CDS curves for different rating classes. The ratings provided by rating agencies do not change as frequently as CDS spreads. Therefore, it is not uncommon that a CDS spread with a better rating of the underlying is higher than a CDS spreads with a worse rating of the underlying. Such situations may lead to crossing of the estimated rating-based hazard rate curves. The shape of the fitted curves also reflects the investor preference for short-term or long-term CDS contracts at a given point in time, and contract liquidity may play a role too. Potential crossing of the curves, however, does not necessarily imply the existence of practically exploitable arbitrage opportunities, due to high

[9]In a later section, we show that our approach is superior to the median in prediction for CDS movement.

transaction costs and the OTC structure of the market.

4 Data

The CDS spreads are collected from the Markit database for U.S. firms that are written on their senior unsecured debts. Our CDS sample is from May 2002 to May 2012. We exclude CDSs with default rating because there are too few observations, not enough for an adequate Nelson-Siegel fit. The time to maturity of the CDSs ranges from 6 months to 10 years.[10] Markit reports composite CDS prices, which are the average prices for a given CDS as provided on that day by different contributors. When computing composite prices, Markit performs several checks related to the data quality, to make sure that the market value of the contracts is correctly reflected. For example, Markit tries to eliminate any bias in CDS spreads that may be due to the staleness of reported prices by contributors. Stale prices may be reported, for example, if the CDS quotes are not updated by institutions. Markit ranks all contributors in terms of the number of days the submitted quote for the most liquid 5-year CDS contract remains unchanged. Then in the final calculations, the 50% of quotes with the smallest number of stale days are used, if the total number of contributors is below 13, or 67% of quotes if there are 13 or more contributors.[11]

Overall, our sample covers 431 firms (see Table 1). The firms are relatively evenly distributed across different industries, with the exception of financial firms, which are the smallest group with only seven firms in our sample. Vast majority of firms have CDSs with all maturities. Even the most rarely used 6-month CDS contract is issued for about 80% of the firms, with all but 2 firms having 5-year CDSs. As far as the rating is concerned, the most frequent rating in our sample is BBB, which represents about 39% of the firms. The least frequent rating is AAA, here we have only 3 firms, representing less than 1% of our sample.

[Insert Table 1 around here]

The descriptive statistics of our entire sample are reported in Table 2. Panel A reports

[10] The times to maturity of the CDSs in Markit are 6 months, 1, 2, 3, 4, 5, 7, 10, 15, 20, and 30 years. We select the CDSs with time to maturity 10 years or less, because these CDSs are traded more frequently.

[11] See Markit (2012) for more details on the data cleaning process.

the descriptive statistics for different CDS maturities, and Panel B further splits the sample according to rating classes. Our CDS sample includes more than 3.6 million observations. The average CDS spread is 150.51 bps, with the maximum of more than 20,000 bps and the minimum of just 0.6 bps. The extraordinarily large maximum spread is due to the procedure used to annualize CDS spreads. Normally, the CDS spread should be within 10,000 bps; otherwise, the CDS buyers pay more than the nominal of the CDS contract. However, if firm's default is expected to happen within one year, the premium payment during a protection period is close to 10,000 bps, which results in the annualized CDS spread being above 10,000 bps.[12] When we break down our sample into groups by time to maturity, the 5-year CDS has the largest number of observations (544 thousand observations) while 6-month CDS has the smallest number of observations (308 thousand observations). We also observe that the sample average CDS spread increases with the length of time to maturity; 6-month CDSs have the smallest sample average of 94 bps, while 10-year CDSs have the largest average of 187 bps. There is substantial differences in the CDS spreads across rating classes, with CDS spreads monotonically increasing from AAA- to C-rated bonds for all maturities. For example, for the 6-moth maturity the average CDS spread of C rated bond is more than 40 times larger than that of AAA rated bond (482.45 bps vs. 11.88 bps, respectively).

[Insert Table 2 around here]

The reported average recovery rates are around 40% for all rating classes (see Table 3). There is, however, some variation in the recoveries. AAA-rated securities have the smallest variation in the reported recovery rates, with the standard deviation being only 0.42%, whereas the volatility of the reported recovery rates for C-rated bonds is as high as 6.41%. Since the recoveries are reported per security, CDS contracts with different maturities but with the same underlying bond have the same recovery rates.

[Insert Table 3 around here]

Figure 1 plots the time series of the average CDS spreads and the average recovery rates for different rating classes. During the financial crisis 2007-2010, CDS spreads increase considerably, especially for speculative grade bonds, while recovery rates decrease, consistent with

[12] See Hull, Predescu, and White (2004) for further explanation.

the findings on the negative correlation between default probability and recovery rates.[13] Although changes in CDS spreads for speculative grade bonds are much larger in absolute values, reaching over 60% on March 2009 for C-rated bonds, investment grade securities exhibit the same time series pattern of their CDS spreads.[14] For example, for AA-rated bonds, the CDS spreads have increased by a factor of 12 from 8.9 bps in March 2007 to 110 bps in December 2008. Interestingly, this pattern is not so evident for recovery rates. During the finial crisis the reported recovery rates went substantially down for BB-, B-, and C-rated bonds, but remained relatively stable for higher rated bonds. It suggests that the extremely high CDS spreads for speculative grade bonds during the financial crisis were driven by both increasing default probability and decreasing recovery rates, whereas investment grade bonds were subject only to increasing default risk.

[Insert Figure 1 around here]

To facilitate the empirical analysis, we assign a numerical value to each rating class. We start with assigning 1 to AAA, and then move in steps of one down the ratings, such as, for example, BBB is assigned the numerical value of 4, and C is assigned 7.

5 Fitted CDS curves

The Nelson-Siegel model is fitted using all CDS spreads of the same rating class for a particular day. This process is repeated for each rating class and for each day in our sample period. As an illustration, we first show the fitting results for 23 December 2008, and then discuss the overall properties of the fitted curves and corresponding residuals.

5.1 Fitted CDS curves: Example

Figure 2 shows the estimation results for 23 December 2008. The fitted CDS curves do not cross, and the fitted values are consistent with the order of the ratings. The CDS-implied

[13] See, e.g., Moody's Investor Service, Annual Default Study: Corporate Default and Recovery Rates, 1920-2015 https://www.moodys.com/researchdocumentcontentpage.aspx?docid=PBC_1018455.

[14] Further looking at the time-series dynamics of CDS spreads for different maturities, we find that the pattern is almost identical for all maturities, with the only difference that spreads of shorter-term CDS contracts are generally smaller than those of longer-term contracts.

hazard rates for firms with the best rating (AAA) are the lowest, and the implied hazard rates for the firms with the worst rating (C) are the highest. Furthermore, the CDS curves of the investment grades are flatter than those for the junk grades, suggesting a stable and constant outlook for the investment grade firms. In contrast, with the convex curve for the junk grade firms, the CDS market appears to be more concerned about the short-term solvency of firms with low credit quality.

To alleviate a potential concern that the fitted curves are affected by outliers, Figure 3 plots the fitted curves together with the actual CDS spreads for each rating class on 23 December 2008. In general, the Nelson-Siegel model captures well the variations in CDS spreads. For some ratings, for example AAA, where there are only few observations, the fitted curve just smooths over the observations. Where there are more observations, for example BBB, the curve reflects the main trend.[15]

[Insert Figure 3 around here]

5.2 Properties of the fitted CDS curves and the residuals

Table 4 reports the average values of the parameters of the Nelson-Siegel model over our complete sample for seven rating classes. β_0 monotonically increases from 0.007 for AAA to 0.141 for C rating classes, indicating the increase in the long-term hazard rate for bonds with worse rating classification.

[Insert Table 4 around here]

The resulting average rating curves are presented in Figure 4. We can see that all the rating curves are in the correct order and do not cross. Since we do not impose any restrictions on crossings of the rating curves, we further check if and how often crossings happen in our sample period. A crossing would indicate that the rating-implied hazard rate of better ratings is higher than that of worse ratings. To this extend, we compute a percentage of days per year during which any of the rating curves is misplaced relative to other curves. We find that this

[15]Note that since there is no active secondary market for CDS contracts, the composite spreads reported by Markit represent the spreads of newly issued contracts with set maturities from 6 months to 10 years.

happens, on average, in 6.68% of days per year. This number is largely driven by the years 2003 and 2008. In 2003, the crossings happened in 28% of days predominantly between BB, B, and C rating curves. This is likely to be due to low liquidity of these CDS contracts during the early periods. During the financial crisis of 2008, we observe crossings in 35% of days. These crossings are associated with AA and A rating curves. Before the financial crisis, AA rated firms were considered as very low default risk; but during the financial crisis, AA-rated securities were perceived as riskier. Excluding these two years, the average share of days with curves' crossings is just about 1% per year. Thus, we are confident that the Nelson-Siegel model provides a reasonable fit for the rating-implied hazard rates.

[Insert Figure 4 around here]

Table 5 reports the descriptive statistics of the fitted values y from the Nelson-Siegel model, and Table 6 reports those of the residual components e. The average fitted value, y, monotonically increases from 207 bps for the 6-month CDSs to 341 bps for the 10-year CDSs.[16] Also, within each tenor, the average fitted values monotonically increase from AAA rating to C rating, indicating that the model captures well the pattern in hazard rates. The average residuals, e, vary from 1.21 bps for 5-year AAA CDSs to -484 bps for 6-month CDSs written on C-rated securities. Overall, the average values of the residuals are largely negative, but exhibit substantial variation.[17]

[Insert Tables 5 and 6 around here]

We now analyze the properties of the residual term (e) in more detail and its relation to individual firm characteristics. We choose 5-year CDS contracts as representative and compute relative deviations from the fitted value $e_{i,t,5-year}/y_{r_i,t,5-year}$. We next sort the CDSs into quintiles based on their relative deviations. Panel A of Table 7 reports the average firm characteristics sorted based on the relative deviation. The group with the largest positive deviations contains slightly larger (average size over $77 billion) and riskier firms (debt-to-assets ratio of

[16]Note that the reported minimum for 6-months fitted values is negative of -2.49 bps. This is a single negative observation in our sample, obtained for an AAA curve on 25th of July, 2006. The reason for such result is poor quality of calibration, as on that date there are only two observations to calibrate four parameters. There are no other instances of negative fitted values in our sample.

[17]Further looking at the median residuals, we find that they are closer to zero in absolute values, although remain negative.

0.72), characterized also by higher CDS spreads. The group with the largest negative deviations contains smaller firms (average size over $29 billion) with the lowest leverage ratios (the average debt-to-assets ratio of 0.64). The average deviation for the highest quintile group is 1.16 (with the average CDS spread being 439 bps) and that for the lowest quintile group is -0.64 (with the average CDS spread being 75 bps). There is no systematic difference in liquidity of the CDS contracts across the quintiles. The average number of contributors per CDS contact is very similar across the sub-groups and lies between 5.52 and 5.77 contributors per CDS. We do not find any obvious trend for the firms' rating. The average rating for the lowest quintile group is 4.46 (approximately BBB rating) and that for the highest quintile group is 4.24 (approximately BBB rating, too). This is to be expected: as we form our curves based on ratings, a firm's rating should not be a categorizing factor for the deviations.

The analysis above does not suggest, however, that larger firms have higher CDS spreads and higher deviations. When sorting the firms by size (Panel B of Table 7), the size variation across the portfolios is substantially larger than the size variation across the portfolios sorted on the relative deviation. The average firm size in the first quintile is about $2 billion and in the fifth quintile $226 billion. We found that CDS spreads decrease from 297 bps for small firms to 126 bps for large firms. Larger firms also tend to have better rating compared to small firms (3.39 vs. 5.05) and more liquid CDS contracts. The average number of contributors increases from 3.83 for small firms to 6.43 for large firms. This indicates that in each relative deviation quintile there is a mixture of large and small firms and that firm size is not the key determinant of the relative deviation. Consequently, we do not observe much variation in relative deviations when sorting on firm size.

[Insert Table 7 around here]

6 CDS convergence to the fitted curves

To further assess the importance of the fitted CDS curves, we test if the residual components are persistent or transient. If the former is true, one needs to search for other factors that drive long-term average CDS spreads; if the latter is proved to be the case, rating based information

could be sufficient to assess long-term average CDS spread.

As a preliminary step, we test each individual time series of firm-tenor specific CDS-implied hazard rates (h) and rating-implied hazard rates (y) for stationarity. In particular, for each individual time series, we run the augmented Dicky-Fuller test, allowing for a time trend and using 20 lags. The results in Table 8 illustrate that for the vast majority of the individual time series we cannot reject the null of a unit root at any convectional level. We further run individual time series regressions of the CDS-implied hazard rates on the rating-implied hazard rates and repeat the unit root test based on the residuals from this regression. In majority of cases, the unit root of the residuals can be rejected (at least at the 10% significance level), suggesting that individual CDS-implied hazard rates rating-implied hazard rates are cointegrated.

[Insert Table 8 around here]

Having established that most of individual time series of the CDS-implied hazard rates and Nelson-Siegel fitted values are conintegrated, we now test if positive (negative) deviation induces a decrease (increase) in h over time. To answer this question, we estimate a panel regression in the spirit of the error correction model. Here we regress changes in the individual CDS-implied hazard rates (h) onto changes in rating-implied hazard rates (y), and the past deviations (e). The model allows us to test if, on average, the deviations are corrected over time and the individual CDS-implied hazard rates converge towards the rating-based hazard rates. Specifically, we run the following panel regression with firm-maturity fixed effects and report cluster-robust standard errors (clustered by firms) for the estimated coefficients:

$$\Delta h_{i,t,\tau} = \beta_0 + \beta_1 \, \Delta y_{r_i,t,\tau} + \beta_2 \, e_{i,t-j,\tau} + \eta_{i,t,\tau} \tag{7}$$

where Δ indicates a change in the variable between time t and time $t - j$. We consider the weekly and monthly difference in our panel regression (i.e. $j = 5$ and $j = 20$ trading days). $y_{r_i,t,\tau}$ is the hazard rate obtained from the relevant CDS curve for firm i and CDS maturity τ at the corresponding rating r. Δy could be due to changes in the various market factors and conditions, such as liquidity, risk premia, perception of the aggregate credit risk in the economy, or supply and demand shocks in the CDS market. e measures the past deviation of the CDS-implied hazard rate, h, from the fitted rating curve, y. A negative β_2 indicates

convergence of h towards y, further supporting the importance of the rating curves as a source of credit-risk related information for investors.

Table 9 reports the panel regression results. Model 1 reports the results for one week changes and Model 2 reports the results for one month changes. The loadings on $\Delta y_{r_i,t,\tau}$ and $e_{i,t-j,\tau}$ are all significant at the 1% level. Positive loadings on $\Delta y_{r_i,t,\tau}$ indicate that times-series movement of the fitted rating curves explains the movement of the individual-CDS implied hazard rates. Regarding the past residual term, we observe negative loadings on $e_{i,t-j,\tau}$ for both 5- and 20-day differences. CDS-implied hazard rate increases to correct for a negative residual in the previous period, and decrease for a positive residual, thus, converging to the corresponding rating based curve over time.

[Insert Table 9 around here]

To assess the robustness of our results, we repeat the analysis separately for each individual year from 2002 to 2012, different rating classes, individual CDS maturities, and industries. The results are tabulated in Appendix A. The robustness check confirms that our results are not driven by any particular sub-set of data. In particular, over 7 rating classes, the convergence results are not significant only for AA class.[18] The results for all other rating classes are consistent with the main findings. The estimated coefficients are also quite similar across rating classes, with those for monthly changes being somewhat larger in absolute values for CDSs written on low-rated bonds (B and C rating classes), indicating faster convergence to the rating curves for riskier underlyings. Over the period 2002 to 2012, the convergence in hazard rates is statistically significant in all years. The fastest convergence can be seen in year 2002, whereas the slowest convergence is detected during the year 2007, thus, at the start of the financial crisis. Splitting the sample by the CDS maturity also produces statistically significant convergence rate for all maturities. As far as different industries are concerned, the loadings on the past residual term are always negative; however, they lack strong statistical support for Consumer Goods, Financials, and Telecommunication Services. Overall, we find positive loadings on $\Delta y_{r_i,t,\tau}$ (not reported to save space) and negative loadings on $e_{i,t-j,\tau}$ throughout all specification. The results reinforce our previous finding that the individual CDS-implied

[18]Further inspection of the annual variation of the convergence speed for this rating class finds convergence in most of years, except during financial crisis in 2008 and 2009.

hazard rates tend to converge to the respective fitted rating curves over time.

