What Drives the Price Convergence between Credit Default Swap and Put Option: New Evidence

Article *in* SSRN Electronic Journal · January 2018

DOI: 10.2139/ssrn.3188892

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April 17, 2019

Abstract

Credit default swaps (CDSs) and deep out-of-the-money put (DOOMP) options can both be used as a credit protection instrument. However, partial market segmentation results in deviations between firm hazard rates implied by these contracts. These deviations are driven by a systematic component–difference in the consensus rating-based levels of hazard rates in the two markets, and an idiosyncratic component, arising due to market frictions. We show that both components diminish over time, but their convergence is asynchronous. A trading strategy based on a joint signal of both systematic and idiosyncratic deviations delivers a positive arbitrage return after transaction costs and outperforms a conventional approach on trading on the absolute deviations between CDS- and DOOMP-implied hazard rates.

Keywords: Credit Default Swap (CDS), Deep Out-of-the-Money Put Option, Market Segmentation, Convergence, Trading Strategy

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Acknowledgment: Funding from Westminster Strategic Research Funding and De Montfort University Research Funding are gratefully acknowledged. This paper updates and replaces the previous working paper titled "Anatomize DOOM-CDS Linkage".

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Abstract

Credit default swaps (CDSs) and deep out-of-the-money put (DOOMP) options can both be used as a credit protection instrument. However, partial market segmentation results in deviations between firm hazard rates implied by these contracts. These deviations are driven by a systematic component–difference in the consensus rating-based levels of hazard rates in the two markets, and an idiosyncratic component, arising due to market frictions. We show that both components diminish over time, but their convergence is asynchronous. A trading strategy based on a joint signal of both systematic and idiosyncratic deviations delivers a positive arbitrage return after transaction costs and outperforms a conventional approach on trading on the absolute deviations between CDS- and DOOMP-implied hazard rates.

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1 Introduction

Both deep out-of-the-money put(DOOMP) options and credit default swaps (CDS) provide protection against firms' defaults. Protection buyers have the right to sell the underlying stock in the case of a put option or a bond in the case of a CDS, if a pre-specified firm's default event takes place. Although CDS and DOOMP have different pricing structures, both products can be converted into a unit recovery claim (URC), which pays $1 if the firm defaults and zero otherwise.

Carr and Wu (2011) suggest that, if the Law of One Price holds, then a URC written on a given firm should have the same price regardless of the market where the claim is traded. Thus, any price deviations between URCs obtained from CDS and DOOMP should eventually converge, unless the convergence is prevented by market frictions.

The law of one price, however, may not always hold in financial markets if the markets are segmented or only party integrated. In such cases, capital moves quickly within one asset class, but it takes time to move across asset classes (Hanson et al., 2018). The CDS and option markets are structurally different, with the former being an over-the-counter market and the latter a "classical" exchange market. The contracts traded on them also vary significantly in terms of their maturity: the most common CDS contract has a maturity of 5 years (over 80% of our sample), but the most common DOOMP option matures less than six months (77% of our sample). Hence, although CDS and DOOMP can both be used for hedging firms' credit risk, these markets attract different types of traders, with different investment horizons, distinct trading strategies, liquidity preferences and risk-aversions. The DOOMP market is likely to be populated by short-term sophisticated institutional investors, such as hedge funds, whereas insurance companies and banks represent a large share of CDS market participants (Mengle, 2007).

In this paper we extend the work of Carr and Wu (2011) by taking the partial market segmentation into account. We show that the URCs are priced differently in the two markets. The two derivatives are not perfect substitutes for one another and therefore have a different term-structure of consensus URC prices for a given level of credit risk – the rating curves.

We use the rating curves from the two markets to compute the between-market and within-market deviations. Between-market curve deviations are the differences in the curves, capturing the systematic price differences between CDS and put option markets, while within-market deviations capture the idiosyncratic departures from the consensus prices in each of the markets (due to mispricing, liquidity shocks, and other factors).[1] As suggested by the market segmentation theory, market participants may react faster to within-market deviation than to between-market deviation. Importantly, if these two types of deviations move against one another, that is, have different signs, this weakens the market reaction. Thus, the overall time-series convergence (as implied by the Law of One Price) in prices of URCs across the two markets is more pronounced if both systematic and idiosyncratic deviations move into the same direction (as implied by the law of one price); however, our evidence shows that this happens only in 20% of cases, consistent with partial market segmentation.

Methodologically, we, first, recover the CDS- and put-implied hazard rates from individual contracts. We recognize that credit rating of an underlying firm is an important source of information for the individual CDS spreads and also very likely for the put option prices (Aunon-Nerin et al., 2002), because it provides a robust outlook on firm's default risk (Altman and Rijken, 2004; Löffler, 2004). Thus, on the second step, we group the CDS and DOOMP hazard rates by firm's credit rating, and fit the Nelson-Siegel (NS) term structure model, following Kolokolova et al. (2018), separately in each of the two markets. This process enables us to separate each hazard rate into two components–a NS-model fitted value and a residual term. The fitted values represent the consensus prices in each of the markets based on a particular credit rating, whereas residuals capture idiosyncratic deviations from the consensus.

Next, we show that idiosyncratic deviations diminish over time, with both CDS- and DOOMP-implied hazard rates converging to their respective rating curves. This is further reflected in a time-series reduction of cross-market residual deviations. As for the between-market curve deviations, they increase when the markets become less close substitutes from the point of view of their participants, for example, when the put option delta or implied volatility moves up. However, over time we still find the evidence of curve-convergence.

Finally, the decomposition of CDS- and DOOMP-implied hazard rates into their systematic and idiosyncratic components allows us to extract trading signals related to their potential convergence. The pairs of CDSs and DOOMPs are traded only if both systematic and idiosyncratic deviations point to the same convergence direction. We use a unique CDS trading data from GFI to test our strategy. The dataset contains the traded prices, as opposed to composite (average) prices often used in CDS research. Using the actual trades, we are able to construct

[1]Throughout this paper, we use between-market curve deviation or systematic deviation interchangeably; we use within-market deviation or idiosyncratic deviation interchangeably; and we use total deviation or cross-market deviation to stand for the sum of the systematic and idiosyncratic deviations.

a realistic trading strategy, in which each position has its own specific time of entering and unwinding, and trading costs are taken into consideration. Our proposed long-short strategy results in positive expected returns after transaction costs, whereas a trading strategy, based simply on the absolute deviations between CDS and DOOMP prices following Carr and Wu (2011) delivers negative expected returns. The key reason for such poor performance is that out of potential 2,930 trades identified based on the absolute deviation between CDS- and DOOMP-implied hazard rates, only one fifth (585 trades) lead to convergence.

Our paper contributes to the discussion of the financial market integration, and illustrates, that although the CDS and DOOMP markets are related, they are not perfectly integrated, and the exploitable realistic cross-market arbitrage opportunities are rather limited.

2 Related Literature

Our paper is closely related to studies under the Carr-Wu framework. Carr and Wu (2011) argue that CDS and DOOMP can both be used for hedging firm's default risk; they show that both products contain the same information about firm's default. Using the weekly observations of 121 companies in 2005–2008, the authors document that the unit recovery claims (URCs) derived from DOOMP option and CDS have similar magnitude in price; and the deviations, if any, between them can be used to predict their respective future market movements. The authors also outline the criteria for matching CDS and DOOMP, although some of the criteria are criticized to be restrictive. One of the most criticized points is to restrict option strike price under \$5. Although such restriction, the authors claim, automatically excludes "too big to fail" firms, the exclusion seems arbitrary, and naturally limits the CDS-DOOMP sample size (Kim et al., 2013).

To further expand the CDS-DOOMP linkage, Kim et al. (2013) propose to use IURC (implied URC), whose URC price is derived from option implied volatility among a boarder range of options.[2] They show that their IURC for option class is more strongly connected than Carr-Wu's URC during financial crisis. They argue that the credit market deteriorated and became dysfunctional during the crisis, leading to a weaker linkage. At the same period, the price deviation of CDS and DOOMP option were strongly influenced by macroeconomic variables (e.g. VIX).

[2]Carr-Wu uses options with put delta less than -15%, while Kim-2013 includes options with put delta up to -70%.

In addition, CDS-DOOMP deviations are found to be heterogeneous with respect to firm's credit quality. DOOMP-implied URCs tend to be much more expensive than CDS-implied URCs for firms with poor credit quality (Angelopoulos et al., 2013; Park et al., 2014). Our study contributes to this strand of literature and provides insights into the CDS-DOOMP co-movements according to firms' rating classes.

The research on CDS pricing connection to other markets has a long history and can be broadly grouped into three categories. The first and most established area is the connection between CDS and equity, and, in the case of sovereign CDS, its relationship with the strength of the currency. The second area is anchored on the Law of One Price (LOP) and arbitrage opportunities based on price discrepancies. The third and most recent line of research focuses on liquidity of the traded securities. Among the first group, researchers usually view CDS as a hedging tool for equities. Their focus is largely on the comparison of the default risk views from the risk-neutral (CDS) and the physical (stock) perspectives. Berndt et al. (2008) find a strong connection between CDS implied hazard rates and Moody's KMV Expected Default Frequency (EDF) in four industries in the U.S. market. Stock prices reflect default risk, together with business and operating risks (Vassalou and Xing, 2004). Friewald et al. (2014) show that CDSs can be used to gauge equity risk premia. The authors find that the excess credit risk premia extracted from CDS spread are strongly and positively related to Merton's equity risk premia. Schneider et al. (2014) show that the same credit risk premia in Friewald et al. (2014) is also related to higher moments of equity returns such as volatility and skewness. However, the link can become weaker when CDS market conditions change. Alexander and Kaeck (2008) show that iTraxx Europe Indices are sensitive to stock volatility when the CDS market is turbulent, but they also find strong regime changes in CDS spreads. Similarly, Fonseca and Gottschalk (2014) study the term structure of CDS spread and the option-implied volatility surface for five European countries from 2007 to 2012. They find that, during that period, the cross-hedging strategy between credit and equity markets may be jeopardized because of larger deviations between credit and equity markets.

Recently, several studies establish connections between CDS and various other markets. Della Corte et al. (2016), for example, find that sovereign CDS explains the price of currency options better than traditional factors, such as treasury rates. The study of price discrepancies has been concentrated on the linkage among CDS, equity, and corporate bonds, since they are all linked to firm's credit risk (e.g. Norden and Weber, 2009; Jorion and Zhang, 2007; Kiesel et al., 2016). The linkage between CDS and equity option markets is not yet fully explored, and our study fills this gap in the literature.