6.1 Convergence speed

The panel regression results in the previous section suggest that individual CDS spreads tend to converge to the respective fitted CDS curves over time. In this section, we further investigate the speed of this convergence on the aggregate level and based on individual CDS deviation.

The key characteristic of the convergence speed at the aggregate level is the estimated parameter β_2. To assess the average speed of convergence, we conduct the impulse-response analysis, using the estimated coefficients of Equation 7. In our panel regression framework, the expected change in the CDS-implied hazard rate can be expressed as:

$$E[\Delta h_t] = \beta_0 + \beta_1 \, \Delta y_t + \beta_2 \, e_{t-1}. \tag{8}$$

Equation (8) implies that, if there is a unit increase in residual term $e_0 = 1$ at $t = 0$, then the resulting time-series of CDS-implied hazard rates can be expressed as $h_t = (1 + \beta_2)^t$, assuming that $y_0 = 0$ and $\beta_0 = 0$. If $\beta_2 < 0$, then h_t converges to 0. The impulse-response analysis is detailed in Appendix B.

Figure 5 plots the impulse response functions based on our estimates of β_2 for 5- or 20-day periods. For the 5-day case, after one year (52 weeks) 15% of a unit shock in the residual e is still reflected in the individual CDS-implied hazard rates. During slow convergence periods, such as year 2007, about 17% of the unit shock is still visible in the CDS-implied hazard rates after one year. At the same time, during periods of fast convergence (e.g., year 2002) the unit shock decreases to 15% of its level already after 9 weeks, and it becomes negligibly small in less than 20 weeks.

[Insert Figure 5 around here]

Since the estimate of β_2 is obtained from a panel regression, it can be interpreted as the average convergence speed. Since there may be substantial variations in individual CDSs over time, we now analyze the individual realized convergence speed in our sample. We define the

individual realized convergence speed, s, as

$$s_{i,t,\tau} = \log \frac{|h_{i,t,\tau} - y_{r_i,t,\tau}|}{|h_{i,t-j,\tau} - y_{r_i,t-j,\tau}|},\ j = 5 \text{ or } 20 \text{ days}, \tag{9}$$

where $h_{i,t,\tau}$ is the time t, τ-maturity CDS-implied hazard rate from Equation (4) for firm i, and $y_{r_i,t,\tau}$ is the time t, τ-maturity hazard rate for the rating r to which firm i belongs. Therefore, if the distance between $h_{i,t,\tau}$ and $y_{r_i,t,\tau}$ (i.e. $|h_{i,t,\tau} - y_{r_i,t,\tau}|$) is smaller than the distance between $h_{i,t-j,\tau}$ and $y_{r_i,t-j,\tau}$ (i.e. $|h_{i,t-j,\tau} - y_{r_i,t-j,\tau}|$), it means that h is approaching y from time $t-j$ to t. If $|h_{i,t,\tau} - y_{r_i,t,\tau}|$ is larger than $|h_{i,t-j,\tau} - y_{r_i,t-j,\tau}|$, it means that h is moving away from y. The smaller the ratio of the two, the faster is the convergence speed.

After taking natural logarithm of the ratio, the convergence speed is interpreted as follows:

$$s_{i,t,\tau} \begin{cases} < 0, & h \text{ is approaching } y \text{ (convergence);} \\ \geq 0, & h \text{ is moving away from } y \text{ (divergence).} \end{cases} \tag{10}$$

Larger positive values of $s_{i,t,\tau}$ indicate h is moving faster away from y, while the *larger negative* values of $s_{i,t,\tau}$ indicate h is approaching *faster* towards y.

Figure 6 plots the monthly convergence speed for $j = 5$ and 20 days. Here we use all daily observations in a month to calculate monthly convergence speed s_m as the average of daily $s_{i,t,\tau}$ within this month. Not surprisingly, we find a mixed level of convergence speed over the sample period and s_m is particularly volatile during the 2008 financial crisis.

[Insert Figure 6 around here]

The descriptive statistics for convergence speed s_m are reported in Table 10 (5-day intervals) and Table 11 (20-day intervals). The average s_m for the 5-day and 20-day cases are both negative. There is, however, considerable variations across maturities and ratings. For example, on average the strongest convergence is observed for 20-day steps for 6-month CDS contracts written on AA underlying. The convergence of -0.022 is 10 times stronger than that of the average contract. Some tenors, e.g., 4-year CDS contracts even exhibit divergence on average (the average $s_m = 0.01$). At the same time, even for these tenors the convergence speed is highly volatile (0.136) and for individual contacts can vary from 0.439 to -0.382.

[Insert Tables 10 and 11 around here]

Given that there is no clear pattern in individual convergence speed across ratings and maturities, we test if the convergence speed depends on the magnitude of the deviation ($|e_{i,t-j,\tau}|$): if $h_{i,t-j,\tau}$ is close to $y_{r_i,t-j,\tau}$, the propensity to converge may be smaller, whereas the propensity to converge may be higher for larger deviations. We use the relative deviation measure ($e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$) to remove the scale of y and to prevent undue influence of outliers. To test our hypothesis, we sort our daily $s_{i,t,\tau}$ into five portfolios, based on their past relative deviations, $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$: portfolio 1 consists of the largest negative $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$ and portfolio 5 consists of the largest positive $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$. We expect portfolios 1 and 5 to converge faster than other portfolios. We repeat the previous procedure to produce the monthly average convergence speed for the five portfolios ($s_{p,m}, p = 1, 2, ..., 5$).

Table 12 reports the results of the one-sided t-test for the null hypothesis that the monthly average convergence speed is non-negative for the five portfolios. The last two columns of the table report the paired t-test results if the convergence speeds of portfolio 1 (portfolio 5) is faster and more negative than portfolio 3. The results are reported for all CDS contracts in our sample, as well as separately for individual rating classes. Panel A reports the results for 5-day time difference, while Panel B reports the results for 20-day time difference. The results for the 20-day difference are stronger, compared to those for the 5-day difference. Among the five portfolios, portfolio 5 with the largest positive relative deviation has the largest negative (or fastest) convergence speed on average. In most cases, the convergence speed is U-shaped; portfolio 3 has usually slower convergence speed as compared to portfolios 1 and 5. Portfolios 3 and 4 also often exhibit divergence, with the convergence speed being positive. The convergence speed for the rating C lacks statistical support for almost all portfolios. This suggests that high risks of the underlying and corresponding CDS contracts make individual CDS-implied hazard rates more volatile and strongly driven by the idiosyncratic firm characteristics rather than average rating-implied hazard rates. Another remarkable feature is that, although portfolio 5 (with the highest positive deviations) exhibits on average stronger convergence speed, the speed is quite volatile across rating classes and is even positive for the AA rating. The convergence speed of portfolio 1 (with the largest negative deviations) is more stable across rating classes and is always negative.

This finding reflects that CDS spreads of the relatively undervalued contracts are more likely to increase, than the spreads of overvalued contracts to decrease. This pattern sheds some light on the structure and the bargaining powers in the CDS market. The CDS is traded in the OTC market, with lower transparency relative to e.g. the stock market. The key participants are banks, insurance companies, and hedge funds. According to Mengle (2007), banks tend to be net buyers of CDSs, whereas hedge funds and insurance companies are net sellers. Fast and stable reversion of relatively low spreads to the rating-based curves suggests that the sophisticated protection sellers are more concerned with under pricing and, thus, quickly raise their quotes in the following transactions. Protection buyers, on the contrary, are less effective in pushing for lower price for the overvalued contracts. This may be due to various reasons, including the lack of bargaining power of the protection buyers, higher demand for protection compared to its supply, or the different ways the protection sellers and buyers use the contracts. If a buyer purchases the CDS for hedging purposes, the contract is likely to be held until maturity. The frequency of trading on the buy side is lower, thus, overpricing may not be always corrected. Protection sellers, on the contrary, can sell CDS contracts on a more frequent basis, and quote a higher price, if the contract has been underpriced.

[Insert Table 12 around here]

As for time variation of convergence speed, Figure 7 plots the time series of monthly average convergence speed for portfolios 1 and 5 for the 20-day time difference. The time-series plot clearly shows that although the convergence speed for these portfolios is mostly negative, it is quite volatile. The volatilities of both portfolios are similar around 13%. We also see worse convergence during the financial crises years 2007 and 2008 (showing positive $s_{5,m}$).

6.2 Convergence as a trading signal

The convergence results in the previous section suggest a potential profit-making opportunity. Since we observe a significantly negative loading on $e_{i,t-j,\tau}$ in our panel regressions, we can predict the future movement of the individual CDS spreads. Define the 5- or 20-day holding-period return of the CDS spreads (k) as:

$$r_{i,t,\tau} = \frac{k_{i,t,\tau}}{k_{i,t-j,\tau}} - 1, \ j = 5 \ \text{ or 20 days.} \tag{11}$$

One can expect a positive holding period return if one takes a long position in a CDS with a negative $e_{i,t-j,\tau}$ at time $t-j$ and then a short position in the CDS with the same terms at time t when the CDS spread moves up from time $t-j$ to t. Likewise, in the case of a positive $e_{i,t-j,\tau}$, a positive holding period return can be expected if one lakes a short position in a CDS with a positive $e_{i,t-j,\tau}$ at time $t-j$ and a long position in the identical contract at time t, as the CDS spread moves down from time $t-j$ to t. Moreover, since the larger deviation between h and y has a stronger tendency to converge, more profit per trade is expected if one trades between the largest negative $e_{i,t-j,\tau}$ and the largest positive $e_{i,t-j,\tau}$.

To test this proposition, we construct the following trading strategy. Every day we identify CDS contracts with a negative (positive) relative deviation and take long (short) position. We hold these contracts for 5 (or 20) trading days, and then add to this portfolio the opposite positions in the CDSs with the same underlying firms and maturity. This portfolio is kept until the CDS maturity. On the next day, a new portfolio is formed in a similar way. We then assess the properties of the average returns an investor earns per year while following such a trading strategy.

Consider a simplified example: assume that at time t we identify an underpriced (with negative relative deviation) 3-year CDS on company XYZ with a spread of k_t bps and take a long position. After 5 days at time $t+5$ we reverse the strategy and take a short positing in a 3-year CDS contract written on XYZ, with the spread being k_{t+5}. Nowadays CDS contracts are standardized, i.e. all the future payments happen at the end of a calendar period (e.g., end of quarter) regardless of the day when the contract was signed. Our model the predicts a profit of $k_{t+5} - k_t$ bps per year over the next three years.

To test this strategy, we assess the performance of portfolios sorted on the relative deviations, and the performance of a long-short portfolio that longs portfolio 1 (largest negative $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$) and shorts portfolio 5 (largest positive $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$).

Table 13 reports the average returns and their standard deviations for the five portfolios and the long-short strategy for our sample, as well as the t-statistics for the mean difference from zero. Panel A reports the returns for 5-day holding period and Panel B reports the returns for 20-day holding period. As expected, we find a positive and highly significant mean return for portfolio 1 (3.2% and 8.2%, respectively, for 5- and 20-day cases), and a negative and significant mean return for portfolio 5 (-0.4% and -0.8%, respectively, for 5- and 20-day cases). The mean returns monotonically decrease from portfolio 1 to 5, with the long-short strategy producing 3.7% and 9% for the 5- and 20-day holding periods, respectively. Note, that the returns in Equation (11) are relative to the CDS spread at the beginning of the investment period. Thus, 8.2% strategy return per year is equivalent to 12.3 extra bps per year, given the average CDS spread of 150 bps.

[Insert Table 13 around here]

We next examine the portfolio performance for different years, CDS maturities, rating classes, and industries. We discuss below the key findings of the sub-sample analysis; the full set of results is tabulated in Appendix C. The results are generally consistent with our main findings for all sub-samples, with the long-short portfolio delivering positive and highly significant average returns. The year 2002 is the only period where the average long-short portfolio returns for the 20-day trading strategy are not statistically significant, albeit the difference between portfolios 1 and 5 is still positive. At the same time, consistent with our convergence results, it is portfolio 1 (with the largest negative relative deviations) that consistently delivers positive returns, whereas the performance of portfolio 5 (with the largest positive deviations) is unstable. For example, portfolio 5 diverges in 2002 and 2008, as well as for the rating C and Financial sector. The corresponding trading strategy returns are all positive and significant, whereas convergence to rating-based curves should have lead to negative returns. We also do not see substantial converge for longer maturity CDSs (i.e. 4 years or longer). Here the average returns of portfolio 5 are not statistically significant. These results again highlight that investors (in particular, protection sellers) are more concerned with under pricing CDS contracts, than over pricing them. Negative deviations from the rating-based curves are quickly corrected in the market, presenting a persistent profitable investment opportunity. Positive deviations, on the contrary, are not always corrected. The revisions are especially rare during turbulent

market conditions (e.g., the financial crisis) or for longer maturity CDSs, for which pricing mistakes have prolonged impact.

6.3 Portfolio returns in the presence of transaction costs

The portfolio performance discussed above seems quite attractive. Practically achievable returns, however, may be lower given substantial transaction costs in the CDS market. In this section we adjust the trading strategy returns to the potential transaction costs in order to more precisely quantify the achievable investor returns.

Since the actual bid-ask spreads are not available in Markit, we rely on the estimated transaction costs from the literature. Biswas, Nikolova, and Stahel (2015) suggest that in the CDS market a round trip transactions costs account for 14 bps. Similar estimate can be found in Tang and Yan (2017). Given that the average CDS spread in our sample is around 150 bps, we set the expected transaction costs to be 10% of the spread to be consistent with the literature.

The payments for a CDS contract are made periodically, until maturity of the contract, so are the cash flows generated by our trading strategy. The trading costs, however, are incurred only twice: when taking long (short) positions in the contracts the first time and then taking the opposite positions 5 or 20 trading days later. Obviously, paying 14 bps of costs for an average return of 12 bps earned for one year makes little economic sense. If this return is earned for 10 years, however, the 14 bps costs do not jeopardise the overall profitability of the strategy. Thus, in order to properly account for the impact of the transaction costs on the documented strategy returns, we need to amortize the costs over the lifetime of the contract.