Research to date has already discovered some systematic factors that explain CDS spread movement. Galil et al. (2014) find that the sector median CDS spread can explain the individual CDS spread movements. Other studies (see Longstaff et al., 2011; Tang and Yan, 2013) show that macroeconomic or market factors such as VIX systematically affect the individual CDS spreads. Also, Kolokolova et al. (2018) show that the term structure of individual CDS spreads can be explained by the firm's rating. Specifically, the authors construct rating-based CDS curves using Nelson-Siegel (NS) model and document that the more an individual CDS is away from the corresponding NS curves, the more likely that CDS spread move toward the NS curve. We explore the systematic drivers in CDS and equity option markets, and focus in particular on firm's credit rating as a source of the systematic information, thus, extending the work of Kolokolova et al. (2018) to option markets.

Our paper also complements the literature related to the financial market Law of One Price (LOP) and financial market integration. Studies on the LOP often investigate the foreign exchange rate or commodity price in different regions or countries (see, e.g., Parsley and Wei, 1996; Goldberg and Verboven, 2005), and for international trades (Goodwin et al., 1990), as well as compare stock prices across multiple (overseas) listings (e.g. Foerster and Karolyi, 1999; Howe and Kelm, 1987). Our paper further contributes to the discussion of LOP and market integration across CDS and DOOMP markets.

3 Research Design and Hypotheses

To study the relation between CDS and DOOMP markets, we first use the Carr and Wu (2011) framework and recover the implied hazard rates from CDSs (H^C) and DOOMPs (H^P). Then following Kolokolova et al. (2018) we decompose the hazard rates into the rating-based fitted values (F^C and F^P) and the residual components (R^C and R^P) using the Nelson-Siegel (NS) approach. The detailed technical steps are described in Section 4.

3.1 Cross-market Deviations

The total deviation between implied hazard rates (D^H) can be decomposed into a sum of the systematic deviation (D^F) and idiosyncratic deviation (D^R) as follows:

$$\begin{aligned} D^H &= H^P - H^C = (F^P + R^P) - (F^C + R^C) \\ &= (F^P - F^C) + (R^P - R^C) = D^F + D^R. \end{aligned} \tag{1}$$

Carr and Wu (2011) have shown that the option factors impact the total CDS-DOOMP deviation. If the Law of One Price holds, one would expect that the consensus prices on the CDS and DOOMP markets are the same, thus, the systematic deviation of hazard rates is a white noise. The option market factors, suggested by Carr and Wu (2011), should influence the total deviation through the idiosyncratic deviation component. Due to the differences in the structure of the two markets (OTC vs exchange markets), in maturity of the majority of traded contracts, and in market liquidity and transaction costs, the CDS and DOOMP markets are likely to attract different types of investors and to be only partially integrated. This results in some persistent differences in the systematic deviations of implied hazard rates, which should be reduced during times when the two markets behave more similarly to one another. This reasoning leads to our first hypothesis:

Hypothesis H1: Systematic CDS-DOOMP cross-market deviation is not a white noise. It is positively related to factors capturing disintegration of the two markets.

Even when two markets start behaving more aligned, for example, when they have similar levels of liquidity, other things being equal, this does not necessarily imply that the pricing process is more efficient. For example, low levels of liquidity can lead to more mispricing within each market, increasing idiosyncratic deviation between the implied hazard rates. Our follow up hypothesis is, thus, as follows:

Hypothesis H1a: Idiosyncratic CDS-DOOMP cross-market deviation is positively related to factors capturing market inefficiency.

To test these hypotheses, we estimate a contemporaneous pooled panel regression:

$$D(i,t) = \beta_0 + \beta_1\, X(i,t) + d(i,t) \tag{2}$$

where D is either systematic or idiosyncratic deviation (D^F, or D^R) between the implied hazard rates in different markets for the same firm i, X is the set of explanatory variables, and d is the residual term of the regression. We also include time and rating fixed effects in all the regressions.

Following prior literature, we identify a set of potential explanatory variables. We classify each of them according to its relation to CDS-DOOMP market integration and market efficiency, to form expectations about the direction of its impact on the deviations.

The first two factors – the level of credit risk and option delta – capture the likely reasons for investors to trade on either of the markets.

(1) $0.5 \times (H^P + H^C)$: The average of the implied hazard rates measures credit risk of the underlying. Higher hazard rates indicate higher credit risk, thus, DOOMPs are more likely to be used as credit protection instruments, making them more aligned with CDSs. We expect the systematic deviation to be reduced if credit risk increases. At the same time, higher credit risk often leads to higher price volatility. Hence, idiosyncratic deviations are likely to increase with the level of credit risk.

(2) |Delta|: Option delta represents the option price sensitivity to the underlying stock price change. When the underlying stock price is below the strike price, the put option is more sensitive to the stock price, as the option buyer has the right to exercise the option. In other words, when |Delta| is larger, put option is closer to the in-the-money condition, and it is likely to behave more like a traditional option, instead of a credit risk protection. Therefore, we expect a positive relationship between the systematic deviation and the |Delta|. At the same time, when a put option becomes less related to the credit risk, it's connection to the rating-implied curves weakens and the idiosyncratic deviation between CDS and DOOMP can also be expected to increase.

The second three factors – put option maturity and CDS and put bid-ask spreads – capture structural similarity between the markets.

(3) Put Maturity: CDS and put markets are characterised by maturity mismatch between the contracts. Option maturity, on average, is shorter than one year, whereas most CDSs have a maturity of 5 years. Increasing put maturity narrows this mismatch[3] making the contracts more similar. Hence, we expect a negative relation between put maturity and systematic deviation. Similarly, increasing put maturity makes DOOMPs a more attractive tool for hedging credit

[3]We use 5-year CDS in our test; therefore, we focus only on put option maturity.

risk. Thus, their prices are likely to be more aligned with the rating curves, which leads to reduction in idiosyncratic deviations. In the regressions, we use a natural logarithm of the put maturity expressed in days.

(4) Put BAS: Put option bid-ask spread measures the level of the illiquidity of the put option. Less liquid put options are more similar to generally less liquid CDSs; they are more likely to be used as a credit protection instrument than for short-term speculation on stock price movements. Thus, a larger option bid and ask spread is expected to be negatively related to the systematic deviation in hazard rates. At the same time, low option liquidity makes this market less efficient. The put option price is more likely to deviate from its fundamental value, hence, the idiosyncratic deviations are expected to rise with bid-ask spreads.

(5) CDS BAS: CDS bid-ask spread measures the level of the illiquidity of the CDS contract. Less liquid CDSs are more distinct from generally more liquid puts. Thus, a larger CDS bid and ask spread is expected to be positively related to the systematic deviation in hazard rates. Similarly to the put option bid-ask spread, the idiosyncratic deviations are expected to rise with CDS bid-ask spreads, and the prices within the market are more likely to depart from their consensus level.

Next two factors – open interest and the number of CDS intra-day trades – capture the market depth, and, thus, the ease for an investor to switch between the markets.

(6) Open Interest: Option open interest captures the demand for the put options. Higher open interest could indicate that potential protection buyers have switched from the CDS market to the put option market. Therefore, we higher open interest can reduce the systematic cross-market deviation, as put prices are more likely to be driven by credit-risk related information.

(7) CDS Trade: The number of CDS intra-day trades also captures the CDS market depth and liquidity. We expect that the systematic deviations between put options and CDSs to be negatively related to the number of CDS trades.

Last but not least we capture the risk-aversion of put option investors though option implied volatility.

(8) Implied Vol: Option-implied volatility reflects investor's expectation regarding underlying stock price risk, as well as their risk attitude. Under the classical Black and Scholes (1973) option pricing framework, higher implied volatility reflects a higher (put) option price, thus, a

higher put-implied hazard rate. If the implied volatility increases due to increasing risk aversion of put-market participants, then we can expect the systematic cross-market deviation to increase. At the same time, if a higher implied volatility reflected the objective expectations of higher stock price volatility, this implies that the probability of hitting the default barrier of the underlying firm also increases, and, thus, CDS spreads and their implied hazard rates should go up too, and the cross-market systematic deviation can be reduced. Wang et al. (2013) find evidence that option variance risk premium (calculated by option implied volatility subtracted by the risk-neutral expected volatility) increases the CDS spread. Hence the expected sign of the effect of the implied volatility on systematic cross-market deviation cannot be determined ex-ante, as it depends on the reasons for changes of implied volatility.

3.2 Within-market convergence to the curve

Hypotheses *H1* and *H1a* allow us to establish if there are persistent differences in rating-based curves of hazard rates, implied by CDSs and DOOMPs, linked to market segmentation, and if the idiosyncratic deviations are linked to other market imperfections. If the idiosyncratic deviations are indeed driven by market imperfections, then they are likely to diminish over time, leading to convergence of individual hazard rates to the rating-implied curves. Kolokolova et al. (2018) show that this is true for the CDS market, and CDS-implied hazard rates tend to converge for their NS rating curves, especially if the deviations are substantial. Since DOOMPs can be used for hedging credit risk, we test if there idiosyncratic deviations from the NS rating curves diminish over time as well and the put-implied hazard rates converge to their NS rating curves, similar to CDS-implied hazard rates.

> *Hypothesis H2: CDS and DOOMP option implied hazard rates converge to their market-specific rating-based curves.*

To test this hypothesis, we estimate the following model:

$$\Delta H(i, t_1, t_2) = \alpha + \beta_1 \, \Delta F(i, t_1, t_2) + \beta_2 \, R(i, t_1) + e(i, t_1), \tag{3}$$

where $\Delta H(i, t_1, t_2)$ is the time-series changes in the hazard rate from time t_1 to t_2, $\Delta F(i, t_1, t_2)$ is the corresponding change in the NS-fitted value, and $R(i, t_1)$ is the residual at time t_1. We estimate Equation (3) for CDS and put option separately. We also include calendar day and rating fixed effects in the regression.

Negative and significant β_2 coefficients will indicate that the recovered hazard rates converge to their respective NS-curves over time.

3.3 Between-market curve convergence

Convergence of individual hazard rates to their respective rating curves, suggested in the previous section, implies that the cross-market idiosyncratic deviation also tends to zero. Recall that the idiosyncratic deviation is defined as $D^R = R^P - R^C$. If both $R^P \to 0$ and $R^C \to 0$, then indeed D^R approaches 0 as well. If the CDS and put markets were fully disintegrated, then each of them could have its own rating-based curve of hazard rates. The markets are likely, however, to be only partly segmented. As suggested by our hypothesis *H1*, higher market integration leads to closer rating-based hazard rate curves. Carr and Wu (2011) also show that the total deviation between CDS and put option implied hazard rates is narrowed over a period of time, after controlling for possible deviation drivers. Hence, we formulate out final hypothesis, which refines the general findings of Carr and Wu (2011):

> *Hypothesis H3: Systematic deviations in hazard rates between CDS and DOOMP markets diminish over time, leading to rating-implied curve convergence. Diminishing idiosyncratic deviations further contribute to the overall convergence between CDS and put implied hazard rates.*

To test this hypothesis, we regress the time-series changes of the implied hazard rates on the cross-market deviation measures:

$$\Delta H^P(i, t_1, t_2) = \beta_0^P + \beta_1^P \, d^F(i, t_1) + \beta_2^P \, d^R(i, t_1) + e^P(i, t_1) \tag{4}$$

$$\Delta H^C(i, t_1, t_2) = \beta_0^C + \beta_1^C \, d^F(i, t_1) + \beta_2^C \, d^R(i, t_1) + e^C(i, t_1) \tag{5}$$

where $\Delta H^P(i, t_1, t_2)$ (or $\Delta H^C(i, t_1, t_2)$) is the time-series change of the put option (or CDS) implied hazard rate from time t_1 to t_2, and d^F (or d^R) is the regression residual term obtained from Equation (2). We also include calendar dummies to control for time fixed effect. We do not include rating dummies because the rating effect has been already captured in d^F. Here, we use the residual term from Equation (2), instead of their original deviations (D^F or D^R), to control for the known cross-market drivers.[4]

[4] As a robustness check, we estiamte the regressions in (4) and (5) replacing d^F and d^R by D^F and D^R, respectively. The results remain qualitatively similar, implying that that one can use the CDS-DOOMP deviations directly as a trading signal.

Recall that the systematic deviation captures the (signed) distance between the put-implied fitted values of hazard rates and the CDS-implied ones, while the idiosyncratic deviation captures the (signed) distance between the residuals in the put and CDS markets. Thus, a negative values of β_1^P and a positive values of β_1^C would indicate convergence in NS-fitted value F to one another across the two markets. For example, if one observes a positive systematic deviations d^F at time t_1, then H^P is expected to decreases from time t_1 to t_2, and H^C is expected to increase, leading to smaller systematic deviation between two markets at time t_2. Similarly, a negative value of β_2^P and a positive values of β_2^C would further show that diminishing residual components R also contribute to the convergence between the hazard rates over time.

Importantly, as the signs of β_1 and β_2 are expected to be the same in each of the two equations, the magnitude of time-series change in H is stronger, if d^F and d^R share *the same* sign. In other words, we expect a stronger price convergence between CDS and put option if both systematic and idiosyncratic deviation go in the same direction, and a weaker price convergence when the directions of deviations are different ($d^F > 0$ and $d^R < 0$, for example).

4 Hazard Rate Construction and Deviation Decomposition

4.1 URC-implied Hazard Rate

According to Carr and Wu (2011), a unit recovery claim (URC) is a security that pays \$1 if a firm defaults before time T. The price of a URC (denoted as U) can be expressed as follows:

$$U(t,T) = \mathbb{E}^Q\left[e^{-r\tau} I_{\{\tau<T\}}\right] \tag{6}$$

where r is the risk-free interest rate, τ is the default time, I is an indicator function taking the value of 1 if default happens before T and zero otherwise, and $\mathbb{E}^Q$ is the expectation operator under the risk neutral measure.

If default events follow a Poisson distribution with constant hazard rate H, then

$$U(t,T) = H\frac{1-e^{-(r+H)(T-t)}}{r+H}. \tag{7}$$

Based on Equation (7), the CDS-implied URC (denoted as U^C) can be written as

$$U^C = \zeta Price^C \frac{1 - e^{-(r+\zeta Price^C)(T-t)}}{r + \zeta Price^C} \tag{8}$$

where ζ is the inverse of loss-given-default (i.e. $1/(1 - RR)$, with RR being the bond recovery rate) and $Price^C$ is the price of a CDS contract, that is, the CDS spread. Equation (8) holds when the default arriving rate has a flat term-structure with $H = Price^C/(1 - RR)$.

Consider now a put-implied URC. An American put option allows investors to sell the underlying security at the pre-determined strike price. In case of a DOOMP, the exercise event is most likely to coincide with the firm's default. Thus, the current put price $Price_0^P$ can be expressed as:

$$Price_0^P(K, T) = \mathbb{E}^Q \left[e^{-r\tau}(K - S_\tau) I_{\{\tau<T\}}\right] \tag{9}$$

where K is strike price and S_τ is the asset value at the time when the firm defaults, K is the option strike price, and T is time to maturity.

Carr and Wu (2011) prove that as long as the stock price is bounded below by a strictly positive barrier $B > 0$ before default, but drops below a lower barrier $A < B$ at default, and stays below A thereafter, the price of the DOOMP is entirely driven by the default probability and not by the stock price or the stock volatility. In particular, the DOOMP option price at time t has the following analytical representation:

$$Price_t^P(K, T) = K \left[H \frac{1 - e^{-(r+H)(T-t)}}{r + H}\right] - Ae^{-rT} \left[1 - e^{-H(T-t)}\right]. \tag{10}$$

Using any two American puts (with the same underlying) with strike prices being within the default corridor $[A, B]$, one can replicate a pure credit insurance that pays off if and only if the company defaults prior to the option expiry. Combining Equations (7) and (10), the put-recovered URC (denoted as U^P) can be valued as a scaled difference between the two put option prices

$$U^P = \frac{Price^P(K_2, T) - Price^P(K_1, T)}{K_2 - K_1}. \tag{11}$$

For the special case in which stock price falls to zero at default time (i.e. $A = 0$), $K_1 = 0$, and

$K_2 = K < B$, Equation (11) simplifies to:

$$U^P = Price^P(K,T)/K. \tag{12}$$

After we obtain U^C and U^P following Carr and Wu (2011) framework, we calculate the URC-implied hazard rates based on U^C and U^P. We calculate the put-implied hazard rate (denoted as H^P) based on Equations (7) and (12). The CDS-implied hazard rate (denoted as H^C) is computed as $H^C = Price^C/(1 - RR)$; here, we set RR as 0.4 for all our CDSs.

4.2 Rating-based URC Curves

Hazard rates recovered in the previous section capture the credit risk, associated with the underlying of every contract. Kolokolova et al. (2018) show that rating-based hazard rate curves serve as a benchmark to which investors anchor the CDS prices. Following the authors, we fit a Nelson and Siegel (1987) model for the hazard rates in DOOMP and CDS markets separately to construct market specific rating-based hazard rate curves, and obtain daily fitted values of hazard rates $F(\tau)$ for each maturity τ, and each rating class in both markets.

The Nelson and Siegel (1987) model allows for a humped-shape term structure:

$$F(\tau|\beta_0, \beta_1, \beta_2, m) = \beta_0 + \beta_1 \left(\frac{1 - e^{-\tau/m}}{\tau/m} \right) + \beta_2 \left(\frac{1 - e^{-\tau/m}}{\tau/m} - e^{-\tau/m} \right) \tag{13}$$

where β_0 and β_1 are parameters reflecting the long-term and short-term hazard rates, β_2 captures a hump at the medium term, and m determines the shape and the position of the hump. Equation (13) is estimated separately for put option and CDS. The estimation steps are detailed in Kolokolova et al. (2018).

We next decompose the CDS and DOOMP implied hazard rates into their fitted rating based component and a residual:

$$H(\tau) = F(\tau) + R(\tau) \tag{14}$$

where H is the URC-implied hazard rate obtained from a put or CDS with maturity τ, F is the fitted value specific to the credit rating class, and R is the residual. These fitted values and the residuals are then used to construct our deviation measures as shown in Equation (1).

5 Data

5.1 CDS Data

In a CDS contract, a protection buyer pays periodic payments (based on the quote) to the protection seller, and the protection seller agrees to compensate the buyer for the loss in a credit event. There are two types of quotes in the CDS market–par spread and points upfront. Par spread quote (denoted as k) is the amount the protection buyer pays periodically per \$1 notional; it is determined such that the protection buyer's pay-off (or premium leg) is equal to the seller's pay-off (or protection leg), in terms of expected present value. Therefore, a CDS contract based on a par spread quote has zero initial value for the protection buyer or seller.

In points upfront quote, the periodic payments of a CDS are restricted to a standardized coupon value (denoted as c). The common fixed coupon is 25, 100, 300, or 500 bps. Since the coupon value is unlikely to equate premium leg with protection leg, one party of the CDS contract may have advantage over the other. To compensate for this advantage, a one-off upfront payment (denoted as u) is made to the disadvantaged party. As a result, a points upfront quote contains two pieces of information–upfront payment (u) and periodic fixed coupon (c). For example, if the fixed coupon c is smaller than than the par spread k, then the protection buyer pays less than the fair value of the contract. In this case, the protection buyer is asked to pay an upfront payment to the protection seller. In practice, par spread quote is more popular than points upfront quote.[5]

A number of data providers supply CDS quote data in the market. The major ones include GFI, Markit, CMA, Reuters, and Bloomberg. Yet, there is a concern about the consistency and price representativeness of the CDS data provided by these sources, because none of these data providers cover all the CDS trades; also, the approaches for constructing CDS prices used by data providers vary substantially. For example, Reuters provides CDS data in the form of a daily 'composite price' which is computed from the quotes taken from the contributors; some of these quotes can be doubtful as they neither represent an actual trading price nor a firm commitment for trading based on the quoted price. CMA uses an aggregation methodology which is based on intra-day prices and the application of different weights to the contributions.[6]

The main CDS quotes used in this study is obtained from GFI credit market data. GFI is

[5]In our dataset, over 95% of quotes are expressed as par spreads.

[6]Mayordomo et al. (2014) pointed out these inconsistencies and provide detailed discussion and comparison among CDS data sources.

a leading inter-dealer broker in credit derivatives, and the company collects, cleans, and stores trading prices in its electronic trading platform, CreditMatch, as well as in its global brokerage desks. Unlike other CDS data providers, the CDS quotes in GFI data are actual prices with firm commitments from protection buyers and sellers for trading. The GFI CDS data contain intra-day trading information, including bid/ask prices, CDS maturity, credit event trigger (i.e. restructure type), and underlying debt seniority, but it does not include protection buyer and seller information.

Our CDS sample is from July 2012 to April 2016 and consists of 46,495 observations on U.S. single-name CDSs with non-restructure type on senior debt. The sample contains both types of quotes. Of our 46,495 observations, only 4.09% (1,901 quotes) are expressed in points upfront, and the rest are expressed in par spread quote. To standardize all trading information, we convert points upfront quote to par spread quote. The conversion procedure is explained in Appendix A.

Table 1 reports the descriptive statistics of our CDS sample. The average CDS price is 278.50 bps, with the standard deviation of 856.77 bps. For less than 1% of quotes only bid (or ask) price is available. In these cases, we use the bid (or ask) price as mid price. The average bid-ask spread (BAS) is 0.13 bps. The average time to maturity of the CDS is 4.7 years, ranging from a few days to 10 years. When we break down CDS's maturity (reported in Panel B), we find that 5-year CDS constitutes the majority of the CDS trades (roughly 81%); the least frequently traded maturities are from 7 to 9 years.