To adjust the returns for transaction costs we spread the total costs of 10% of the CDS spread across two transactions (resulting in 5% cost per transaction) and the number of protection periods (N) during which the contracts are valid. For those cases in which we first take long positions in CDSs, and then short positions (e.g., portfolio 1 with negative relative deviations), we adjust the quoted CDS spreads ($k_{i,t-j,\tau}$ and $k_{i,t,\tau}$) in the following way:

$$\tilde{k}_{i,t-j,\tau} = (1 + 5\%/N) \cdot k_{i,t-j,\tau} \tag{12}$$

$$\tilde{k}_{i,t,\tau} = (1 - 5\%/N) \cdot k_{i,t,\tau} \tag{13}$$

$$\tilde{r}_{i,t,\tau} = \frac{\tilde{k}_{i,t,\tau}}{\tilde{k}_{i,t-j,\tau}} - 1, \; j = 5 \text{ or } 20 \text{ days.} \tag{14}$$

This cost adjustment implies that an investor pays more on the long leg of the trade and receives less on the short leg of the trade, leading to smaller returns. When considering portfolio 5, in which short positions should be taken first in order to achieve profits, we reverse the order of adding and subtracting 5% of the spread, in order to assure that the trading costs lead to smaller in absolute values return of portfolio 5.[19]

Table 14 reports the transaction cost adjusted returns for portfolios 1 and 5, as well as the performance of the long-short portfolio with 5- and 20-day trading periods. The long-short portfolio still delivers positive and significant returns, although transaction costs reduce their magnitude. The returns drop from 0.037 to 0.009, and from 0.090 to 0.062 for 5- and 20-day trading respectively. The transaction costs turn out to be more harmful for portfolio 5 (with overprices CDSs). The average return of this portfolio is no longer negative. Any gains from the convergence of the CDS spreads to the rating-implied curves are completely offset by the transaction costs. At the same time, the average returns on portfolio 1 remain positive and significant. Even after accounting for transaction costs, the returns for the 20-day trading strategy are as high as 6.5% per year. Betting on relatively underpriced CDS contracts remains a profitable strangely, consistent with the strong and stable convergence results for CDSs with negative deviations relative to the corresponding rating curves.

[Insert Table 14 around here]

We further assess the impact of transaction costs for different years, CDS maturities, ratings, and industries. The detailed results are tabulated in Appendix D. All the sample splits consistently indicate significant profitable opportunities for portfolio of underprices CDS contracts,

[19] We apply the transaction costs only to portfolios 1 and 5, since the trading direction in these portfolios is clearly determined, and we attempt to verify if the performance of the long-short portfolio remains positive after inclusion of transaction costs.

whereas profitability of the trading based on overpriced contracts often disappears. Betting on spread increase of the underpriced CDSs have been especially profitable in 2008, with the average return being 24% per year. The strategy lost money only in 2003 (-4.7% average return for 20-day trading periods). We do not document any other instances of significantly negative average returns for portfolio 1 across any of the sub-samples.

7 Robustness

The results reported in this paper are based on the initial calibration of the rating-based hazard rates using the Nelson-Siegel model. As a robustness check, we use two simple specifications for the the systematic component of CDS-implied hazard rates. The first one is the median of the hazard rates across all CDS contracts with the same maturity. The second one is the median with respect to the rating class and maturity. We re-estimate the panel regression in Equation (7), using these medians as new measures of the systematic component y, and the deviations from them as e. The results in Table 15 indicate that CDS-implied hazard rates also converge to the median hazard rates. These results confirm the importance of the systematic information for CDS pricing. When the convergence to the Nelson-Siegel based rating component and the median is considered jointly, we cannot find any evidence of the convergence towards the median, whereas we still find significant convergence towards the Nelson-Siegel based hazard rates. The loadings on the deviations from the fitted values are negative and significant for both 5- and 20-day trading periods, but they are not significant for deviations from the median. Thus, we conclude that our approach of using the Nelson-Sigel model to back out the systematic component allows us to extract a stronger convergence signal, as compared to using median values.

[Insert Table 15 around here]

8 Conclusion

In this paper, we use individual senior unsecured tier CDS spreads of U.S. firms from May 2002 to May 2012 and construct daily rating-based hazard rate curves using the Nelson-Siegel model.

These rating curves are shown to be good proxies for the long-run mean of CDS-implied hazard rates. The individual deviations from these curves are not persistent, and the individual CDS-implied hazard rates converge towards the rating curves already over 5- and 20-day periods. Moreover, the larger the deviation is, the faster the hazard rate converges to the fitted curve. Hence, by taking a long position in the portfolio of CDSs with the largest negative deviation and a short position in the portfolio of CDSs with the largest positive deviation, one can generate an average profit of 3.7% (9%) per year for the 5-day (20-day) trading strategy. The convergence results are stronger and more stable for relatively undervalued CDSs. This suggests a prompt reaction on the side of protection sellers, who revise CDS spreads upwards trying to avoid under pricing.

The rating-based CDS curves, proposed in this paper, provide long-run means for CDS-implied hazard rates and, hence, CDS spreads themselves, across rating classes and maturities. Thus, they are potentially useful in credit risk management. The documented convergence of CDS spreads towards the fitted curves over time has two implications. First, on a theoretical level, it suggests that other factors that impact CDS spreads in the short-run, such as liquidity or shocks to supply/demand, do not have persistent impact on top of anything which is already incorporated into the average CDS spread within each rating class. Second, on a practical level, the deviations from the fitted curves serve as trading signals, indicating exploitable profit-making opportunities in the CDS market, which are still pronounced even after accounting for transitions costs. The results are robust to changes in sample periods, CDS maturities, and industries.

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Table 1: Sample Firm Distribution

The table reports the number and percentage of firms in our sample having different rating classes, belonging to different industries, and having CDSs with different maturities from May 2002 to May 2012. The total number of firms with different ratings is different form the total number of firms with different industry classification, due to the fact that some firms have change their rating class during our sample.

Industry	#Firms	Percentage	Maturity	#Firms	Percentage	Rating	#Firms	Percentage
Basic Materials	34	7.89	6-month	344	79.81	AAA	3	0.70
Consumer Goods	76	17.63	1-year	388	90.02	AA	11	2.55
Consumer Services	73	16.94	2-year	383	88.86	A	74	17.17
Energy	44	10.21	3-year	402	93.27	BBB	167	38.75
Financials	7	1.62	4-year	351	81.44	BB	85	19.72
Healthcare	38	8.82	5-year	429	99.54	B	73	16.94
Industrials	62	14.39	7-year	401	93.04	C	20	4.64
Technology	42	9.74	10-year	395	91.65			
Telecommunications Services	13	3.02						
Utilities	31	7.19						
Other	11	2.55						
Total	431	100.00						

Table 2: CDS Descriptive Statistics

This table reports descriptive statistics for the sample CDS spreads from May 2002 to May 2012. Panel A splits CDS contracts according to their times to maturity and reports sample means (in basis points), standard deviations, maximum and minimum values, and the number of observations. Panel B further splits each of the maturities according to the rating class and reports the average CDS spreads for a given rating-maturity sub-group.

Panel A: Full Sample Period

	All	6-month	1-year	2-year	3-year	4-year	5-year	7-year	10-year
Mean	150.51	93.50	109.65	126.23	143.17	169.99	173.65	179.17	186.55
Std	314.29	311.06	358.90	336.07	312.24	340.50	296.33	283.21	266.02
Max	24,559.17	14,652.77	24,559.17	11,462.29	10,637.10	10,120.71	10,291.38	9,980.42	9,643.90
Min	0.60	0.60	0.81	0.79	1.28	1.45	2.33	3.27	4.34
# Obs	3,658,096	308,245	468,378	471,722	506,898	359,003	544,392	504,271	495,187

Panel B: Rating class averages

	6-month	1-year	2-year	3-year	4-year	5-year	7-year	10-year
AAA	11.88	11.98	16.21	19.74	24.07	26.29	31.54	36.46
AA	22.40	20.81	24.66	27.42	36.66	35.16	40.60	45.60
A	24.53	31.48	37.08	44.89	51.19	58.38	65.10	73.00
BBB	51.46	62.39	73.26	85.00	96.70	106.48	115.49	124.60
BB	159.45	168.40	200.88	228.04	275.67	274.62	292.81	302.47
B	331.31	330.78	372.86	395.26	479.70	435.33	459.54	460.97
C	482.45	629.55	658.31	654.90	889.55	668.25	670.6	654.80

Table 3: Recovery Rates Descriptive Statistics

This table reports descriptive statistics (in percent) for the reported recovery rates from May 2002 to May 2012, for all CDS contracts as well as splitting the sample according to the rating class of the underlying security.

	All	AAA	AA	A	BBB	BB	B	C
Mean	39.40	39.88	39.90	39.66	39.67	39.16	38.14	37.61
Std	2.67	0.42	0.84	1.16	1.42	2.94	5.57	6.42
Max	75.00	43.75	45.45	50.00	50.00	75.00	72.50	63.38
Min	7.50	36.92	20.00	26.08	20.83	15.00	7.50	7.50
# Obs	3,658,096	27,702	114,406	786,611	1,707,637	545,326	389,567	86,847

Table 4: Average Values of Fitted Nelson-Siegel Parameters

This table reports the average values of the parameters of the Nelson-Siegel model for different rating classes fitted from May 2002 to May 2012.

	AAA	AA	A	BBB	BB	B	C
β_0	0.007	0.010	0.009	0.012	0.018	0.056	0.141
β_1	-0.006	-0.004	-0.003	-0.001	0.010	0.007	-0.029
β_2	0.002	0.006	0.017	0.040	0.093	0.072	-0.013
m	5.518	5.255	5.749	6.852	5.838	4.056	3.390

Table 5: Descriptive Statistics of Nelson-Siegel Rating-based Fitted Values of Hazard Rates (y)

This table reports descriptive statistics of the fitted values of the hazard rates using the Nelson-Siegel model (y) to the sample of CDS spreads from May 2002 to May 2012. Panel A splits the fitted hazard rates according to the time to maturity, and it reports sample means (in basis points), standard deviations, maximum and minimum values. Panel B further splits each of the maturities according to the rating class and reports the average hazard rates for a given rating-maturity subgroup.

Panel A: Fitted Value by Tenor

	6-month	1-year	2-year	3-year	4-year	5-year	7-year	10-year
Mean	207.10	224.74	251.24	278.81	320.30	319.49	328.90	341.42
Std	398.22	369.97	350.80	346.31	368.16	341.21	331.54	325.59
Max	7,439.95	7,407.89	7,345.04	7,283.92	7,224.56	7,166.99	7,057.25	6,905.98
Min	-2.49	2.25	2.69	3.70	4.98	5.08	8.31	11.13
#Obs	308,245	468,378	471,722	506,898	359,003	544,392	504,271	495,187

Panel B: Fitted Value by Tenor and Rating

	6-month	1-year	2-year	3-year	4-year	5-year	7-year	10-year
AAA	20.86	20.86	27.49	33.62	40.79	42.52	51.75	60.51
AA	56.89	51.19	59.63	65.99	88.14	78.89	89.70	99.03
A	64.31	71.15	83.94	94.96	115.85	112.99	124.83	135.98
BBB	113.44	132.45	154.41	173.05	198.41	201.15	219.32	234.20
BB	291.68	307.73	361.07	399.01	477.31	459.08	486.01	500.57
B	765.89	718.59	764.18	808.07	923.06	852.81	884.43	889.61
C	1,216.57	1,183.34	1,181.09	1,167.16	1,264.78	1,137.98	1,161.84	1,163.06

Table 6: Descriptive Statistics of Nelson-Siegel Residuals (e)

This table reports descriptive statistics of the residuals e (in basis points), measured as deviations of individual CDS-implied hazard rates from their fitted values based on Nelson-Siegel model from May 2002 to May 2012. Panel A splits the residuals according to the time to maturity, and it reports sample means (in basis points), standard deviations, maximum and minimum values. Panel B further splits each of the maturities according to the rating class and reports the average hazard rates for a given rating-maturity sub-group.

Panel A: NS Residual by Tenor

	6-month	1-year	2-year	3-year	4-year	5-year	7-year	10-year
Mean	-60.05	-52.06	-51.16	-49.98	-49.15	-39.29	-39.75	-39.44
Std	363.44	397.59	362.29	337.77	349.60	326.91	304.59	291.36
Max	10,711.70	22,213.45	10,495.51	9,281.39	9,331.23	9,046.60	8,992.77	8,695.71
Min	-4,688.37	-3,983.70	-3,429.36	-3,122.73	-3,001.48	-3,569.45	-3,221.28	-4,276.76
#Obs	308,245	468,378	471,722	506,898	359,003	544,392	504,271	495,187

Panel B: NS Residual by Tenor and Rating

	6-month	1-year	2-year	3-year	4-year	5-year	7-year	10-year
AAA	-1.10	-0.94	-0.52	-0.79	-0.74	1.21	0.71	0.15
AA	-19.59	-16.54	-18.56	-20.33	-27.11	-20.33	-22.08	-23.08
A	-23.71	-19.18	-22.63	-20.78	-30.97	-16.39	-17.13	-15.21
BBB	-28.37	-29.58	-33.59	-32.59	-38.21	-25.09	-28.36	-28.07
BB	-33.57	-35.03	-35.32	-27.81	-26.86	-9.12	-9.01	-7.12
B	-276.79	-220.87	-196.12	-196.99	-185.51	-170.31	-163.56	-163.87
C	-484.42	-255.54	-204.10	-182.72	57.99	-110.55	-129.04	-146.32

Table 7: Properties of the Residual Term

This table sorts all CDS observations into quintile portfolios based on the size of the relative deviation of the CDS-implied hazard rate from the rating-implied one (e/y) (Panel A) and based on firm size (Panel B). For each quintile portfolio, it reports the average relative deviation, firm size, debt value, leverage ratio, rating, as well as the number of CDS contributors and the corresponding CDS spreads. The sample period is from May 2002 to May 2012.

Panel A: Sort on Relative Deviation

	Negative = [1]	[2]	[3]	[4]	Positive = [5]
e/y	-0.64	-0.42	-0.22	0.08	1.16
Size ($ Million)	29,104.76	45,104.07	48,436.61	65,587.98	77,567.74
Debt ($ Million)	21,507.23	35,357.75	38,304.26	55,428.44	69,144.39
Lev = (Debt/Assets)	0.64	0.64	0.66	0.69	0.72
Rating	4.46	4.04	4.02	4.18	4.24
# Contributor	5.52	5.69	5.77	5.65	5.54
CDS Spread (bp)	74.67	100.57	137.69	215.98	438.95

Panel B: Sort on Firm Size

	Small Size = [1]	[2]	[3]	[4]	Large Size = [5]
e/y	0.00	-0.04	-0.04	-0.03	0.07
Size ($ Million)	2,071.66	4,942.45	9,843.25	21,802.22	225,922.31
Debt ($ Million)	1,393.45	3,163.38	6,156.92	14,321.33	193,697.99
Lev = (Debt/Assets)	0.69	0.63	0.62	0.65	0.74
Rating	5.05	4.56	4.15	3.81	3.39
# Contributor	3.83	5.09	6.02	6.79	6.43
CDS Spread (bp)	297.29	230.85	164.80	152.59	125.88

Table 8: Augmented Dicky-Fuller Test for Stationarity of the Hazard Rates

This table reports the percentage (%) of individual time series of CDS-implied hazard rates (h), Nelson-Siegel rating-based fitted values (y), and residuals from the individual time series regressions of h on y, for which the augmented Dicky-Fuller test with a time trend and 20 lags fails to reject the null hypothesis of no unit rout. The results are reported for all CDSs in our sample from May 2002 to May 2012, as well as for individual rating classes, using different critical values (corresponding to 1%, 5%, and 10% significance levels).

	Hazard Rate (h)			Nelson-Siegel Fitted Value (y)			Residual from regressing h on y		
Sign. level	1%	5%	10%	1%	5%	10%	1%	5%	10%
ALL	91.69	83.83	76.10	96.31	92.31	87.90	43.60	25.16	17.97
AAA	100.00	100.00	87.50	100.00	100.00	100.00	8.33	0.00	0.00
AA	98.68	92.11	81.58	94.74	82.89	72.37	13.16	9.21	5.26
A	90.16	83.24	73.41	94.90	91.80	86.52	27.87	12.57	8.38
BBB	88.88	78.82	70.65	94.60	89.45	84.87	44.08	25.06	18.61
BB	93.43	86.13	80.66	98.36	95.62	92.34	54.63	33.94	24.14
B	97.26	93.52	88.53	99.75	98.25	95.26	56.27	38.08	27.03
C	94.57	86.05	75.97	99.22	93.02	87.60	43.41	15.50	8.53

Table 9: Panel Regression Results for Convergence of CDS-implied Hazard Rates to their Rating Curves

This table reports the panel regression results of the changes in individual CDS-implied hazard rates onto changes in the rating-implied hazard rates, as well as past deviation. The sample period is from May 2002 to May 2012. Model 1 uses time difference of one week (5 trading days), and Model 2 uses time difference of one month (20 trading days). The robust standard errors clustered by firm are used, and the corresponding t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

	Model 1	Model 2
$\Delta y_{r_i,t,\tau}$	0.285***	0.545***
	[6.93]	[7.25]
$e_{i,t-5,\tau}$	-0.035***	
	[-8.34]	
$e_{i,t-20,\tau}$		-0.127***
		[-8.41]
Firm-maturity dummies	Yes	Yes
Adj R-sqr	0.05	0.15
# Obs	3,482,714	3,342,077

Table 10: Descriptive Statistics for Convergence Speed: 5-Day Intervals

This table reports the descriptive statistics (average, standard deviation, maximum, and minimum) for the monthly average of convergence speed. The sample period is from May 2002 to May 2012 (121 months). s_m is the monthly convergence speed of the daily calculation within the month. The calculation for convergence speed is based on Equation (9).