[Table 1 is about here.]

We further explore time-series pattern of CDS trades over our sample period. Figure 1 illustrates the numbers of monthly trades (bars) and of the average daily traded names (the line graph) over the period from July 2012 to April 2016. We observe that CDSs were traded intensively during the period from July 2013 to October 2014. The number of average daily traded names follows a similar trend as the number of monthly trades. The recent decline in CDS trades was partly due to, according to the senior manager's reply from the GFI company, its clients' trading shift to multi-name CDS products (a bundled transaction with more than one single-name CDSs).

[Figure 1 is about here.]

As our CDS data is from a single dealer, one might be concerned if the CDS prices in GFI database are representative for the whole CDS market. Hence, we compare the GFI CDS prices with composite CDS prices reported by Markit. We do not find any significant difference in either average prices or their dynamics. The detailed analysis is reported in Appendix B.

5.2 Put Option Data

Our put option data is obtained from OptionMetrics. We follow three selection criteria (out of five) described in Carr and Wu (2011) to select matched DOOMP options. We use put options with (1) the absolute value of put option delta less than 15%, (2) option bid price larger than zero, and (3) the trading volume of the corresponding option larger than zero.

We relax the last two selection criteria from the original Carr and Wu (2011) study. We do not restrict option strike price to be under $5[7]. Carr and Wu (2011) assume that CDS contracts for underlying names that have greater default risk (and lower stock price) are usually more common. However, recent studies (see Kolokolova et al., 2018; Yu, 2006) suggest that the popular traded names are not always firms with greater default risk. In fact, CDS contracts for investment grade firms are often more popular than those for junk grade firms. Since the investment grade firms are unlikely to have traded option with strike price under $5, applying this criterion would exclude a large number of CDS trades unnecessarily (Kim et al., 2013), and therefore we do not use it.

The other criterion we relax is the one-to-one matching between a CDS and a put option. In Carr and Wu (2011), if there are multiple put options matching to a CDS (due to different put maturities), the authors chose the put option with the highest option open interest. We retain this criterion for pairing CDSs and DOOMPs (as will be discussed later), however, for construction of the put-implied hazard rate curves we keep all available put options as long as they fit other selection criteria.

Based on our three selection criteria and using the underlying equity ticker maintained by the GFI, we have matched 82,623 put option observations, Table 2 reports the descriptive statistics for the put option. The average put mid price is $0.44 with the standard deviation of 0.61. We also observe a rather high bid-ask spread, with the sample average of 0.09. Such high bid-ask spread indicates higher transaction cost for illiquid put options. In addition, the average time to maturity for the put option of 0.38 years is much shorter than that of CDS contracts.

[7] Carr and Wu (2011) restrict option strike price to be under $5.

Panel B of Table 2 reports the maturity distribution of the matched put options. Most of the observations have maturity within 1 year, and we do not find matched options with time to maturity more than 3 years.

[Table 2 is about here.]

5.3 Pairing CDSs and DOOMP Options

Before proceeding with our analysis, to properly measure cross-market deviations, we construct paired CDS and put option. Every day and for every underlying we choose a 5-year CDS contract (if available) and match it to a put option with the nearest maturity. We fix the time to maturity for CDSs since 5-year CDSs are the the most popular contract (in general and in our sample) and the price should encounter lower illiquidity effect. If there are multiple put options matching the same CDS (e.g. put options with the same maturity but different strike prices), we choose the one with the highest open interest. Eventually, we are able to have 4,268 pairs of CDS and put options over the sample period from July 2012 to April 2016. These 4,268 CDS-DOOMP pairs also indicate the plausible trading opportunities where one can trade on both a CDS and a put option on a given day. We trace option ID, provided in OptionMetrics, to make sure we do not mismatch the option.

After the cross-sectional matching for the CDS and put option, we further match these pairs along the time-series dimension. The purpose of time-series consistency is twofold: (1) we need a consistent time-series changes in CDS and DOOMP option prices, required in our proposed regression, and (2) with time-series matching, we are able to further develop a plausible trading strategy, i.e. specific time to engage in securities and time to unwind the portfolio.

If one plans to construct an implementable trading strategy, one should take into consideration that CDSs and put options are relatively illiquid products. It may happen that one is not able to unwind their CDS-put positions before the option position expires (recall that the option in the sample has relatively short time to maturity). Therefore, holding period is another important factor for time-series matching. A long holding period would increase the uncertainty of strategy implementation; a too short holding period may result in insufficient price convergence and the trading profit may be consumed by the transaction costs. Based on previous studies (Carr and Wu, 2011; Kolokolova et al., 2018), we restrict the holding period between 7 and 30 calendar days. We further filter among our 4,268 CDS-put pairs those with the opportunity to unwind, such that (1) the holding period is within 7 and 30 days, and (2) we choose the earliest date to unwind, given the nature of these illiquid products.[8]

Overall, we identify 2,134 time-series trades in our sample. Each trade consists of two trading opportunities $\{[C(t_1), P(t_1)], [C(t_2), P(t_2)]\}$, where $[C(t_1), P(t_1)]$ is the CDS-DOOMP pair of prices for building a trading strategy at time t_1 and $[C(t_2), P(t_2)]$ is the CDS-put pair of prices for unwinding the position at time t_2. Note that the holding period $(t_2 - t_1)$ varies for each trade and we use the daily CDS prices, instead of intra-day prices, as we consider daily trading strategy.

6 Results

6.1 NS-Fitted Curves

We form our rating curves for the CDS and put samples every trading day. Since almost all the GFI CDS contracts are traded on 5-year tenor, we find that there are insufficient tenors to form a stable curve. Therefore, for CDS curves, we match GFI CDSs to Markit CDSs, and include the CDS spreads from other tenors too. The observations are grouped according to the Markit implied rating when fitting Nelson-Siegel (NS) curves.[9] Having estimated the daily sets of NS parameters $[\beta_0, \beta_1, \beta_2, m]$ in Equation (13) for different rating classes of our CDSs and put options, we calculate the NS-fitted value for the securities using their ratings and the corresponding time to maturity.[10]

To illustrate the time-series dynamics of the NS-fitted values, we use the daily sets of parameters to calculate the 5-year fitted value (i.e. set $\tau = 5$ in Equation (13))and then average

[8]For example, if we observe that one CDS-put pair can be unwound after 9, 10, and 12 days, we choose to unwind the position on the ninth day. When implementing the trading strategy, we also unwind the positions at the earliest opportunity, instead of choosing the most profitable one.

[9]We use Markit implied rating, because the rating information is not available in our sample period. Implied rating is determined by comparing the corresponding CDS spread to nearest preset rating boundaries Markit (2011). The discrepancy between actual rating and implied rating gives an indication of gaps between the viewpoints of market perception and rating agency perception regarding firm's default risk (see Markit analyses: `http://www.markit.com/Commentary/Get/23112015-Credit-CDS-implied-and-credit-agency-ratings-diverge`). Our actual rating information is available only from 2002 to 2012. For this sample we compare the actual rating and implied rating and find a high correlation coefficient between them (66.03% over the period from 2002 to 2012, and 70.79% over the period from 2010 to 2012). Since the implied rating does not systematically deviate from the actual rating, but reflects more promptly market conditions, we use the implied rating information as our grouping criterion.

[10]Note that, since the parameters are calibrated for a group of contracts with the same rating, two CDSs or put options will have the same NS-fitted values of the hazard rates if they have the same rating of the underlying asset and time to maturity.

them across each months. Figure 2 plots the time series of NS-fitted hazard rates for CDS and put options for investment-grade and junk-grade underlyings. The two figures show that the NS-fitted rates increase for poor credit quality underlyings. The CDS-implied fitted hazard rates are also much more volatile than put-implied rates for both investment and junk grades, indicating that there are more "disagreements" or market frictions in the CDS market.

[Figure 2 is about here.]

Table 3 reports the descriptive statistics of the NS-fitted values for CDS and put options. Overall, the mean and median values tend to increase as the rating worsens, and the standard deviations of the hazard rates also go up for poor rating classes. Panel C further reports the differences between put- and CDS-impled hazard rates for contracts matched on the underlyings. On average, there is a U-shape relation between the difference in the implied hazard rates and the rating, with put-implied hazard rate being higher than CDS-implied ones for AA and B ratings, but lower for BBB and B ratings.

[Table 3 is about here.]

6.2 Results: Cross-Market Deviations

Table 4 reports the results for determinants of the cross-market deviations. Consistent with our hypothesis *H1*, the systematic deviation is not white noise. It increases when CDS and put markets become more disintegrated and is reduced when the markets become more similar to one another. The idiosyncratic deviation increases with higher levels if market frictions, consistent with our hypothesis *H1a*.

Notably, as some factors capture markets' similarity as well as market frictions, they have the opposite effect on the systematic and idiosyncratic deviations. For example, the systematic deviation is smaller for riskier underlyings, as the puts are more likely to be used as a credit protection tool. But the idiosyncratic deviation increases for riskier underlyings, as there is more noise and volatility in their prices. Similarly, put bid-ask spread is negatively related to the systematic deviation but positively related to the idiosyncratic one. As a result, the effect of these factors on the total deviation is milder in absolute value, as reported in column [3] of Table 4, albeit still statistically significant. Option delta and put maturity, on the contrary, have the same effect on systematic and idiosyncratic deviations, thus, amplifying the overall positive relation between the total deviation and option delta, and the negative relation between the total deviation and put maturity.

[Table 4 is about here.]

Table 5 reports the results of the deviation drivers for D^F and D^R in different sub-samples (sub-periods, sectors, and underlying credit ratings). In the case of idiosyncratic deviations, the sign and significance are comparatively consistent across the sub-samples. The strongest and robust effect is the positive relation of the deviation and the average hazard rates. Controlling for rating of the underlying, there is more disagreement in prices of puts and CDSs for riskier cases. The notable exception is the implied volatility. It has no significant effect on the idiosyncratic deviation during 2012-2013, a significantly negative effect in 2014, and significantly positive effect in 2015-2016. It has also a significantly positive relation with deviations for firms from Materials sector, and a significantly negative relation with deviations in the Financial sector. The drivers of systematic deviations are relatively less stable. The average hazard rate, option delta, and implied volatility all flip signs at least in one of the sub-samples.

[Table 5 is about here.]