Panel A: 5-day Convergence Speed by Tenor

	All	6-month	1-year	2-year	3-year	4-year	5-year	7-year	10-year
Mean	-0.000	0.005	-0.001	-0.000	-0.000	0.003	0.000	0.000	0.000
Std	0.040	0.067	0.049	0.044	0.042	0.039	0.037	0.036	0.036
Max	0.125	0.209	0.166	0.149	0.135	0.125	0.120	0.108	0.138
Min	-0.103	-0.176	-0.116	-0.126	-0.110	-0.101	-0.107	-0.101	-0.094
# Obs	121	116	121	121	121	80	121	121	121

Panel B: 5-day Convergence Speed by Tenor and Rating

	6-month	1-year	2-year	3-year	4-year	5-year	7-year	10-year
AAA	-0.013	0.025	0.032	-0.049	0.016	0.044	0.074	0.002
AA	0.017	0.003	0.008	0.002	0.006	-0.001	-0.000	0.003
A	0.011	0.000	0.001	-0.000	0.005	-0.000	0.000	-0.000
BBB	0.004	-0.001	-0.001	-0.001	0.002	-0.000	-0.001	-0.001
BB	0.003	-0.003	0.003	0.003	0.002	0.001	0.003	0.003
B	0.003	0.004	0.003	0.003	0.001	0.004	0.001	0.004
C	-0.003	0.011	0.009	0.004	0.002	0.004	0.005	0.001

Table 11: Descriptive Statistics for Convergence Speed: 20-Day Intervals

This table reports the descriptive statistics (average, standard deviation, maximum, and minimum) for the monthly average of convergence speed. The sample period is from May 2002 to May 2012 (121 months). s_m is the monthly convergence speed of the daily calculation within the month. The calculation for convergence speed is based on Equation (9).

Panel C: 20-day Convergence Speed by Tenor

	All	6-month	1-year	2-year	3-year	4-year	5-year	7-year	10-year
Mean	-0.002	0.033	-0.006	-0.002	-0.002	0.010	0.000	-0.000	-0.001
Std	0.141	0.309	0.179	0.154	0.144	0.136	0.128	0.123	0.123
Max	0.449	1.457	0.569	0.467	0.458	0.439	0.453	0.419	0.394
Min	-0.411	-0.634	-0.484	-0.416	-0.376	-0.382	-0.392	-0.397	-0.372
# Obs	121	116	121	121	121	80	121	121	121

Panel D: 20-day Convergence Speed by Tenor and Rating

	6-month	1-year	2-year	3-year	4-year	5-year	7-year	10-year
AAA	-0.011	-0.028	0.014	0.004	0.140	0.058	0.054	0.025
AA	-0.022	0.011	0.025	0.004	0.019	-0.000	-0.005	0.001
A	0.028	-0.006	-0.004	-0.000	0.019	0.001	0.001	0.001
BBB	-0.001	-0.009	-0.004	-0.006	0.007	-0.003	-0.004	-0.004
BB	0.004	-0.008	0.004	0.001	0.004	0.005	0.006	0.010
B	0.002	0.018	0.022	0.023	0.009	0.017	0.015	0.010
C	-0.034	0.038	0.013	-0.000	-0.001	0.012	0.010	-0.008

Table 12: Convergence Speed

This table reports the t-test results for the monthly average convergence speed of the five portfolios; portfolio 1 (5) consists of the most negative (positive) relative deviations. The sample period is from May 2002 to May 2012. Columns 1–5 test if the individual portfolio convergence speed is significantly less than zero (i.e. one-sided t-test), and Column 6 (Column 7) reports the result of whether convergence speed of portfolio 1 (portfolio 5) is statistically faster than portfolio 3 (i.e. $s_{1,m}$ or $s_{5,m}$ is more negative than $s_{3,m}$). Panel A reports the results for 5-day time difference and Panel B reports the results for 20-day time difference. The t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

		Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	[1] - [3]	[5] - [3]
Panel A: 5-day Time Difference								
All	Average	-0.022***	-0.023***	-0.032***	0.139***	-0.068***	0.010***	-0.036***
	t-stat	[-6.38]	[-6.14]	[-7.19]	[18.05]	[-17.81]	[4.16]	[-6.93]
AAA	Average	-0.160***	-0.005	0.351***	0.087*	-0.122***	-0.516***	-0.452***
	t-stat	[-2.71]	[-0.11]	[5.67]	[1.71]	[-2.75]	[-7.77]	[-7.22]
AA	Average	-0.059***	-0.037***	-0.009	0.069***	0.043***	-0.050***	0.052***
	t-stat	[-7.64]	[-5.19]	[-0.96]	[4.56]	[3.01]	[-5.62]	[3.58]
A	Average	-0.037***	-0.026***	-0.018***	0.096***	-0.017*	-0.020***	0.000
	t-stat	[-6.38]	[-4.97]	[-2.96]	[7.62]	[-1.89]	[-4.33]	[0.03]
BBB	Average	-0.019***	-0.016***	-0.025***	0.109***	-0.058***	0.006**	-0.033***
	t-stat	[-4.97]	[-4.36]	[-5.10]	[11.69]	[-11.07]	[2.30]	[-5.27]
BB	Average	-0.011***	-0.035***	0.065***	0.023**	-0.039***	-0.076***	-0.103***
	t-stat	[-2.84]	[-5.01]	[5.55]	[2.32]	[-7.92]	[-6.82]	[-7.54]
B	Average	-0.013***	-0.007	0.004	0.076***	-0.049***	-0.017*	-0.052***
	t-stat	[-2.82]	[-1.02]	[0.38]	[6.12]	[-5.02]	[-1.84]	[-3.15]
C	Average	-0.015	-0.009	0.012	0.032*	0.001	-0.027*	-0.011
	t-stat	[-1.36]	[-0.82]	[0.74]	[1.90]	[0.09]	[-1.74]	[-0.44]
Panel B: 20-day Time Difference								
All	Average	-0.053***	-0.060***	-0.050***	0.277***	-0.169***	-0.003	-0.118***
	t-stat	[-4.48]	[-4.65]	[-3.01]	[12.11]	[-14.01]	[-0.32]	[-7.69]
AAA	Average	-0.321***	-0.004	0.666***	0.075	-0.246***	-0.963***	-0.766***
	t-stat	[-4.34]	[-0.06]	[4.50]	[0.94]	[-2.96]	[-5.73]	[-6.51]
AA	Average	-0.112***	-0.073***	-0.002	0.116***	0.094**	-0.110***	0.096**
	t-stat	[-4.95]	[-3.07]	[-0.06]	[3.20]	[2.20]	[-4.65]	[2.32]
A	Average	-0.074***	-0.060***	-0.005	0.167***	-0.050**	-0.069***	-0.045
	t-stat	[-4.22]	[-3.54]	[-0.22]	[6.03]	[-2.13]	[-4.70]	[-1.53]
BBB	Average	-0.045***	-0.049***	-0.058***	0.250***	-0.160***	0.013	-0.102***
	t-stat	[-3.39]	[-3.61]	[-3.19]	[9.76]	[-10.55]	[1.13]	[-5.52]
BB	Average	-0.029**	-0.067***	0.168***	0.003	-0.119***	-0.197***	-0.289***
	t-stat	[-2.32]	[-3.54]	[5.27]	[0.13]	[-7.19]	[-7.19]	[-8.05]
B	Average	-0.030**	-0.005	0.051	0.162***	-0.147***	-0.081***	-0.183***
	t-stat	[-2.11]	[-0.25]	[1.64]	[5.58]	[-5.31]	[-3.24]	[-4.12]
C	Average	-0.035	-0.016	0.049	0.044	0.007	-0.084	-0.042
	t-stat	[-1.09]	[-0.46]	[0.89]	[0.94]	[0.13]	[-1.59]	[-0.58]

Table 13: Portfolio Holding Period Returns

This table reports the portfolio returns for 5- and 20-day holding periods. The sample period is from May 2002 to May 2012. The individual holding period return is defined as a ratio of CDS spreads: $r_{i,t,\tau} = k_{i,t,\tau}/k_{i,t-j,\tau} - 1, j = 5$ or 20 days. Each day, we sort the calculated returns into five portfolios, according to the relative deviation from its fitted CDS curve, $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$. Portfolio 1 has the largest negative deviation, while portfolio 5 has the largest positive deviation. The and the last column reports the difference between portfolios 1 and 5. The t-statistics for the mean difference from zero are reported in the last row of each panel. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

	Lowest = [1]	[2]	[3]	[4]	Highest = [5]	[1]-[5]
Panel A: 5-day trading						
Mean	0.032***	0.011***	0.004***	0.000	-0.004***	0.037***
Std	0.062	0.051	0.049	0.050	0.052	
t-stat	25.896	10.818	3.605	0.062	-3.851	45.552
Panel B:20-day trading						
Mean	0.082***	0.033***	0.017***	0.007***	-0.008***	0.090***
Std	0.161	0.131	0.127	0.133	0.142	
t-stat	25.328	12.379	6.584	2.586	-2.785	47.737

Table 14: Portfolio Holding Period Returns: Transaction Costs Adjusted

This table reports the portfolio returns for 5- and 20-day holding periods, after adjusting for transaction costs. The sample period is from May 2002 to May 2012. The individual holding period return is defined as a ration of transaction costs adjusted CDS spreads: $\tilde{r}_{i,t,\tau} = \tilde{k}_{i,t,\tau}/\tilde{k}_{i,t-j,\tau} - 1, j = 5$ or 20 days. Each day, we sort the calculated returns into five portfolios, according to the relative deviation from its fitted CDS curve, $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$. Portfolio 1 has the largest negative deviation, while portfolio 5 has the largest positive deviation. The last column reports the difference between portfolios 1 and 5. The t-statistics for the mean difference from zero are reported in the last row of each panel. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

	Lowest = [1]	Highest = [5]	[1]-[5]
Panel A: 5-day trading			
Mean	0.016***	0.007***	0.009***
Std	0.060	0.053	
t-stat	13.029	6.868	10.907
Panel B: 20-day trading			
Mean	0.065***	0.003	0.062***
Std	0.157	0.144	
t-stat	20.551	1.057	33.485

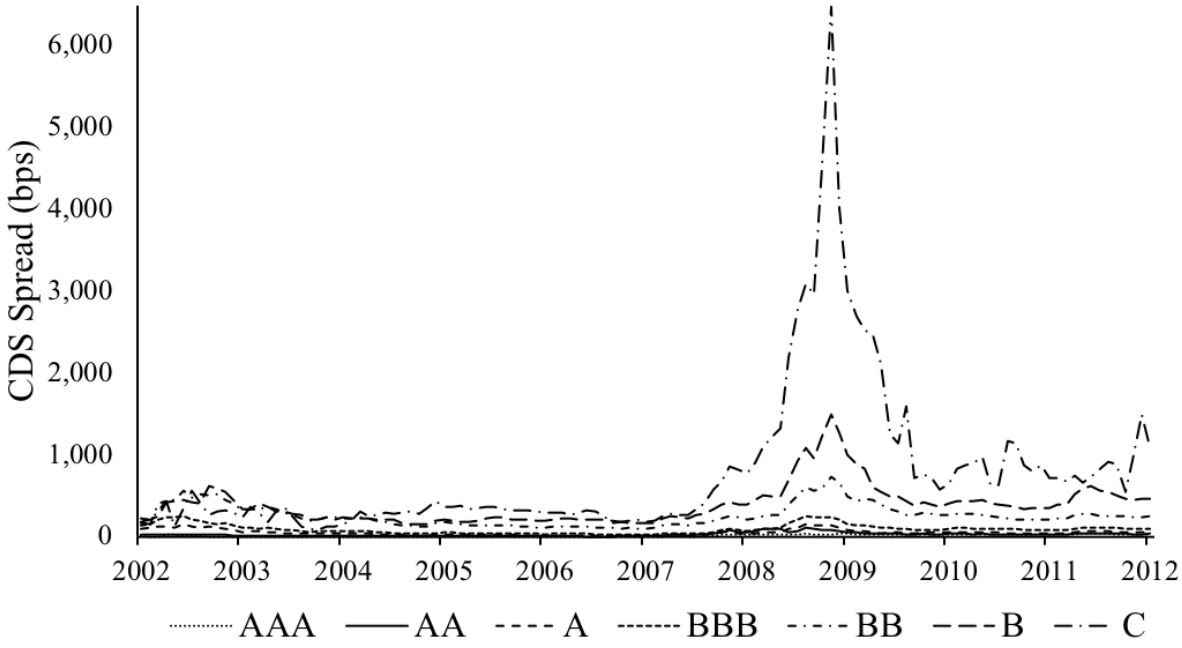
Table 15: Panel Regression Results for Convergence of CDS-implied Hazard Rates to Median Hazard Rates

This table reports the panel regression results of the changes in individual CDS-implied hazard rates onto changes in the median hazard date across CDSs with the same maturity (Panel A) and the same maturity and rating (Panel B), as well as past deviations from the medians. The sample period is from May 2002 to May 2012. Models 1 and 2 use the time difference of one week (5 trading days), and Models 2 and 4 use the time difference of one month (20 trading days). Models 2 and 4 also include the changes in the fitted values of the rating-based hazard rates from the Nelson-Siegel model, and the deviations from them. The robust standard errors clustered by firm are used, and the corresponding t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

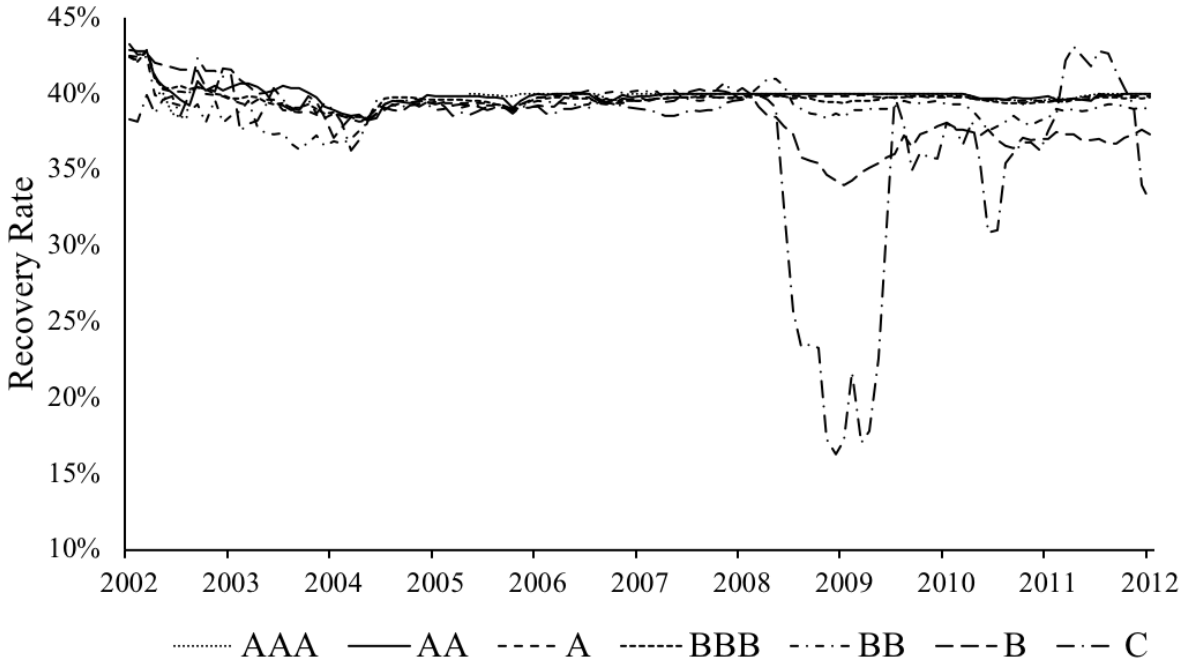
	5-day		20-day	
	Model 1	Model 2	Model 3	Model 4
Panel A: Tenor Median				
$\Delta y_{r_i,t,\tau}$		0.283***		0.540***
		[6.59]		[6.40]
Δ Median	1.254***	0.004***	1.477***	0.013***
	[10.18]	[3.67]	[10.29]	[2.63]
$e_{i,t-j,\tau}$		-0.030***		-0.120***
		[-3.41]		[-3.65]
$h_{r_i,t-j,\tau} - Median$	-0.028***	-0.005	-0.104***	-0.008
	[-14.34]	[-0.82]	[-12.54]	[-0.34]
Adj R-sqr	0.034	0.048	0.090	0.149
# Obs	3,482,714	3,482,714	3,342,077	3,342,077
Panel B: Rating-Tenor Median				
$\Delta y_{r_i,t,\tau}$		0.280***		0.525***
		[6.78]		[7.01]
Δ Median	0.613***	0.010***	0.771***	0.046***
	[5.12]	[2.62]	[6.53]	[2.59]
$e_{i,t-j,\tau}$		-0.028***		-0.125***
		[-4.17]		[-4.96]
$h_{r_i,t-j,\tau} - Median$	-0.035***	-0.008	-0.120***	-0.001
	[-13.00]	[-1.55]	[-9.91]	[-0.04]
Adj R-sqr	0.104	0.050	0.220	0.156
# Obs	3,482,714	3,482,714	3,342,077	3,342,077

Figure 1: Time series plot of CDS spreads and recovery rates

The top panel of the figure plots the time series of average CDS spreads for different rating classes. While taking the average, CDS with all maturities were considered. The bottom figure plots the time series of the recovery rates.



(i) CDS spreads

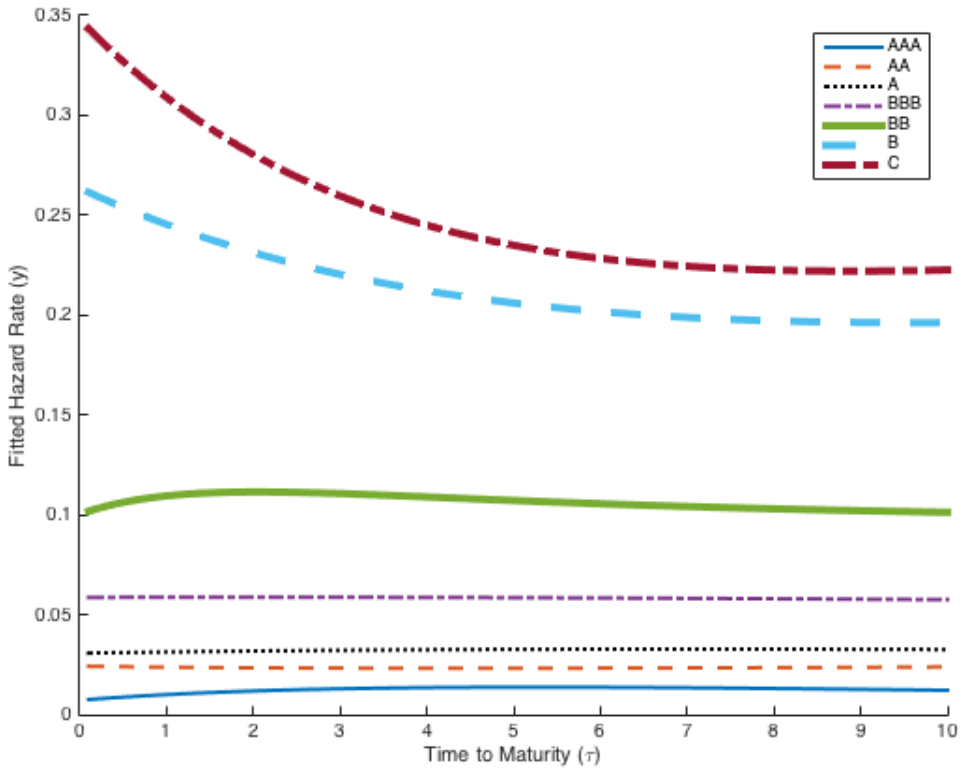


(ii) Recovery rates

Figure 2: Rating-Based CDS Curves and Parameter Values for 23 December 2008

This figure plots the rating-based CDS curves fitted using the Nelson-Siegel model below:

$$y(\tau|\beta_0,\beta_1,\beta_2,m) = \beta_0 + \beta_1\left(\frac{1-\exp\left(-\tau/m\right)}{\tau/m}\right) + \beta_2\left(\frac{1-\exp\left(-\tau/m\right)}{\tau/m} - \exp\left(-\tau/m\right)\right)$$

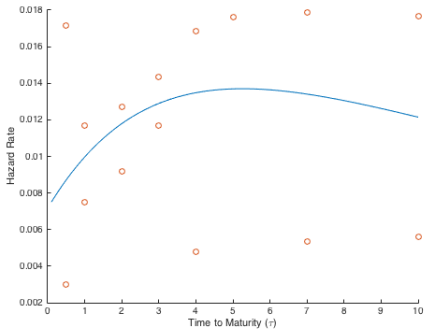


Model Parameters for Each Rating Class

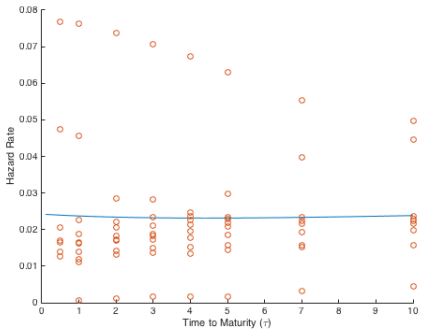
	AAA	AA	A	BBB	BB	B	C
β_0	0.000	0.030	0.014	0.042	0.094	0.285	0.308
β_1	0.007	-0.006	0.017	0.017	0.006	-0.022	0.040
β_2	0.034	-0.012	0.031	0.019	0.048	-0.263	-0.348
m	3.913	5.176	9.849	9.871	1.363	5.950	4.319

Figure 3: Rating-Based CDS Curves for 23 December 2008

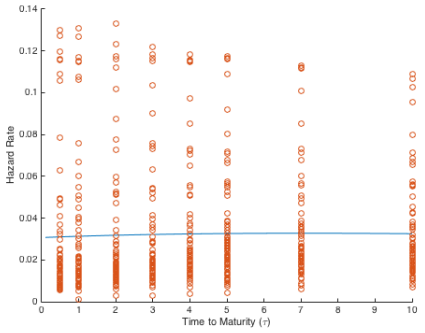
This figure plots the rating-based CDS curves, $y(\tau)$, fitted using the Nelson-Siegel model for each rating class. The symbol 'o' denotes the actual CDS-implied hazard rate (h).



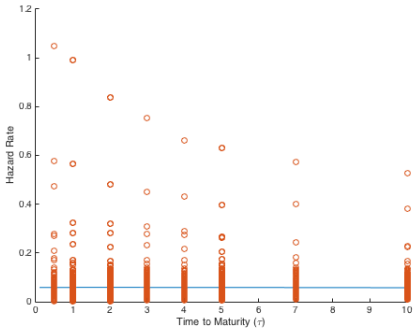
(i) AAA



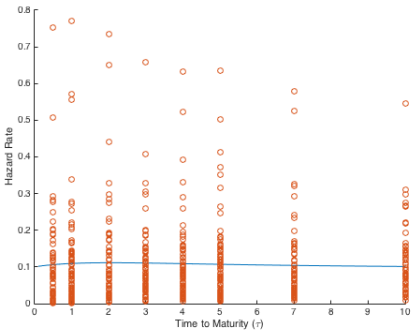
(ii) AA



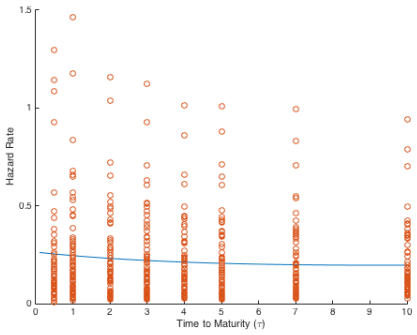
(iii) A



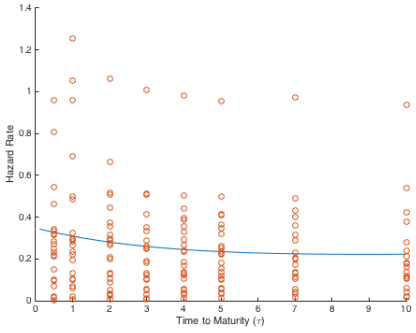
(iv) BBB



(v) BB



(vi) B



(vii) C

Figure 4: Average Rating-Implied Hazard Rate Curves

This figure plots the average rating-implied hazard rate curves for different rating classes based on the calibration of the Nelson-Siegel model for the sample period is from May 2002 to May 2012.

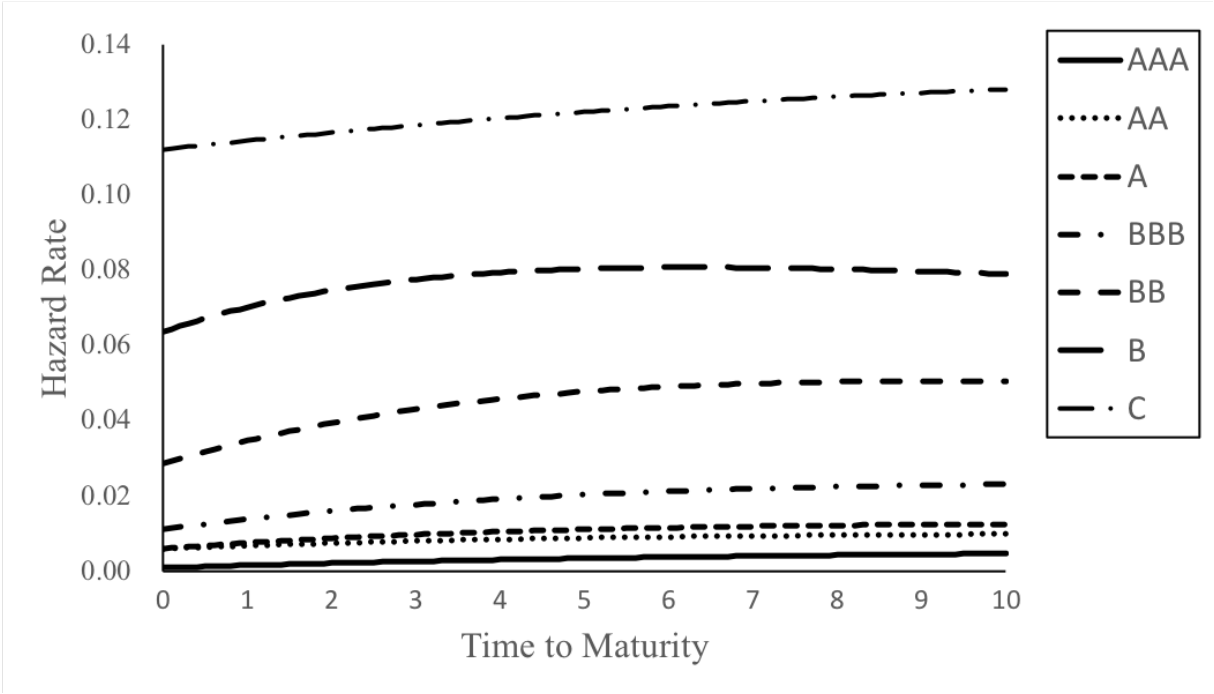
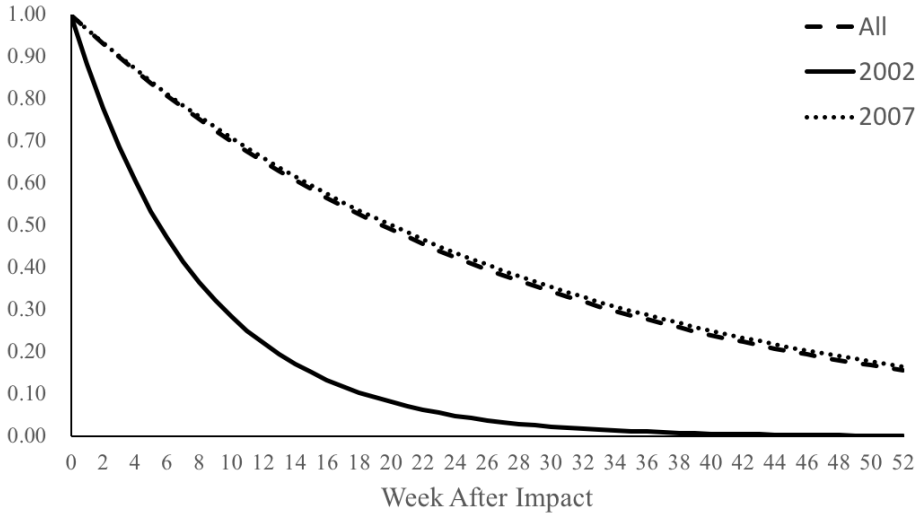
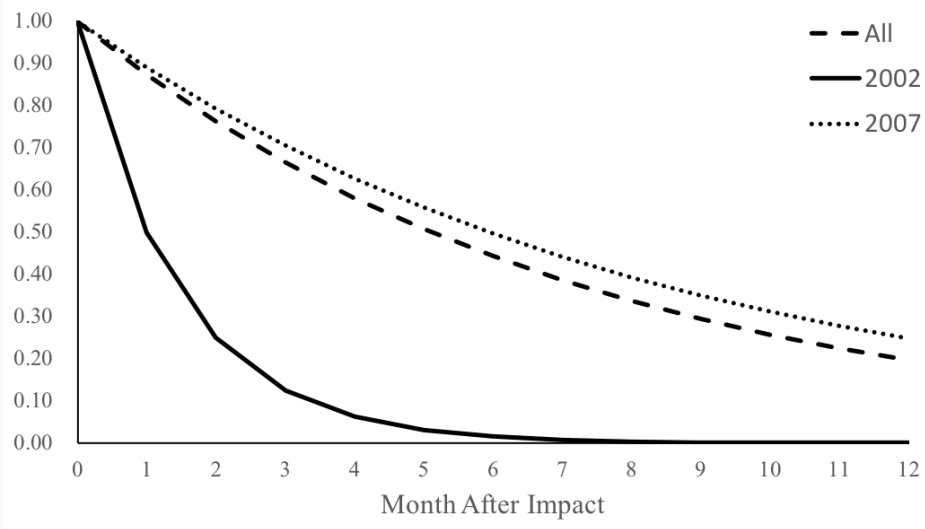


Figure 5: Impulse-Response Function

This figure plots the impulse-response function of the changes in the individual CDS-implied hazard rates to a unit shock to the deviation from the rating-implied hazard rate curves. The upper plot uses one-week intervals, and the bottom plot uses monthly intervals. Each plot depicts the functions related to the average estimated convergence speed, as well as the ones estimated for the year 2002 (the fastest convergence) and 2007 (the slowest convergence).