6.3 Results: Within-market convergence to the rating curve

Table 6 reports the results for hazard rate convergence to the rating-based curve, as specified in Equation (3), for the CDS market. Based on the complete sample (Panel A) we find that the loading on the change in the fitted values β_1^C is 0.158 and the loading on past residuals β_2^C is -0.063, both significant at the 1% level. The results indicate that the time-series movement of CDS-implied hazard rate is mainly captured by the NS-fitted value F^C. The negative loading on the NS residual R^C further supports convergence of CDS-implied hazard rates to the rating-based curves, consistent with Kolokolova et al. (2018). Panels B to D further report the results for different sub-samples. The convergence results are robust, pronounced in all sub-periods, for most of industries, and for both investment grade and junk grade underlyings. This further highlights the importance of credit rating in the CDS market as a driver of the consensus prices.

[Table 6 is about here.]

Table 7 reports the results for put options. On the complete sample, β_1^P is positive and significant at the 5% level, indicating that changes in the rating-implied consensus values of hazard rates do drive changes of individual put-implied hazard rates. The coefficient β_2^P is negative, but not statistically significant. It means that even though there can be some convergence to NS-fitted rating-based curve, it is less pronounced than in the CDS market. The sub-sample analysis confirms, that although the β_2^P coefficients are almost always negative, they often lack statistical support. The convergence is strongly pronounced for two industries – Materials and Industrials – where the corresponding β_2^P coefficients of -0.188 and -0.086 and both significant at the 1% level. The lack of strong convergence to the rating-based curve is likely to be explained by the fact that, when CDS and DOOMP markets become more disintegrated (e.g., when the option delta or implied volatility increases), the impact of the credit-related part of the put-implied hazard rate weakens, and other option factors drive the dynamics. This further highlights the fact that CDS and DOOMP are only partial substitutes and one cannot expect the Law of One Price to perfectly work across these markets.

[Table 7 is about here.]

6.4 Results: Between-Market Curve Convergence

The estimation results for the cross-market curve convergence (Equations (4) and (5)) are reported in Table 8. We use several ways to estimate d^F and d^R: first, the residuals are computed from Equation (2), controlling for only one of the deviation drivers at a time, and then for all the drivers jointly.

The left-hand side panel of the table reports the results for CDSs and the right-hand side panel report the results for put options. β_1^C and β_2^C are positive and significant at the 1% level in in all the specifications, whereas β_1^P and β_2^P are negative and almost always significant at the 1% level. This means that positive systematic deviation between put and CDS-implied hazard rates predicts an increase in the CDS-implied hazard rate and a decrease in the put-implied hazard rates thus, supporting our hypothesis *H2* of convergence of the NS-implied curves over time. Meanwhile, positive β_2^C and negative β_2^P together indicate that a CDS and a put option also move toward their corresponding NS-curves, contributing to the overall CDS-DOOMP convergence.

[Table 8 is about here.]

As a robustness check (Panel B), we use unconditional deviation (D^F and D^R) in Equations (4) and (5), and find that the CDS-DOOMP convergence still holds, even without controlling for other drivers of the deviations. It also implies that one can construct a trading strategy by exploiting the systematic and idiosyncratic deviations without controlling for the deviation drivers.

Table 9 reports the sub-sample results. Overall, the results indicate convergence of the NS-curves across the markets, but they are more volatile due to reduced size of sub-samples.

[Table 9 is about here.]

7 Convergence Exploiting Trading Strategy

The documented convergence between put and CDS implied hazard rates suggests that it may be possible to exploit the information on relative mispricing of these two products and construct a profitable trading strategy. Using a signal at time t_1 for future convergence, one takes a long position in the security (a CDS or a put option) with a lower hazard rate H (i.e. $\min(H^P, H^C)$) and a short position in the security with a higher H (i.e. $\max(H^P, H^C)$), both securities written on the same firm. The positions are unwound after the two hazard rates have converged at some time t_2. The challenge in implementation of such a strategy is that the actual contracts bought have a different structure, and do not have a one-to-one correspondence like the implied hazard rates analyzed in the previous section. Thus, for the real world implementation, one should decide what is the expected proportion of a change in the CDS spread one desires to "hedge" with the put option. For example, for a long-CDS and short-put case, the strategy return (denoted by r^A) can be calculated as:

$$r^A = r^C - \frac{\Delta Price^P}{\Delta Price^C} \times r^P \tag{15}$$

$$r^S = \frac{\log Price^S(t_2) - \log Price^S(t_1)}{t_2 - t_1}, \text{ for } S = \{C, P\}, \tag{16}$$

where $Price^S$ is the price of the instrument of interest, C and P stand for a CDS a put respectively, the holding period is from t_1 to t_2, and $\frac{\Delta Price^P}{\Delta Price^C}$ is the hedge ratio for put side.

The theoretical hedge ratio equals to[11]:

[11]The derivation is detailed in Appendix C.

$$\frac{dPrice^P}{dPrice^C} = K[k^{-1} + \zeta\tau^C - \zeta(r + \zeta k)^{-1})]U^C, \tag{17}$$

where K is the put strike price, k is the CDS spread, r is a risk-free rate, ζ is the inverse of the loss-given-default, and U^C is a price of a unit recovery claim implied by the CDS contract.

We use three different levels of hedge ratios in our trading strategy. First, we allow for hedging of the complete change in the CDS price. Second, we hedge the average CDS spread. Last, our hedge ratio covers 1 standard deviation of a CDS spread. Thus, the three considered hedge rations are:

$$\frac{\Delta Price^P}{\Delta Price^C} = \begin{cases} 1, \\ \frac{dPrice^P}{dPrice^C} \times Avg(CDS), \\ \frac{dPrice^P}{dPrice^C} \times Std(CDS), \end{cases} \tag{18}$$

where $Avg(CDS)$ is the pooled average CDS spread in our sample and $Std(CDS)$ is the pooled standard deviation of the CDS spreads.

We consider two ways to determine the trading signal. First, as a *Benchmark* strategy, we use the total deviation between put and CDS hazard rates D^H as a signal. If D^H is positive (negative), we long (short) CDS and short (long) put option at time t_1, and unwind the position at time t_2, as theoretically $D^H \to 0$ over time. This signal would be consistent with the Law of One Price and the Carr and Wu (2011) framework. Second, we propose a *Decomposition* strategy, based on the signal devised from the NS-components of the hazard rate. Recall that $D^H = D^F + D^R$; the magnitude of the convergence in hazard rates is expected to be stronger, if D^F and D^R have the same sign (see Equations (4) and (5) and the corresponding results in Table 8). Thus, in our *Decomposition* strategy, we trade on the D^H only when D^F and D^R have the same sign. Specially, we long (short) CDS and short (long) put option at time t_1, only if D^F and D^R are *both* positive (negative); and we unwind the position at time t_2. This strategy is more stringent because the number of potential trading opportunities is smaller, but the additional information is expected to enhance the prediction of convergence.

As for the holding time of the portfolio, we choose the time t_2 to unwind the position at the first opportunity after 7 trading days.[12]

[12]In our regression results we restrict the holding period between 7 and 30 days. Here, to avoid any selection

The trading returns discussed above do not consider the transaction costs, which are likely to be substantial in DOOMP and CDS markets. So on the next step we adjust the returns for transaction costs using the reported bid-ask spreads (BAS). The adjusted returns are computed as:

$$r^S = \frac{\log Price^{S'}(t_2) - \log Price^{S'}(t_1)}{t_2 - t_1}, \text{ for } S = \{C, P\}, \tag{19}$$

where $Price^{S'} = Price^S + BAS/2$ for a purchase price or $Price^{S'} = Price^S - BAS/2$ for a selling price, and BAS in the bid-ask spread of the corresponding security.

Recall that CDS spread is an annualized periodic payment for credit protection, and the protection payment is paid quarterly, while a put option premium is a one-off payment. Therefore, in order to properly account for return generating payment structure, we amortize both CDS bid-ask spread, by dividing it by 20 for a 5-year contract, as well as the return, by dividing it by 4, to convert annual values into quarterly ones.

7.1 Trading Strategy Performance

For the *Benchmark* strategy, we identify 2,930 trades with the holding periods ranging from 7 days to more than 1 year. Our *Decomposition* strategy, requiring D^F and D^R to have the same sign, reduces the number of trading signals and consecutive trades to 585. Table 10 reports the distribution of holding times for all trade, as well as for the trades with the same and different signs of two deviation measures. The average duration of trades with the same sign of the deviations is 26.52 days, whereas the average duration of trades with different signs is 35.81 days, pointing towards more trading opportunities for those cases for which the convergence is expected to be stronger.

[Table 10 is about here.]

Table 11 reports the strategy performance in terms of daily returns. For the case of full hedge and no transaction costs, the average return for the *Benchmark* strategy (Ret^B) is positive of 0.827%, significantly greater than zero at the 1% level. The *Decomposition* strategy delivers a much higher average return of 1.873% (Ret^D), with fewer number of trade than our *Benchmark* strategy. The return difference of 1.046% is significantly different from zero at the 1% level. We further evaluate the performance of those trades which are excluded from the *Decomposition*

bias and make the strategy implementable, we relax this restriction.

strategy. If the signs of D^F and D^R differ, the propensity of convergence is weaker; the average return (Ret^O) is merely 0.566%. Hedging the average CDS spread or 1 CDS standard deviation substantially increases the returns for all strategies, as reported in Panels B and C of the table. The largest gains are associated with the *Decomposition* strategy. Here the daily returns per trade increase to 6.38%, whereas for the *Benchmark* strategy they are 2.75%.

Most importantly, the *Decomposition* strategy is the only one which is able to generate positive returns after transaction costs. In general, transaction costs severely reduce the return. With the full hedge, the *Benchmark* strategy results in a negative return of -0.87% significant at the 1% level, whereas the return for the *Decomposition* strategy, is not statistically significant, although also negative of -0.17%. Using alternative hedge ratios, the *Decomposition* strategy generates positive returns of 0.56% and 0.66%, significant at the 10% level, whereas the *Benchmark* strategy results in even larger losses for investors of -1.66% and -1.91% signifiant at the 1% level.

These results combined provide strong evidence that the suggested decomposition into the systematic and idiosyncratic components of the implied hazard rates and their respective deviations provide a more precise signal for the convergence between CDS and put option, than the overall deviation in the implied hazard rates between the two markets. Using the refined signal, it is possible to develop a trading strategy with a positive expected arbitrage return even after transaction costs.

8 Conclusion

CDS and DOOMP options provide protection against firm default. If the Law of One Price holds, the hazard rates implied by these two contracts written on the same underlying firm should be identical or very close, and any discrepancy between them should diminish over time, unless prevented by market frictions (Carr and Wu, 2011).

In this paper we argue that these two markets are not perfectly integrated, however. They attract different types of investors, with different utility functions, levels of risk aversion, information sets, and optimization horizons. Thus, the Law of One Price does not always hold. Instead, the consensus levels of hazard rates – the systematic components of implied hazard rates – prevail in each of the markets. We recover the systematic term structure of hazard rates using the fitted values from the Nelson-Siegel term structure of implied hazards rates for different rating classes. Any deviations of individual hazard rates from their respective term structure form the idiosyncratic components of hazard rates.