(i) 5-day intervals



(ii) 20-day intervals

Figure 6: Monthly Average Convergence Speed

This figure plots the monthly average convergence speed, s_m, for the 5-day and 20-day time difference. The sample period is from May 2002 to May 2012.

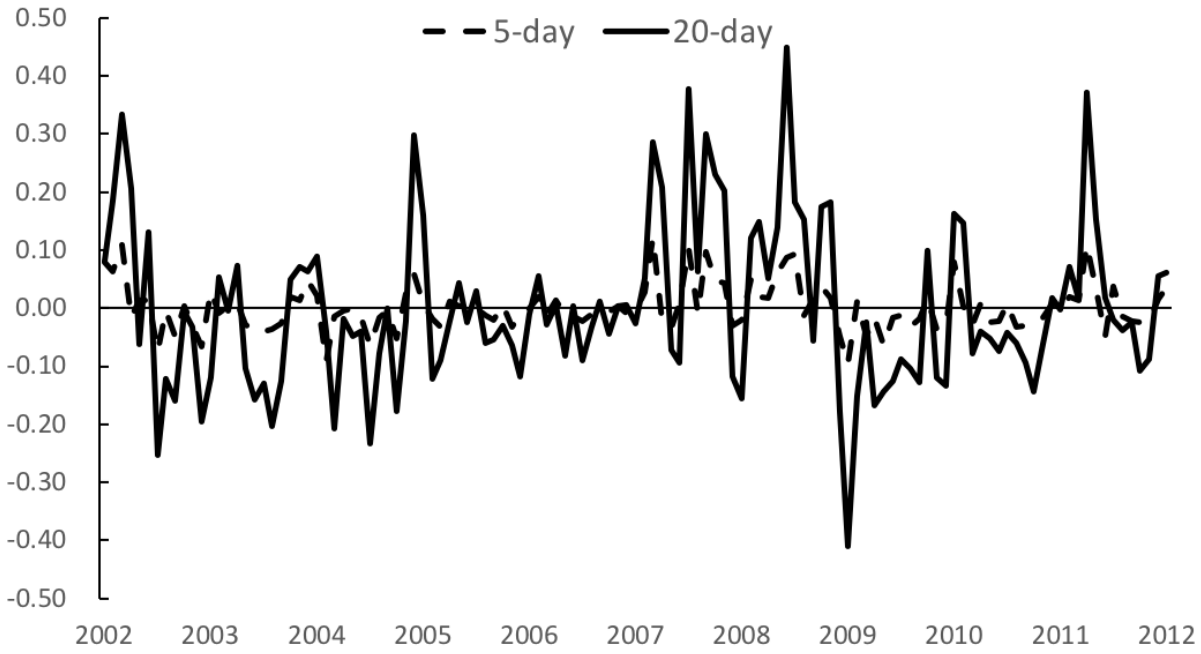
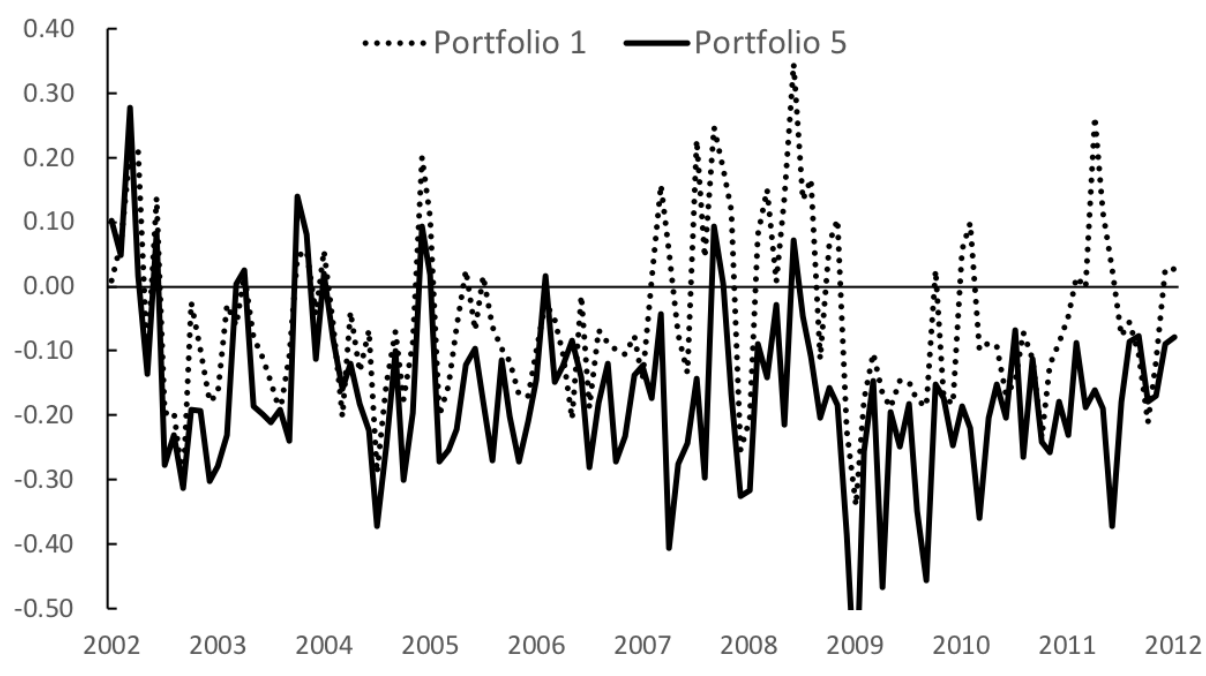


Figure 7: Portfolio Monthly Average Convergence Speed (20-day Time Difference)

This figure plots the monthly average convergence speed, $s_{p,m}$ for portfolios 1 and 5; portfolio 1 (5) consists of the most negative (positive) relative deviations. The sample period is from May 2002 to May 2012.



Appendix

A Robustness checks for convergence of CDS-implied hazard rates to their rating curves

In this section, we provide the CDS-implied hazard rare convergence results for different years (Table A.1), CDS maturities (Table A.2), ratings (Table A.3), and industries (Table A.4). We use a panel regression as specified in Equation (7). Overall, the results are consistent with the main results reported in the body of the paper.

Table A.1: Panel Regression Results for Convergence of CDS-implied Hazard Rates to their Rating Curves: Year-by-Year

This table reports the panel regression results of the changes in individual CDS-implied hazard rates onto changes in the rating-implied hazard rates, as well as past deviation, estimated for individual years. The sample period is from May 2002 to May 2012. Panel A uses time difference of one week (5 trading days), and Panel B uses time difference of one month (20 trading days). We only report the β_2 coefficient (the loading on $e_{i,t-j,\tau}$) to conserve space. The robust standard errors clustered by firm are used, and the corresponding t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

	Panel A: 5-day trading			Panel B: 20-day trading		
	β_2	Adj R-sqr	# Obs	β_2	Adj R-sqr	# Obs
Y2002	-0.188***	0.102	85,369	-0.501***	0.260	72,455
	[-3.22]			[-6.58]		
Y2003	-0.100***	0.073	141,210	-0.313***	0.273	128,339
	[-5.19]			[-6.79]		
Y2004	-0.048***	0.030	217,123	-0.163***	0.098	203,133
	[-3.77]			[-3.90]		
Y2005	-0.061***	0.032	314,864	-0.193***	0.117	293,106
	[-3.06]			[-3.96]		
Y2006	-0.067**	0.032	390,680	-0.188**	0.086	373,290
	[-2.03]			[-2.30]		
Y2007	-0.034***	0.038	438,783	-0.110***	0.104	423,541
	[-4.46]			[-5.05]		
Y2008	-0.064***	0.115	423,921	-0.179***	0.208	415,593
	[-4.63]			[-4.76]		
Y2009	-0.088***	0.087	422,318	-0.313***	0.248	408,019
	[-6.04]			[-7.80]		
Y2010	-0.092***	0.085	441,800	-0.311***	0.230	432,824
	[-10.78]			[-6.13]		
Y2011	-0.082***	0.067	432,428	-0.224***	0.197	422,277
	[-4.84]			[-4.97]		
Y2012	-0.126*	0.060	174,218	-0.356**	0.211	169,500
	[-1.95]			[-2.47]		

Table A.2: Panel Regression Results for Convergence of CDS-implied Hazard Rates to their Rating Curves: by CDS Maturity

This table reports the panel regression results of the changes in individual CDS-implied hazard rates onto changes in the rating-implied hazard rates, as well as past deviation, estimated for different CDS maturities. The sample period is from May 2002 to May 2012. Panel A uses time difference of one week (5 trading days), and Panel B uses time difference of one month (20 trading days). We only report the β_2 coefficient (the loading on $e_{i,t-j,\tau}$) to conserve space. The robust standard errors clustered by firm are used, and the corresponding t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

	Panel A: 5-day trading			Panel B: 20-day trading		
	β_2	Adj R-sqr	# Obs	β_2	Adj R-sqr	# Obs
6-month	-0.059***	0.048	285,912	-0.189***	0.167	256,130
	[-4.91]			[-5.94]		
1-year	-0.037***	0.050	445,080	-0.127***	0.154	425,250
	[-11.30]			[-7.69]		
2-year	-0.038***	0.056	449,475	-0.132***	0.171	432,359
	[-7.54]			[-8.84]		
3-year	-0.033***	0.057	484,095	-0.123***	0.164	468,327
	[-9.35]			[-10.03]		
4-year	-0.032***	0.062	343,285	-0.124***	0.171	332,711
	[-5.33]			[-6.09]		
5-year	-0.032***	0.046	520,496	-0.124***	0.140	504,311
	[-6.55]			[-8.42]		
7-year	-0.031***	0.050	481,678	-0.123***	0.140	466,226
	[-6.26]			[-6.66]		
10-year	-0.034***	0.040	472,693	-0.134***	0.131	456,763
	[-6.12]			[-6.64]		

Table A.3: Panel Regression Results for Convergence of CDS-implied Hazard Rates to their Rating Curves: by Rating

This table reports the panel regression results of the changes in individual CDS-implied hazard rates onto changes in the rating-implied hazard rates, as well as past deviation, estimated for different rating classes of the underlying. The sample period is from May 2002 to May 2012. Panel A uses time difference of one week (5 trading days), and Panel B uses time difference of one month (20 trading days). We only report the β_2 coefficient (the loading on $e_{i,t-j,\tau}$) to conserve space. The robust standard errors clustered by firm are used, and the corresponding t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

	Panel A: 5-day trading			Panel B: 20-day trading		
	β_2	Adj R-sqr	# Obs	β_2	Adj R-sqr	# Obs
AAA	-0.100***	0.297	26,025	-0.278***	0.459	23,964
	[-4.82]			[-7.02]		
AA	0.027	0.068	109,150	0.033	0.132	104,961
	[1.62]			[0.95]		
A	-0.021***	0.118	750,156	-0.077***	0.206	721,945
	[-8.07]			[-6.61]		
BBB	-0.034***	0.083	1,629,846	-0.099***	0.193	1,572,053
	[-4.69]			[-9.77]		
BB	-0.031***	0.038	517,047	-0.081***	0.109	491,154
	[-7.21]			[-5.08]		
B	-0.039***	0.064	369,635	-0.152***	0.169	352,521
	[-5.69]			[-5.71]		
C	-0.033***	0.038	80,855	-0.137***	0.139	75,479
	[-3.37]			[-6.97]		

Table A.4: Panel Regression Results for Convergence of CDS-implied Hazard Rates to their Rating Curves: by Industry

This table reports the panel regression results of the changes in individual CDS-implied hazard rates onto changes in the rating-implied hazard rates, as well as past deviation, estimated for different industries. The sample period is from May 2002 to May 2012. Panel A uses time difference of one week (5 trading days), and Panel B uses time difference of one month (20 trading days). We only report the β_2 coefficient (the loading on $e_{i,t-j,\tau}$) to conserve space. The robust standard errors clustered by firm are used, and the corresponding t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

	Panel A: 5-day trading			Panel B: 20-day trading		
	β_2	Adj R-sqr	# Obs	β_2	Adj R-sqr	# Obs
Basic Materials	-0.036***	0.033	273,506	-0.104***	0.114	261,178
	[-4.62]			[-4.87]		
Consumer Goods	-0.028	0.050	644,603	-0.140*	0.145	619,241
	[-1.33]			[-1.90]		
Consumer Services	-0.038***	0.049	614,689	-0.127***	0.159	590,911
	[-7.64]			[-5.69]		
Energy	-0.022***	0.105	345,310	-0.085***	0.206	332,339
	[-4.98]			[-5.39]		
Financials	-0.033	0.031	65,662	-0.089*	0.110	63,565
	[-1.19]			[-1.84]		
Healthcare	-0.009***	0.057	265,932	-0.029***	0.133	252,949
	[-4.22]			[-4.13]		
Industrials	-0.042***	0.057	582,068	-0.133***	0.161	561,047
	[-10.79]			[-14.86]		
Technology	-0.033***	0.084	313,076	-0.161***	0.257	298,843
	[-4.49]			[-4.22]		
Telecommunications Services	-0.018	0.011	82,260	-0.042	0.030	78,754
	[-1.41]			[-1.41]		
Utilities	-0.043**	0.054	275,665	-0.112***	0.136	264,881
	[-2.50]			[-6.84]		

B Derivation of the impulse-response function

In this section we present the intuitive derivation of the impulse-response function used in Section 6.1.

Consider the model: $\Delta h_t = \beta_1 \Delta y_t + \beta_2 e_{t-1}$, where $h_t = y_t + e_t$. Therefore,

$$\begin{cases} e_{t-1} &= \frac{1}{\beta_2}\Delta h_t - \frac{\beta_1}{\beta_2}\Delta y_t \\ e_{t-1} &= h_{t-1} - y_{t-1} \end{cases}$$

Solving the system of equations above, we obtain:

$$h_t = (1+\beta_2)h_{t-1} + \beta_1 y_t - (\beta_1 + \beta_2)y_{t-1}. \tag{B.1}$$

Consider a shock $e_0 = 1$ at time $t = 0$. Assuming $y_0 = 0$, $h_0 = y_0 + e_0 = 1$. Then,

$$h_1 = (1+\beta_2)h_0 + \beta_1 y_1 - (\beta_1+\beta_2)y_0 = (1+\beta_2) + \beta_1 y_1. \tag{B.2}$$

On the next step, h_2 can be expressed using Equation (B.1): $h_2 = (1+\beta_2)h_1 + \beta_1 y_2 - (\beta_1 + \beta_2)y_1$. Substituting h_1 by its expression in Equation (B.2), we obtain

$$\begin{aligned} h_2 &= (1+\beta_2)[(1+\beta_2) + \beta_1 y_1] + \beta_1 y_2 - (\beta_1+\beta_2)y_1 \\ &= (1+\beta_2)^2 + \beta_1 y_2 + (\beta_1 - 1)\beta_2 y_1 \end{aligned} \tag{B.3}$$

Following the same procedure, we can derive the value for h_3,

$$h_3 = (1+\beta_2)^3 + \beta_1 y_3 + (\beta_1 - 1)\beta_2 y_2 + (\beta_1 - 1)(1+\beta_2)\beta_2 y_1 \tag{B.4}$$

Iterating the process further, the general form for h_t can be expressed as:

$$h_t = (1+\beta_2)^t + \sum_{i=1}^{t} B(\beta_1, \beta_2) y_i, \tag{B.5}$$

where $B(\beta_1, \beta_2)$ is the function of β_1 and β_2.