We show that cross-market deviations between the systematic components of hazard rates are greater when markets are less integrated and they are reduced when markets turn more similar. For example, the systematic deviations decrease for firms with high hazard rates, for which DOOMPs are more likely to be used as credit protections instruments, but they increase with option delta, as in such cases DOOMPs are more likely to behave like an ordinary option. The idiosyncratic deviations are related to market frictions, and increase when markets become less efficient. For example, higher put bid-ask spread leads to higher idiosyncratic deviations.

Despite partial market fragmentation, we document a time series convergence in hazard rates. This convergence is driven by two forces: a within-market convergence of individual hazard rates to their rating curves, and a between-market convergence of the curves. The overall convergence in hazard rates is observed only if both systematic and idiosyncratic deviations decrease, that is, when the markets become closer substitutes for each other and when the market frictions are low.

We further exploit the possibility of using deviations in hazard rates and their components as trading signals for a cross-market arbitrage strategy in DOOMPs and CDSs (written on the same underlying). The *Benchmark* strategy trades on total deviations between two implied hazard rates, which is expected to deliver a positive average return in the Carr and Wu (2011) framework. Our *Decomposition* strategy requires that both systematic and idiosyncratic deviations between hazard rates have the same direction. Without transaction costs, both strategies produce statistically significant positive returns. The return for the *Decomposition* strategy, however, is more than twice that of the *Benchmark* strategy, with only one fifth of the transactions. If realistic transaction costs are incorporated, our results show a negative expected return for the *Benchmark* strategy, whereas using the *Decomposition* strategy it is still possible to achieve a positive return after the costs.

Overall, our paper shows that despite the fact that theoretically DOOMPs and CDSs can both be seen as credit protection instruments, the interaction between their prices is more complex than suggested by the Law of One Price. The dynamics is characterised by a within-market convergence to the consensus prices, captured by the respective rating-based hazard rates curves, and betwen-market convergence of the consensus prices. Often, these two forces go in the opposite directions resulting in a much weaker convergence between the prices of the two instruments than otherwise could be expected.

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Table 1: CDS Intra-day Observation Descriptive Statistics

This table reports the descriptive statistics for the GFI intra-day CDS prices over the sample period from July 2012 to April 2016. Panel A reports the mean, STD, maximum, and minimum for the CDS spreads (mid-price), bid-ask spreads (BAS), and the time to maturity of the sample. Panel B reports the number of observations in CDS time to maturity.

Panel A: CDS Intraday Descriptive Statistics

	Mean	Median	STD	Max	Min	N
Spread (bp)	278.50	105.00	856.77	9,966.40	0.00	46,495
BAS (bp)	0.13	0.00	1.47	60.00	0.00	46,056
Maturity (yr)	4.70	5.00	1.48	10.00	0.00	46,495

Panel B: Maturity Distribution

	$\leq$ 1Y	$>$ 1Y $\leq$ 2Y	$>$ 2Y $\leq$ 3Y	$>$ 3Y $\leq$ 4Y	$>$ 4Y $\leq$ 5Y	$>$ 5Y $\leq$ 6Y	$>$ 6Y $\leq$ 7Y	$>$ 7Y $\leq$ 8Y	$>$ 8Y $\leq$ 9Y	$>$ 9Y $\leq$ 10Y
Count	3,367	994	1,212	968	37,723	334	954	1	0	942
Percent	7.24%	2.14%	2.61%	2.08%	81.13%	0.72%	2.05%	0.00%	0.00%	2.03%
Spread (bp)										
Mean	1000.05	758.92	702.43	625.70	155.72	402.14	697.50	350.00	n.a.	739.03
Median	105.00	192.50	255.00	325.00	91.00	350.00	445.00	350.00	n.a.	475.00
STD	2435.54	1663.42	1473.23	996.14	258.06	251.72	1004.71	0.00	n.a.	1068.08
Max	9966.40	9318.95	9870.27	5900.00	8366.53	2317.12	6425.00	350.00	n.a.	8101.99
Min	0.00	7.00	10.00	9.00	9.00	41.00	31.00	350.00	n.a.	92.00

Table 2: Put Option Daily Observation Descriptive Statistics

This table reports the descriptive statistics for the OptionMetrics options over the sample period from July 2012 to April 2016. Panel A reports the mean, STD, maximum, and minimum for the DOOMP option (mid-price), bid-ask spreads (BAS), time to maturity, option open interest, implied volatility, and option delta (in absolute value, |Delta|) of the sample. Panel B reports the number of observations in option time to maturity.

Panel A: Put Option Descriptive Statistics

	Mean	Median	STD	Max	Min	N
Price ($)	0.44	0.23	0.61	11.65	0.01	82,623
BAS	0.09	0.05	0.15	4.29	0.00	82,623
Maturity	0.38	0.17	0.50	2.38	0.00	82,623
Open Interest	2,964	556	11,045	344,233	1	82,623
Implied Vol	0.34	0.30	0.15	2.91	0.09	82,623
|Delta|	0.08	0.09	0.04	0.15	0.00	82,623

Panel B: Maturity Distribution

	$\leq$ 0.5Y	$>$ 0.5Y $\leq$ 1Y	$>$ 1Y $\leq$ 1.5Y	$>$ 1.5Y $\leq$ 2Y	$>$ 2Y $\leq$ 2.5Y
Count	63,328	9,295	5,770	2,879	1,351
Percent	76.65%	11.25%	6.98%	3.48%	1.64%
Price ($)					
Mean	0.27	0.70	1.16	1.39	1.81
Median	0.17	0.55	0.98	1.18	1.46
STD	0.31	0.60	0.95	1.00	1.25
Max	4.95	6.45	11.65	7.65	7.68
Min	0.01	0.02	0.02	0.03	0.10

Table 3: Descriptive Statistics for the Fitted Rating Curves

This table reports the descriptive statistics for rating based curves using the Nelson-Siegel model. The sample period is from July 2012 to April 2016. Panel A reports the fitted value for the CDS-implied hazard rates and Panel B reports the fitted value for the option-implied hazard rates with parameter τ set to 5 year for different rating classes. Panel C reports the descriptive statistics of the differences between put- and CDS-impled fitted hazard rates based in pairs of put-CDS with the same underlying.

Panel A: CDS Implied $F^C(5)$

	AA	A	BBB	BB	B	C
Mean	0.018	0.039	0.074	0.111	0.073	0.269
Median	0.014	0.025	0.048	0.071	0.059	0.186
STD	0.016	0.043	0.173	0.125	0.071	0.358
Max	0.080	0.282	2.066	0.860	0.591	2.997
Min	0.000	0.000	0.001	0.003	0.000	0.071
N	107	119	152	126	242	142

Panel B: DOOM Put Implied $F^P(5)$

	AA	A	BBB	BB	B	C
Mean	0.034	0.039	0.061	0.082	0.126	0.310
Median	0.029	0.034	0.045	0.045	0.069	0.145
STD	0.025	0.031	0.070	0.295	0.205	1.068
Max	0.358	0.437	0.716	5.627	1.702	12.002
Min	0.003	0.003	0.005	0.003	0.005	0.037
N	462	506	533	402	303	133

Panel C: Paired Differences In DOOM Put and CDS Implied hazard rates $F^P(5) - F^C(5)$

	AA	A	BBB	BB	B	C
Mean	0.012	0.000	-0.019	-0.058	0.037	-0.026
t-stat	6.988	-0.096	-1.331	-3.939	2.429	-0.369
p-value	0.000	0.924	0.185	0.000	0.016	0.714
N Pairs	107	119	150	110	189	60

Table 4: DOOMP-CDS Deviations

This table reports the results for the determinants of systematic (D^F), idiosyncratic (D^R) and total (D^H) deviation between Put and CDS implied hazard rates. The sample period is from July 2012 to April 2016. For each deviation driver, including the average hazard rate, the absolute value of option delta (|Delta|), implied volatility, option open interest, bid-ask spread for CDS or put options, logarithm of option maturity, and the number of CDS trades. The t-statistics are reported in brackets. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

	Dependent Variable		
	[1] D^F	[2] D^R	[3] D^H
Constant	0.037	-0.098	-0.061***
	[0.51]	[-1.33]	[-3.55]
$0.5 \cdot (H^C + H^P)$	-0.274**	1.133***	0.858***
	[-2.54]	[10.36]	[33.64]
|Delta|	0.091***	0.082**	0.173***
	[2.89]	[2.55]	[23.16]
Implied Vol	0.050***	-0.023	0.027***
	[3.10]	[-1.40]	[7.13]
Open Interest	-0.000***	0.000**	-0.000***
	[-3.74]	[2.53]	[-4.99]
CDS BAS	-4.660	6.353	1.693
	[-0.16]	[0.22]	[0.25]
Put BAS	-0.009**	0.012***	0.002***
	[-2.36]	[2.97]	[2.71]
CDS Trade	-0.000	0.000	-0.000
	[-0.15]	[0.12]	[-0.11]
Put Maturity	-0.003***	-0.003***	-0.007***
	[-3.27]	[-3.21]	[-27.60]
Time Dummies	Yes	Yes	Yes
Rating Dummies	Yes	Yes	Yes
Adj. R-sqr	0.22	0.29	0.74
N	4,268	4,268	4,268

Table 5: CDS-DOOMP Component Deviation (Sub-sample)

This table reports the estimation results for the determinants of CDS-DOOMP deviation using different sub-samples. The sample period is from July 2012 to April 2016. Panel A reports the results for $D^F = F^P - F^C = \beta_0^F + \beta_1^F X + d^F$ and Panel B reports the results for $D^R = R^P - R^C = \beta_0^R + \beta_1^R X + d^R$. The coefficient t-stat is reported in brakets. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels.

	Period			Sector					Grade	
	2012–13	2014	2015–16	Consumer	Material	Financials	Industrials	Technology	Investment	Junk
Panel A: Dependent Variable $D^F = F^P - F^C$										
Constant	0.035	-0.006	0.002	-0.031	0.052*	-0.061	-0.019	-0.010	0.040**	0.122
	[0.79]	[-0.23]	[0.07]	[-0.57]	[1.81]	[-0.68]	[-0.77]	[-0.39]	[2.24]	[1.40]
$0.5 \times (H^C + H^P)$	-0.435***	-0.080	0.423**	-0.355	0.550**	-1.189*	0.197	0.158	-0.049	-0.578
	[-2.87]	[-0.42]	[2.24]	[-1.33]	[2.42]	[-1.83]	[0.56]	[0.89]	[-0.70]	[-1.55]
|Delta|	0.070	0.104**	-0.080	0.102	-0.100*	0.344**	0.037	-0.014	0.027*	0.253
	[1.43]	[1.97]	[-1.61]	[1.20]	[-1.81]	[2.00]	[0.64]	[-0.27]	[1.69]	[1.48]
Implied Vol	0.061***	0.057*	-0.074***	0.049	-0.082***	0.268***	0.008	-0.005	0.012	0.117*
	[2.60]	[1.90]	[-2.92]	[0.93]	[-3.33]	[2.85]	[0.28]	[-0.21]	[1.43]	[1.66]
Open Interest	-0.000	-0.000	0.000	-0.000**	0.000	-0.000	0.000	0.000	-0.000	-0.000**
	[-1.19]	[-0.46]	[1.13]	[-2.39]	[0.50]	[-0.89]	[0.29]	[0.47]	[-0.12]	[-2.47]
Put BAS	-0.011	-0.008	-0.004	-0.030*	-0.004	-0.005	-0.004	-0.005	-0.003*	-0.038
	[-0.91]	[-1.38]	[-0.91]	[-1.81]	[-1.08]	[-0.16]	[-0.67]	[-0.76]	[-1.66]	[-1.38]
Put Maturity	-0.003**	-0.003	-0.000	-0.002	0.001	-0.007	0.001	-0.000	-0.001	-0.008
	[-2.12]	[-1.48]	[-0.07]	[-0.80]	[0.46]	[-1.21]	[0.40]	[-0.06]	[-1.12]	[-1.56]
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.37	0.14	0.33	0.36	0.38	0.05	0.30	0.32	0.42	0.42
N	1560	1910	798	1068	1006	664	798	732	3502	766
Panel B: Dependent Variable $D^R = R^P - R^C$										
Constant	-0.103**	-0.006	-0.034	0.021	-0.092***	0.018	0.002	-0.026	-0.106***	-0.259***
	[-2.27]	[-0.22]	[-1.20]	[0.39]	[-3.10]	[0.20]	[0.09]	[-0.95]	[-5.74]	[-2.92]
$0.5 \times (H^C + H^P)$	0.775***	1.517***	0.830***	1.110***	0.714***	2.263***	1.405***	1.734***	1.598***	0.830**
	[4.94]	[7.85]	[4.19]	[4.13]	[3.03]	[3.49]	[3.96]	[9.58]	[21.75]	[2.20]
|Delta|	0.225***	-0.039	0.168***	0.107	0.189***	-0.209	-0.015	0.022	0.022	0.223
	[4.46]	[-0.74]	[3.24]	[1.24]	[3.27]	[-1.21]	[-0.26]	[0.42]	[1.31]	[1.29]
Implied Vol	0.006	-0.063**	0.074***	-0.044	0.107***	-0.288***	-0.013	0.011	-0.007	-0.039
	[0.25]	[-2.10]	[2.81]	[-0.82]	[4.17]	[-3.07]	[-0.46]	[0.48]	[-0.79]	[-0.55]
Open Interest	0.000	0.000	-0.000	0.000**	-0.000	0.000	-0.000	-0.000	-0.000	0.000**
	[0.45]	[0.07]	[-1.37]	[2.02]	[-1.20]	[0.71]	[-0.28]	[-0.49]	[-1.63]	[2.39]
Put BAS	0.017	0.009	0.008*	0.035**	0.007*	0.002	0.001	0.005	0.004**	0.054*
	[1.38]	[1.56]	[1.92]	[2.12]	[1.94]	[0.05]	[0.26]	[0.73]	[2.31]	[1.94]
Put Maturity	-0.005***	-0.001	-0.005***	-0.005*	-0.004**	0.001	-0.001	0.000	-0.002***	-0.008
	[-3.30]	[-0.56]	[-3.07]	[-1.92]	[-2.19]	[0.20]	[-0.60]	[0.04]	[-2.92]	[-1.60]
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.43	0.15	0.47	0.40	0.45	0.09	0.34	0.57	0.55	0.44
N	1560	1910	798	1068	1006	664	798	732	3502	766

Table 6: CDS Convergence to Rating Curves

This table reports the results for CDS convergence to rating curves. The sample period is from July 2012 to April 2016. H^C is the URC-implied hazard rate for CDS; F^C is the NS-fitted value; and R^C is the NS residual. Panel A reports the results for full sample, and Panel B to D report the results for sub-samples. The coefficient t-stat is reported in brackets. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels.

Model: $\Delta H_t^C = \beta_0 + \beta_1 \Delta F_t^C + \beta_2 R_t^C + e_t$

	β_0	β_1	β_2	Time FE	Rating FE	Adj. R^2	N
Panel A: Complete Sample							
Coef.	0.002	0.158***	-0.063***	Yes	Yes	0.29	2134
	[0.80]	[14.29]	[-6.38]				
Panel B: Period							
2012–13	0.002	0.191***	-0.066***	Yes	Yes	0.26	790
	[0.75]	[8.91]	[-4.06]				
2014	0.001	0.095***	-0.153***	Yes	Yes	0.53	945
	[1.42]	[7.17]	[-9.70]				
2015–2016	0.005***	0.212***	-0.122***	Yes	Yes	0.52	399
	[3.04]	[7.00]	[-5.70]				
Panel C: Sector							
Consumer	0.006**	0.066***	-0.007	Yes	Yes	0.61	534
	[2.18]	[3.14]	[-0.37]				
Material	-0.002	0.145***	-0.090***	Yes	Yes	0.66	503
	[-1.23]	[6.37]	[-3.86]				
Financials	0.007**	0.393***	-0.236***	Yes	Yes	0.41	332
	[2.08]	[9.66]	[-4.71]				
Industrials	0.002	-1.103**	0.138	Yes	Yes	0.41	399
	[0.15]	[-2.08]	[0.32]				
Technology	0.003***	0.178***	-0.046	Yes	Yes	0.49	366
	[3.26]	[6.49]	[-1.43]				
Panel D: Grade							
Investment	0.002**	0.180***	-0.110***	Yes	Yes	0.35	1751
	[2.45]	[12.98]	[-12.83]				
Junk	0.004	0.117***	-0.051*	Yes	Yes	0.55	383
	[0.93]	[3.84]	[-1.89]				

Table 7: DOOMP Convergence to Rating Curves

This table reports the results for put convergence to rating curves. The sample period is from July 2012 to April 2016. H^P is the URC-implied hazard rate for a put option; F^P is the NS-fitted value; and R^P is the NS residual. Panel A reports the results for full sample, and Panel B to D report the results for sub-samples. The coefficient t-stat is reported in brackets. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels.

Panel A Model: $\Delta H_t^P = \beta_0 + \beta_1 \Delta F_t^P + \beta_2 R_t^P + e_t$

	β_0	β_1	β_2	Time FE	Rating FE	Adj. R^2	N
Coef.	0.003	0.020**	-0.013	Yes	Yes	0.05	2134
	[0.18]	[2.20]	[-1.25]				
Panel B: Period							
2012–13	0.005	0.003	-0.011	Yes	Yes	0.10	790
	[0.33]	[0.29]	[-0.71]				
2014	0.002	0.041**	-0.019	Yes	Yes	0.04	945
	[0.26]	[2.21]	[-1.00]				
2015–2016	0.038**	0.013	-0.044	Yes	Yes	0.07	399
	[2.23]	[0.54]	[-1.27]				
Panel C: Sector							
Consumer	-0.027	0.000	0.019	Yes	Yes	0.23	534
	[-1.63]	[0.01]	[0.80]				
Material	-0.000	0.099***	-0.188***	Yes	Yes	0.29	503
	[-0.01]	[5.00]	[-7.81]				
Financials	0.004	0.001	0.015	Yes	Yes	0.24	332
	[0.24]	[0.06]	[0.72]				
Industrials	0.007	0.051***	-0.086***	Yes	Yes	0.13	399
	[0.86]	[3.37]	[-3.92]				
Technology	0.005	-0.004	0.093	Yes	Yes	0.36	366
	[0.16]	[-0.07]	[1.29]				
Panel D: Grade							
Investment	0.004	0.008	0.001	Yes	Yes	0.00	1751
	[0.28]	[0.54]	[0.07]				
Junk	0.017	0.010	0.016	Yes	Yes	0.10	383
	[0.65]	[0.41]	[0.59]				

Table 8: CDS-DOOMP Convergence

This table reports the results for the CDS-DOOMP convergence. The sample period is from July 2012 to April 2016. The number of observations is 2,134.The right-hand side panel reports the results for CDSs (Equation (4)) and the left-hand side panel reports the results for puts (Equation (5)). d^F and d^R are residual systematic and idiosyncratic deviations from Equation (2) estimated using different set of control variables, and D^F and D^R are total deviation. The coefficient t-stat is reported in brackets. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels.

Panel A: Controlling for option-related factors

	Model: $\Delta H^C = \beta_0^C + \beta_1^C d^F + \beta_2^C d^R + e$				Model: $\Delta H^P = \beta_0^P + \beta_1^P d^F + \beta_2^P d^R + e$			
	β_1^C	β_2^C	Time FE	Adj. R^2	β_1^P	β_2^P	Time FE	Adj. R^2
$0.5 \times (H^C + H^P)$	0.019***	0.015***	Yes	0.19	-0.106***	-0.098***	Yes	0.06
	[5.49]	[4.36]			[-4.67]	[-4.51]		
|Delta|	0.022***	0.018***	Yes	0.19	-0.049*	-0.040	Yes	0.05
	[5.53]	[4.70]			[-1.91]	[-1.62]		
Implied Vol	0.012***	0.008**	Yes	0.18	-0.103***	-0.095***	Yes	0.06
	[3.55]	[2.42]			[-4.67]	[-4.47]		
Open Interest	0.011***	0.008**	Yes	0.18	-0.104***	-0.096***	Yes	0.06
	[3.33]	[2.36]			[-4.71]	[-4.53]		
CDS BAS	0.013***	0.009***	Yes	0.18	-0.103***	-0.095***	Yes	0.06
	[3.73]	[2.70]			[-4.70]	[-4.52]		
Put BAS	0.013***	0.009***	Yes	0.18	-0.105***	-0.096***	Yes	0.06
	[3.73]	[2.70]			[-4.77]	[-4.57]		
CDS Trade	0.013***	0.009***	Yes	0.18	-0.104***	-0.097***	Yes	0.06
	[3.73]	[2.71]			[-4.74]	[-4.59]		
Put Maturity	0.014***	0.011***	Yes	0.18	-0.179***	-0.168***	Yes	0.07
	[3.74]	[2.84]			[-7.25]	[-7.11]		
ALL Factors	0.017***	0.013***	Yes	0.18	-0.134***	-0.125***	Yes	0.06
	[3.51]	[2.71]			[-4.31]	[-4.12]		

Panel B: Without controlling for option-related factors

	Model: $\Delta H^C = \beta_0^C + \beta_1^C D^F + \beta_2^C D^R + e$				Model: $\Delta H^P = \beta_0^P + \beta_1^P D^F + \beta_2^P D^R + e$			
	β_1^C	β_2^C	Time FE	Adj. R^2	β_1^P	β_2^P	Time FE	Adj. R^2
Model (1)	0.010***	0.006*	No	0.006	-0.137***	-0.129***	No	0.02
	[2.87]	[1.88]			[-6.74]	[-6.60]		
Model (2)	0.013***	0.009***	Yes	0.18	-0.103***	-0.095***	Yes	0.06
	[3.73]	[2.70]			[-4.70]	[-4.52]		

Table 9: CDS-DOOMP Convergence (Sub-sample)

This table reports the results for the CDS-DOOMP convergence for sub-samples. The right-hand side panel reports the results for CDSs (Equation (4)) and the left-hand side panel reports the results for puts (Equation (5)). d^F and d^R are residual systematic and idiosyncratic deviations from Equation (2) estimated using the complete set of the control variabels. The coefficient t-stat is reported in brackets. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels.