Setting $y_i = 0$ for all i, we obtain the equation used in Section 6.1 of the main body of the paper:

$$h_t = (1 + \beta_2)^t. \tag{B.6}$$

C Trading strategy across different types of CDSs and time periods

In this section we tabulate the trading strategy results for different years (Table C.1), CDS maturities (Table C.2), ratings (Table C.3), and industries (Table C.4). We use the past relative deviation ($e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$) to sort CDS contracts into quintile portfolios. The portfolio returns are reported for 5-day and 20-day holding periods.

Table C.1: Portfolio Returns: Year by Year

This table reports the average portfolio returns and return standard deviations for 5- and 20-day holding periods for individual years from May 2002 to May 2012. The individual holding period return is defined as a ratio of CDS spreads: $r_{i,t,\tau} = k_{i,t,\tau}/k_{i,t-j,\tau} - 1, j =$ 5 or 20 days. Each day, we sort the calculated returns into five portfolios, according to the relative deviation from its fitted CDS curve, $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$. Portfolio 1 has the largest negative deviation, while portfolio 5 has the largest positive deviation. The last column in each panel reports the difference between portfolios 1 and 5. The t-statistics for the mean difference from zero are also. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

		Panel A: 5-day trading						Panel B: 20-day trading					
		Lowest = [1]	[2]	[3]	[4]	Highest = [5]	[1]-[5]	Lowest = [1]	[2]	[3]	[4]	Highest = [5]	[1]-[5]
Y2002	Mean	0.031***	0.008***	0.004	0.014***	0.018***	0.013***	0.110***	0.036***	0.033***	0.071***	0.089***	0.020
	Std	0.043	0.035	0.036	0.052	0.067		0.125	0.102	0.108	0.167	0.218	
	t-stat	9.123	2.937	1.391	3.376	3.376	2.655	10.616	4.219	3.698	5.118	4.940	1.393
Y2003	Mean	0.003	-0.009***	-0.013***	-0.016***	-0.022***	0.025***	-0.037***	-0.053***	-0.048***	-0.067***	-0.088***	0.051***
	Std	0.034	0.029	0.032	0.036	0.037		0.066	0.063	0.063	0.071	0.092	
	t-stat	1.537	-4.707	-6.249	-6.910	-9.110	10.014	-8.703	-12.933	-11.869	-14.824	-14.925	10.950
Y2004	Mean	0.024***	0.004**	-0.007***	-0.014***	-0.015***	0.039***	0.029***	-0.002	-0.023***	-0.040***	-0.051***	0.079***
	Std	0.038	0.030	0.036	0.033	0.041		0.096	0.088	0.095	0.072	0.097	
	t-stat	10.097	2.327	-2.883	-6.306	-5.572	16.840	4.636	-0.424	-3.758	-8.615	-8.137	16.818
Y2005	Mean	0.048***	0.020***	0.008**	0.000	-0.004	0.051***	0.119***	0.057***	0.031***	0.017**	-0.005	0.124***
	Std	0.074	0.062	0.056	0.051	0.054		0.167	0.125	0.116	0.122	0.136	
	t-stat	10.103	5.085	2.202	0.071	-1.037	22.834	11.094	7.140	4.169	2.184	-0.566	35.298
Y2006	Mean	0.028***	0.007***	-0.001	-0.006***	-0.013***	0.040***	0.047***	0.005	-0.016***	-0.025***	-0.040***	0.087***
	Std	0.034	0.027	0.023	0.023	0.027		0.072	0.061	0.055	0.053	0.062	
	t-stat	12.680	3.807	-0.979	-4.043	-7.283	25.916	10.129	1.246	-4.526	-7.185	-9.970	33.829
Y2007	Mean	0.046***	0.026***	0.014***	0.010***	0.003	0.042***	0.158***	0.091***	0.061***	0.040***	0.030***	0.128***
	Std	0.061	0.050	0.044	0.039	0.052		0.154	0.126	0.111	0.097	0.134	
	t-stat	11.616	8.021	5.065	3.926	1.034	19.704	15.922	11.211	8.514	6.386	3.434	29.557
Y2008	Mean	0.071***	0.040***	0.035***	0.034***	0.029***	0.043***	0.265***	0.175***	0.163***	0.159***	0.129***	0.136***
	Std	0.089	0.083	0.081	0.083	0.077		0.235	0.218	0.217	0.229	0.200	
	t-stat	12.474	7.613	6.786	6.310	5.818	14.744	17.684	12.513	11.792	10.827	10.132	19.254
Y2009	Mean	0.016***	-0.006*	-0.017***	-0.020***	-0.021***	0.037***	0.016*	-0.033***	-0.062***	-0.069***	-0.076***	0.092***
	Std	0.066	0.051	0.049	0.051	0.055		0.128	0.096	0.091	0.092	0.129	
	t-stat	3.688	-1.725	-5.245	-6.181	-5.918	13.658	1.916	-5.318	-10.496	-11.628	-9.173	13.259
Y2010	Mean	0.038***	0.009***	0.004	0.000	-0.009***	0.046***	0.082***	0.026***	0.012**	-0.004	-0.030***	0.112***
	Std	0.069	0.048	0.044	0.045	0.042		0.149	0.106	0.092	0.090	0.086	
	t-stat	8.513	2.952	1.530	0.085	-3.201	17.951	8.617	3.863	2.067	-0.706	-5.390	18.278
Y2011	Mean	0.027***	0.015***	0.010***	0.005*	-0.001	0.029***	0.073***	0.048***	0.037***	0.024***	0.002	0.071***
	Std	0.054	0.043	0.042	0.042	0.042		0.123	0.098	0.094	0.096	0.090	
	t-stat	7.967	5.293	3.818	1.902	-0.523	17.247	9.312	7.667	6.113	3.837	0.424	19.191
Y2012	Mean	0.012**	-0.003	-0.003	-0.005	-0.004	0.016***	0.015	-0.019***	-0.019***	-0.022***	-0.018***	0.033***
	Std	0.056	0.033	0.032	0.031	0.031		0.099	0.066	0.060	0.060	0.064	
	t-stat	2.197	-0.911	-0.953	-1.648	-1.293	4.945	1.460	-2.842	-3.099	-3.519	-2.790	6.082

Table C.2: Portfolio Returns: by CDS Maturity

This table reports the average portfolio returns and return standard deviations for 5- and 20-day holding periods based on CDSs with different maturities from May 2002 to May 2012. The individual holding period return is defined as a ratio of CDS spreads: $r_{i,t,\tau} = k_{i,t,\tau}/k_{i,t-j,\tau} - 1, j = 5$ or 20 days. Each day, we sort the calculated returns into five portfolios, according to the relative deviation from its fitted CDS curve, $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$. Portfolio 1 has the largest negative deviation, while portfolio 5 has the largest positive deviation. The last column in each panel reports the difference between portfolios 1 and 5. The t-statistics for the mean difference from zero are also reported. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

		Panel A: 5-day trading						Panel B: 20-day trading					
		Lowest = [1]	[2]	[3]	[4]	Highest = [5]	[1]-[5]	Lowest = [1]	[2]	[3]	[4]	Highest = [5]	[1]-[5]
6-month	Mean	0.107***	0.044***	0.018***	-0.001	-0.016***	0.123***	0.219***	0.101***	0.050***	0.013**	-0.026***	0.245***
	Std	0.148	0.114	0.103	0.102	0.084		0.305	0.255	0.251	0.229	0.209	
	t-stat	33.726	18.014	7.948	-0.630	-8.953	43.078	32.793	18.208	9.151	2.533	-5.729	52.960
1-year	Mean	0.056***	0.027***	0.009***	-0.002	-0.009***	0.065***	0.127***	0.066***	0.032***	0.007*	-0.014***	0.141***
	Std	0.093	0.077	0.077	0.072	0.068		0.222	0.195	0.190	0.195	0.191	
	t-stat	29.721	17.538	6.072	-1.600	-6.509	42.549	28.208	16.811	8.410	1.753	-3.650	47.898
2-year	Mean	0.029***	0.015***	0.005***	-0.001	-0.005***	0.034***	0.081***	0.043***	0.022***	0.004	-0.010***	0.091***
	Std	0.068	0.060	0.061	0.061	0.059		0.172	0.157	0.157	0.159	0.164	
	t-stat	21.181	12.187	4.293	-0.673	-3.912	33.315	23.244	13.548	6.990	1.171	-2.916	42.597
3-year	Mean	0.018***	0.009***	0.004***	0.000	-0.003**	0.021***	0.059***	0.030***	0.016***	0.007**	-0.006**	0.065***
	Std	0.055	0.052	0.052	0.054	0.055		0.140	0.134	0.133	0.145	0.148	
	t-stat	16.334	8.836	3.550	0.308	-2.558	25.674	20.681	11.137	6.037	2.440	-2.018	34.079
4-year	Mean	0.017***	0.010***	0.006***	0.004***	0.001	0.016***	0.064***	0.039***	0.027***	0.019***	0.005	0.059***
	Std	0.054	0.050	0.050	0.052	0.053		0.139	0.128	0.132	0.138	0.136	
	t-stat	12.647	7.818	5.016	3.260	0.652	19.995	18.634	12.145	8.191	5.462	1.491	31.254
5-year	Mean	0.013***	0.005***	0.003***	0.002*	-0.001	0.014***	0.047***	0.022***	0.013***	0.008***	-0.004	0.051***
	Std	0.046	0.041	0.043	0.046	0.047		0.117	0.106	0.107	0.120	0.125	
	t-stat	14.086	6.572	3.503	1.796	-1.538	21.812	19.926	10.258	6.021	3.391	-1.490	31.865
7-year	Mean	0.013***	0.006***	0.003***	0.002**	-0.001	0.014***	0.044***	0.023***	0.013***	0.011***	-0.003	0.047***
	Std	0.044	0.039	0.040	0.045	0.046		0.107	0.098	0.100	0.118	0.122	
	t-stat	14.210	7.754	3.325	2.223	-1.016	20.673	20.273	11.324	6.203	4.415	-1.110	32.119
10-year	Mean	0.015***	0.007***	0.002**	0.001*	-0.001	0.016***	0.045***	0.023***	0.011***	0.009***	-0.002	0.047***
	Std	0.043	0.038	0.038	0.043	0.047		0.101	0.089	0.094	0.109	0.121	
	t-stat	17.906	9.710	2.265	1.652	-0.955	22.058	21.949	12.634	6.049	4.046	-0.910	28.778

Table C.3: Portfolio Returns: by Rating

This table reports the average portfolio returns and return standard deviations for 5- and 20-day holding periods based on CDSs with different ratings from May 2002 to May 2012. The individual holding period return is defined as a ratio of CDS spreads: $r_{i,t,\tau} = k_{i,t,\tau}/k_{i,t-j,\tau} - 1, j = 5$ or 20 days. Each day, we sort the calculated returns into five portfolios, according to the relative deviation from its fitted CDS curve, $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$. Portfolio 1 has the largest negative deviation, while portfolio 5 has the largest positive deviation. The last column in each panel reports the difference between portfolios 1 and 5. The t-statistics for the mean difference from zero are also reported. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

		Panel A: 5-day trading						Panel B: 20-day trading					
		Lowest = [1]	[2]	[3]	[4]	Highest = [5]	[1]-[5]	Lowest = [1]	[2]	[3]	[4]	Highest = [5]	[1]-[5]
AAA	Mean	0.069***	0.025***	0.007**	0.003	-0.016***	0.084***	0.189***	0.100***	0.039***	0.011**	-0.022***	0.211***
	Std	0.324	0.237	0.112	0.080	0.084		0.649	0.486	0.243	0.179	0.177	
	t-stat	8.271	4.192	2.515	1.588	-7.278	10.234	10.897	7.685	6.025	2.237	-4.664	12.588
AA	Mean	0.046***	0.014***	0.002	-0.008***	-0.0011	0.047***	0.111***	0.048***	0.014***	-0.007**	0.014***	0.097***
	Std	0.107	0.074	0.066	0.067	0.099		0.249	0.174	0.155	0.151	0.233	
	t-stat	21.343	9.660	1.157	-5.949	-0.545	19.011	22.073	13.495	4.325	-2.319	2.974	20.025
A	Mean	0.042***	0.010***	0.001	-0.001	-0.006***	0.048***	0.095***	0.033***	0.011***	0.008**	-0.012***	0.107***
	Std	0.077	0.062	0.058	0.061	0.064		0.190	0.157	0.147	0.156	0.157	
	t-stat	27.365	8.264	0.962	-0.958	-4.561	38.851	24.523	10.453	3.798	2.426	-3.918	44.281
BBB	Mean	0.035***	0.009***	0.004***	0.000	-0.005***	0.041***	0.086***	0.031***	0.020***	0.006**	-0.012***	0.098***
	Std	0.069	0.055	0.053	0.055	0.057		0.166	0.137	0.140	0.142	0.152	
	t-stat	25.534	8.249	3.284	0.370	-4.654	41.705	25.485	11.339	6.882	1.982	-4.040	43.631
BB	Mean	0.021***	0.011***	0.004***	0.003**	-0.003**	0.024***	0.057***	0.028***	0.021***	0.012***	-0.004	0.061***
	Std	0.067	0.050	0.051	0.057	0.063		0.150	0.120	0.142	0.174	0.165	
	t-stat	15.307	11.077	3.869	2.431	-2.558	15.783	18.661	11.659	7.283	3.506	-1.289	19.123
B	Mean	0.029***	0.008***	0.004***	0.006***	-0.001	0.030***	0.075***	0.033***	0.018***	0.029***	0.004	0.071***
	Std	0.098	0.053	0.055	0.058	0.064		0.197	0.141	0.132	0.152	0.160	
	t-stat	14.785	7.839	3.719	4.881	-0.955	15.900	18.815	11.423	6.841	9.522	1.224	19.357
C	Mean	0.030***	0.013***	0.010***	0.009***	0.007**	0.024***	0.082***	0.056***	0.050***	0.030***	0.027***	0.055***
	Std	0.141	0.112	0.109	0.131	0.158		0.317	0.275	0.295	0.252	0.306	
	t-stat	10.634	5.670	4.629	3.441	2.115	6.098	12.711	10.073	8.424	5.914	4.344	7.945

Table C.4: Portfolio Returns: by Industry

This table reports the average portfolio returns and return standard deviations for 5- and 20-day holding periods based on CDSs from different industries from May 2002 to May 2012. The individual holding period return is defined as a ratio of CDS spreads: $r_{i,t,\tau} = k_{i,t,\tau}/k_{i,t-j,\tau} - 1, j = 5$ or 20 days. Each day, we sort the calculated returns into five portfolios, according to the relative deviation from its fitted CDS curve, $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$. Portfolio 1 has the largest negative deviation, while portfolio 5 has the largest positive deviation. The last column in each panel reports the difference between portfolios 1 and 5. The t-statistics for the mean difference from zero are also reported. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

		Panel A: 5-day trading						Panel B: 20-day trading					
		Lowest = [1]	[2]	[3]	[4]	Highest = [5]	[1]-[5]	Lowest = [1]	[2]	[3]	[4]	Highest = [5]	[1]-[5]
Basic Materials	Mean	0.035***	0.015***	0.003*	-0.002	-0.008***	0.043***	0.084***	0.036***	0.009***	-0.002	-0.017***	0.101***
	Std	0.089	0.069	0.066	0.065	0.062		0.188	0.147	0.132	0.144	0.143	
	t-stat	19.675	10.545	1.901	-1.438	-6.024	25.874	22.207	12.258	3.429	-0.572	-5.748	35.448
Consumer Goods	Mean	0.035***	0.011***	0.004**	0.002***	-0.005***	0.040***	0.088***	0.036***	0.023***	0.016***	-0.009***	0.098***
	Std	0.072	0.054	0.052	0.057	0.058		0.175	0.138	0.134	0.146	0.146	
	t-stat	24.218	10.417	4.249	2.010	-4.068	31.381	24.994	12.872	8.623	5.550	-3.132	35.054
Consumer Services	Mean	0.029***	0.013***	0.005***	0.002*	-0.005***	0.033***	0.073***	0.039***	0.021***	0.010***	-0.008***	0.080***
	Std	0.071	0.059	0.059	0.059	0.056		0.170	0.151	0.143	0.146	0.146	
	t-stat	19.959	10.775	4.403	1.945	-4.271	29.571	21.075	12.747	7.307	3.459	-2.591	34.984
Energy	Mean	0.032***	0.011***	0.002	0.000	-0.005***	0.037***	0.075***	0.032***	0.013***	0.009**	-0.002	0.077***
	Std	0.087	0.068	0.062	0.067	0.080		0.206	0.166	0.162	0.176	0.219	
	t-stat	18.571	8.364	1.402	0.048	-3.068	24.417	18.089	9.494	3.957	2.473	-0.444	20.973
Financials	Mean	0.025***	0.020***	0.013***	0.000	0.005*	0.020***	0.063***	0.058***	0.035***	0.013***	0.036***	0.026***
	Std	0.137	0.124	0.114	0.104	0.130		0.273	0.251	0.251	0.237	0.336	
	t-stat	9.014	8.204	5.560	0.110	1.722	6.166	11.336	11.417	6.924	2.699	5.351	3.641
Healthcare	Mean	0.028***	0.011***	0.003**	0.000	-0.007***	0.035***	0.077***	0.032***	0.012***	0.000	-0.016***	0.093***
	Std	0.079	0.064	0.065	0.072	0.056		0.188	0.150	0.139	0.145	0.134	
	t-stat	17.511	8.596	2.204	-0.077	-6.283	21.877	19.925	10.274	4.048	0.047	-5.869	27.671
Industrials	Mean	0.036***	0.011***	0.003***	-0.002**	-0.005***	0.041***	0.078***	0.034***	0.014***	0.001	-0.008***	0.086***
	Std	0.088	0.060	0.053	0.053	0.056		0.194	0.150	0.133	0.131	0.135	
	t-stat	20.302	9.048	2.974	-2.080	-4.234	28.717	19.935	11.321	5.238	0.450	-2.923	32.450
Technology	Mean	0.033***	0.008***	0.006***	0.002	-0.008***	0.041***	0.087***	0.028***	0.030***	0.007**	-0.022***	0.109***
	Std	0.084	0.061	0.071	0.062	0.063		0.207	0.153	0.192	0.161	0.162	
	t-stat	19.467	6.511	4.294	1.314	-6.400	25.102	20.761	9.161	7.774	2.169	-6.600	30.307
Telecommunications	Mean	0.028***	0.008***	0.004***	0.002	-0.005***	0.033***	0.063***	0.025***	0.013***	0.007**	-0.009**	0.072***
Services	Std	0.093	0.074	0.066	0.079	0.082		0.211	0.146	0.147	0.159	0.178	
	t-stat	13.877	5.142	2.875	0.922	-2.784	13.651	13.502	7.754	4.037	2.008	-2.334	15.721
Utilities	Mean	0.036***	0.011***	0.007***	0.000	-0.003	0.039***	0.086***	0.038***	0.034***	0.009**	-0.002	0.088***
	Std	0.106	0.083	0.081	0.080	0.101		0.246	0.214	0.228	0.207	0.243	
	t-stat	16.623	6.757	4.327	0.147	-1.415	18.525	17.308	8.809	7.475	2.062	-0.329	19.408

D Transaction cost adjusted trading strategy across different types of CDSs and time periods

In this section we tabulate the trading strategy results after adjusting for transaction costs for different years (Table D.1), CDS maturities (Table D.2), ratings (Table D.3), and industries (Table D.4). We use the past relative deviation ($e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$) to sort portfolio into quintiles, and report the performance of portfolio 1 (with the largest negative deviations) and portfolio 5 (with the largest positive deviations). We do not report the transaction costs adjusted performance of portfolios 2 to 4, as the trading direction in these portfolios may not be stable. The portfolio returns are reported for 5-day and 20-day holding periods.

Table D.1: Transaction Cost Adjusted Portfolio Returns: Year by Year

This table reports the average portfolio returns and return standard deviations for 5- and 20-day holding periods for individual years from May 2002 to May 2012. The individual holding period return is defined as a ratio of transaction costs adjusted CDS spreads: $\tilde{r}_{i,t,\tau} = \tilde{k}_{i,t,\tau}/\tilde{k}_{i,t-j,\tau} - 1, j = 5$ or 20 days. Each day, we sort the calculated returns into five portfolios, according to the relative deviation from its fitted CDS curve, $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$. Portfolio 1 has the largest negative deviation, while portfolio 5 has the largest positive deviation. The last column in each panel reports the difference between portfolios 1 and 5. The t-statistics for the mean difference from zero are also. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

		Panel A: 5-day trading			Panel B: 20-day trading		
		Lowest = [1]	Highest = [5]	[1]-[5]	Lowest = [1]	Highest = [5]	[1]-[5]
Y2002	Mean	0.018***	0.028***	-0.010**	0.096***	0.10***	-0.003
	Std	0.042	0.068		0.123	0.220	
	t-stat	5.465	5.195	-2.013	9.452	5.467	-0.216
Y2003	Mean	-0.008***	-0.012***	0.004*	-0.047***	-0.079***	0.032***
	Std	0.034	0.037		0.065	0.093	
	t-stat	-3.661	-5.090	1.719	-11.386	-13.350	6.769
Y2004	Mean	0.010***	-0.003	0.013***	0.016**	-0.040***	0.055***
	Std	0.037	0.042		0.095	0.099	
	t-stat	4.329	-1.020	5.611	2.537	-6.238	11.616
Y2005	Mean	0.029***	0.009**	0.020***	0.099***	0.007	0.092***
	Std	0.072	0.055		0.164	0.138	
	t-stat	6.287	2.577	9.209	9.447	0.810	27.582
Y2006	Mean	0.010***	-0.001	0.010***	0.029***	-0.029***	0.057***
	Std	0.034	0.027		0.071	0.062	
	t-stat	4.530	-0.329	6.713	6.300	-7.088	22.634
Y2007	Mean	0.028***	0.015***	0.013***	0.138***	0.041***	0.097***
	Std	0.060	0.053		0.150	0.136	
	t-stat	7.264	4.369	6.200	14.266	4.716	23.048
Y2008	Mean	0.051***	0.041***	0.010***	0.241***	0.143***	0.098***
	Std	0.088	0.078		0.230	0.202	
	t-stat	9.097	8.189	3.637	16.408	11.035	14.281
Y2009	Mean	-0.000	-0.009**	0.009***	0.000	-0.065***	0.066***
	Std	0.065	0.056		0.126	0.131	
	t-stat	-0.086	-2.571	3.313	0.055	-7.757	9.417
Y2010	Mean	0.020***	0.003	0.017***	0.064***	-0.019***	0.084***
	Std	0.067	0.042		0.146	0.087	
	t-stat	4.603	0.932	6.977	6.870	-3.455	13.969
Y2011	Mean	0.010***	0.010***	0.001	0.056***	0.013**	0.042***
	Std	0.052	0.043		0.120	0.091	
	t-stat	3.128	3.556	0.455	7.236	2.270	11.887
Y2012	Mean	-0.006	0.008**	-0.014***	-0.004	-0.007	0.003
	Std	0.054	0.031		0.097	0.065	
	t-stat	-1.097	2.567	-4.480	-0.379	-0.986	0.543

Table D.2: Transaction Cost Adjusted Portfolio Returns: by CDS Maturity

This table reports the average portfolio returns and return standard deviations for 5- and 20-day holding periods based on CDSs with different maturities from May 2002 to May 2012. The individual holding period return is defined as a ratio of transaction costs adjusted CDS spreads: $\tilde{r}_{i,t,\tau} = \tilde{k}_{i,t,\tau}/\tilde{k}_{i,t-j,\tau} - 1, j = 5$ or 20 days. Each day, we sort the calculated returns into five portfolios, according to the relative deviation from its fitted CDS curve, $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$. Portfolio 1 has the largest negative deviation, while portfolio 5 has the largest positive deviation. The last column in each panel reports the difference between portfolios 1 and 5. The t-statistics for the mean difference from zero are also reported. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

		Panel A: 5-day trading			Panel B: 20-day trading		
		Lowest = [1]	Highest = [5]	[1]-[5]	Lowest = [1]	Highest = [5]	[1]-[5]
6-month	Mean	0.053***	0.034***	0.019***	0.159***	0.024***	0.136***
	Std	0.141	0.089		0.290	0.220	
	t-stat	17.578	18.022	6.844	25.106	4.939	30.813
1-year	Mean	0.030***	0.016***	0.014***	0.099***	0.011***	0.088***
	Std	0.091	0.070		0.216	0.196	
	t-stat	16.277	11.362	9.187	22.573	2.737	30.332
2-year	Mean	0.016***	0.008***	0.008***	0.068***	0.003	0.065***
	Std	0.067	0.060		0.170	0.166	
	t-stat	11.956	6.451	8.246	19.637	0.831	30.514
3-year	Mean	0.010***	0.005***	0.004***	0.050***	0.002	0.047***
	Std	0.055	0.056		0.139	0.149	
	t-stat	8.825	4.869	5.200	17.725	0.747	24.991
4-year	Mean	0.011***	0.007***	0.003***	0.058***	0.011***	0.046***
	Std	0.054	0.053		0.138	0.137	
	t-stat	7.969	5.384	4.326	16.821	3.322	24.457
5-year	Mean	0.008***	0.004***	0.004***	0.042***	0.001	0.041***
	Std	0.045	0.047		0.116	0.126	
	t-stat	8.634	3.741	6.579	17.807	0.472	25.426
7-year	Mean	0.009***	0.003***	0.006***	0.040***	0.001	0.039***
	Std	0.044	0.046		0.106	0.122	
	t-stat	10.197	2.822	9.755	18.616	0.335	27.018
10-year	Mean	0.013***	0.002*	0.011***	0.042***	0.000	0.042***
	Std	0.043	0.047		0.100	0.122	
	t-stat	15.004	1.664	15.254	20.722	0.107	25.607

Table D.3: Transaction Cost Adjusted Portfolio Returns: by Rating

This table reports the average portfolio returns and return standard deviations for 5- and 20-day holding periods based on CDSs with different ratings from May 2002 to May 2012. The individual holding period return is defined as a ratio of transaction costs adjusted CDS spreads: $\tilde{r}_{i,t,\tau} = \tilde{k}_{i,t,\tau}/\tilde{k}_{i,t-j,\tau} - 1, j = 5$ or 20 days. Each day, we sort the calculated returns into five portfolios, according to the relative deviation from its fitted CDS curve, $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$. Portfolio 1 has the largest negative deviation, while portfolio 5 has the largest positive deviation. The last column in each panel reports the difference between portfolios 1 and 5. The t-statistics for the mean difference from zero are also reported. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

		Panel A: 5-day trading			Panel B: 20-day trading		
		Lowest = [1]	Highest = [5]	[1]-[5]	Lowest = [1]	Highest = [5]	[1]-[5]
AAA	Mean	0.052***	-0.003	0.056***	0.171***	-0.010**	0.182***
	Std	0.320	0.085		0.644	0.178	
	t-stat	6.377	-1.547	6.838	9.993	-2.183	10.969
AA	Mean	0.028***	0.011***	0.017***	0.091***	0.026***	0.065***
	Std	0.104	0.101		0.241	0.237	
	t-stat	13.097	5.345	6.713	18.742	5.432	13.510
A	Mean	0.024***	0.005***	0.019***	0.075***	-0.002	0.077***
	Std	0.075	0.065		0.185	0.159	
	t-stat	15.880	3.861	15.370	20.070	-0.554	32.507
BBB	Mean	0.018***	0.006***	0.012***	0.068***	-0.001	0.069***
	Std	0.067	0.058		0.162	0.154	
	t-stat	13.523	5.230	12.703	20.681	-0.420	31.159
BB	Mean	0.006***	0.009***	-0.002	0.042***	0.007**	0.035***
	Std	0.065	0.063		0.147	0.168	
	t-stat	4.868	6.941	-1.640	14.125	2.207	10.831
B	Mean	0.012***	0.009***	0.003*	0.058***	0.014***	0.044***
	Std	0.096	0.064		0.192	0.162	
	t-stat	6.423	7.024	1.726	14.853	4.308	12.062
C	Mean	0.011***	0.016***	-0.005	0.062***	0.035***	0.026***
	Std	0.138	0.159		0.311	0.309	
	t-stat	3.932	4.904	-1.247	9.810	5.671	3.853

Table D.4: Transaction Cost Adjusted Portfolio Returns: by Industry

This table reports the average portfolio returns and return standard deviations for 5- and 20-day holding periods based on CDSs from different industries from May 2002 to May 2012. The individual holding period return is defined as a ratio of transaction costs adjusted CDS spreads: $\tilde{r}_{i,t,\tau} = \tilde{k}_{i,t,\tau}/\tilde{k}_{i,t-j,\tau} - 1, j = 5$ or 20 days. Each day, we sort the calculated returns into five portfolios, according to the relative deviation from its fitted CDS curve, $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$. Portfolio 1 has the largest negative deviation, while portfolio 5 has the largest positive deviation. The last column in each panel reports the difference between portfolios 1 and 5. The t-statistics for the mean difference from zero are also reported. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

		Panel A: 5-day trading			Panel B: 20-day trading		
		Lowest = [1]	Highest = [5]	[1]-[5]	Lowest = [1]	Highest = [5]	[1]-[5]
Basic Materials	Mean	0.018***	0.004***	0.014***	0.066***	-0.006**	0.073***
	Std	0.087	0.063		0.183	0.145	
	t-stat	10.150	2.754	8.710	17.884	-2.088	25.753
Consumer Goods	Mean	0.018***	0.007***	0.012***	0.071***	0.002	0.069***
	Std	0.070	0.059		0.171	0.148	
	t-stat	12.865	5.504	9.234	20.511	0.614	25.062
Consumer Services	Mean	0.013***	0.006***	0.007***	0.056***	0.003	0.053***
	Std	0.069	0.057		0.166	0.148	
	t-stat	9.023	4.951	6.212	16.627	0.883	23.602
Energy	Mean	0.015***	0.006***	0.009***	0.057***	0.009**	0.048***
	Std	0.084	0.081		0.200	0.221	
	t-stat	8.853	3.712	5.925	14.084	1.976	13.189
Financials	Mean	0.009***	0.017***	-0.008**	0.046***	0.049***	-0.002
	Std	0.134	0.132		0.268	0.342	
	t-stat	3.284	6.217	-2.328	8.528	7.021	-0.310
Healthcare	Mean	0.013***	0.004***	0.009***	0.061***	-0.005*	0.066***
	Std	0.077	0.057		0.185	0.136	
	t-stat	8.071	3.545	5.364	16.049	-1.860	19.839
Industrials	Mean	0.018***	0.006***	0.012***	0.060***	0.003	0.058***
	Std	0.086	0.057		0.190	0.137	
	t-stat	10.627	5.661	8.575	15.698	1.020	22.069
Technology	Mean	0.017***	0.003***	0.014***	0.071***	-0.011***	0.081***
	Std	0.082	0.064		0.202	0.164	
	t-stat	10.462	2.570	8.647	17.291	-3.187	23.038
Telecommunications	Mean	0.012***	0.006***	0.006**	0.045***	0.001	0.045***
Services	Std	0.090	0.083		0.203	0.179	
	t-stat	5.865	3.032	2.514	10.121	0.200	9.881
Utilities	Mean	0.019***	0.009***	0.010***	0.068***	0.010**	0.058***
	Std	0.104	0.102		0.240	0.246	
	t-stat	8.874	4.408	4.614	14.026	2.002	12.996