	$\Delta H^C = \beta_0^C + \beta_1^C d^F + \beta_2^C d^R + e$					$\Delta H^P = \beta_0^P + \beta_1^P d^F + \beta_2^P d^R + e$				
	$\beta^{F,C}$	$\beta^{R,C}$	Time FE	Adj. R^2	N	$\beta^{F,P}$	$\beta^{R,P}$	Time FE	Adj. R^2	N
Panel A: Period										
2012–13	-0.003	-0.008	Yes	0.18	790	-0.065	-0.062	Yes	0.09	790
	[-0.33]	[-0.89]				[-1.48]	[-1.46]			
2014	0.047***	0.044***	Yes	0.23	945	-0.206***	-0.192***	Yes	0.04	945
	[7.66]	[7.15]				[-3.91]	[-3.68]			
2015–2016	0.016	0.025**	Yes	0.25	399	-0.096	-0.044	Yes	0.03	399
	[1.32]	[2.31]				[-1.02]	[-0.53]			
Panel B: Sector										
Consumer	-0.005	-0.008	Yes	0.55	534	-0.031	-0.019	Yes	0.15	534
	[-0.47]	[-0.74]				[-0.44]	[-0.27]			
Material	0.031***	0.042***	Yes	0.54	503	-0.540***	-0.508***	Yes	0.35	503
	[3.41]	[5.54]				[-9.16]	[-10.22]			
Financials	-0.005	-0.009	Yes	0.09	332	-0.263**	-0.252**	Yes	0.23	332
	[-0.15]	[-0.29]				[-2.09]	[-1.97]			
Industrials	0.007	0.008	Yes	0.60	399	-0.471***	-0.471***	Yes	0.19	399
	[1.21]	[1.42]				[-5.74]	[-6.09]			
Technology	0.012*	0.007	Yes	0.32	366	0.424**	0.501***	Yes	0.31	366
	[1.68]	[1.00]				[2.43]	[2.89]			
Panel C: Grade										
Investment	0.020***	0.020***	Yes	0.25	1751	0.033	0.046	Yes	0.00	1751
	[4.53]	[4.92]				[0.62]	[0.95]			
Junk	-0.036	-0.038*	Yes	0.45	383	-0.084	-0.062	Yes	0.10	383
	[-1.63]	[-1.74]				[-0.65]	[-0.48]			

Table 10: Holding Time Distribution

This table reports the number and the percentage of trades with different holding durations. Panel A is based on all trades, Panel B uses trades with the same sign of systematic and idiosyncratic deviations (D^F and D^R respectively), and Panel C is based on trades with different signs of the two deviations.

	$\geq 7D$ $\leq 14D$	$> 14D$ $\leq 21D$	$> 21D$ $\leq 30D$	$> 30D$ $\leq 6M$	$> 6M$ $\leq 1Y$	$> 1Y$
Panel A: All Trades						
Count	1289	481	364	713	75	8
Percent	43.99%	16.42%	12.42%	24.33%	2.56%	0.27%
					Mean	33.96
					STD	51.65
Panel B: D^F and D^R have the same sign						
Count	279	106	75	115	10	0
Percent	47.69%	18.12%	12.82%	19.66%	1.71%	0.00%
					Mean	26.52
					STD	36.92
Panel C: D^F and D^R have different signs						
Count	1010	375	289	598	65	8
Percent	43.07%	15.99%	12.32%	25.50%	2.77%	0.34%
					Mean	35.81
					STD	54.56

Table 11: Trading Performance on CDS-DOOMP Convergence

This table reports the strategy performance over the sample period from July 2012 to April 2016. Ret^B is the return for the Benchmark strategy, based on a total deviation trading signal, Ret^D is the return for our Decomposition strategy, based on the both systematic and idiosyncratic deviations, and Ret^O is the return for the trades that are not included in the Decomposition strategy. Panels A to C report the results for different hedge ration. Left-hand side of the table uses raw returns, and the right-hand side of the table reports the results adjusted for transaction costs. ***, **, and ** represents the significance of one sample or two sample t-test at the 1%, 5%, and 10% level, respectively.

	Baseline Return					Transaction Cost Adjusted Return				
	Ret^B	Ret^D	Ret^O	$Ret^D - Ret^B$	$Ret^D - Ret^O$	Ret^B	Ret^D	Ret^O	$Ret^D - Ret^B$	$Ret^D - Ret^O$
Panel A: Hedge Ratio 100%										
Mean (%)	0.827***	1.873***	0.566***	1.046***	1.307***	-0.865***	-0.169	-1.038***	0.696***	0.869***
STD (%)	2.351	3.156	2.021			3.151	3.823	2.935		
t-stat	[19.03]	[14.35]	[13.56]	[7.61]	[9.54]	[-14.85]	[-1.07]	[-17.13]	[4.13]	[5.13]
N Trades	2930	585	2345			2930	585	2345		
Panel B: Hedge Average CDS Spread										
Mean (%)	2.375***	5.522***	1.59***	3.148***	3.933***	-1.659***	0.564*	-2.213***	2.223***	2.777***
STD (%)	9.069	10.76	8.417			8.45	10.488	7.764		
t-stat	[14.17]	[12.41]	[9.15]	[6.62]	[8.23]	[-10.63]	[1.30]	[-13.81]	[4.82]	[6.01]
N Trades	2930	585	2345			2930	585	2345		
Panel C: Hedge One CDS Standard Deviation										
Mean (%)	2.745***	6.382***	1.837***	3.638***	4.545***	-1.914***	0.655*	-2.555***	2.569***	3.21***
STD (%)	10.48	12.435	9.725			9.764	12.118	8.972		
t-stat	[14.18]	[12.41]	[9.15]	[6.62]	[8.23]	[-10.61]	[1.31]	[-13.79]	[4.82]	[6.01]
N Trades	2930	585	2345			2930	585	2345		

Figure 1: Number of Trades and Traded Names

This figure plots the number of CDS trades per month (in bar graph) and the averaged daily traded names per month (in line graph) over the sample period from July 2012 to April 2016.

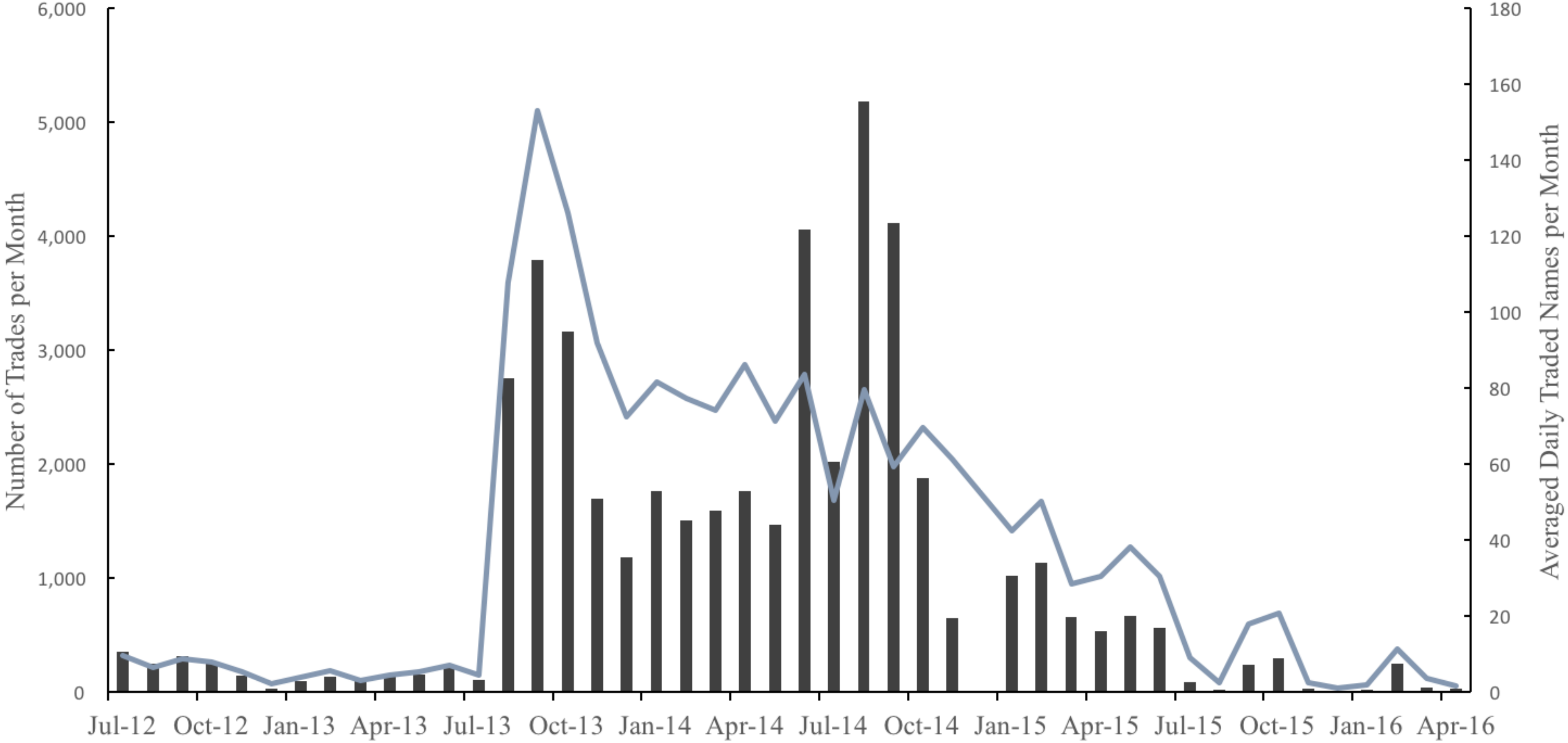
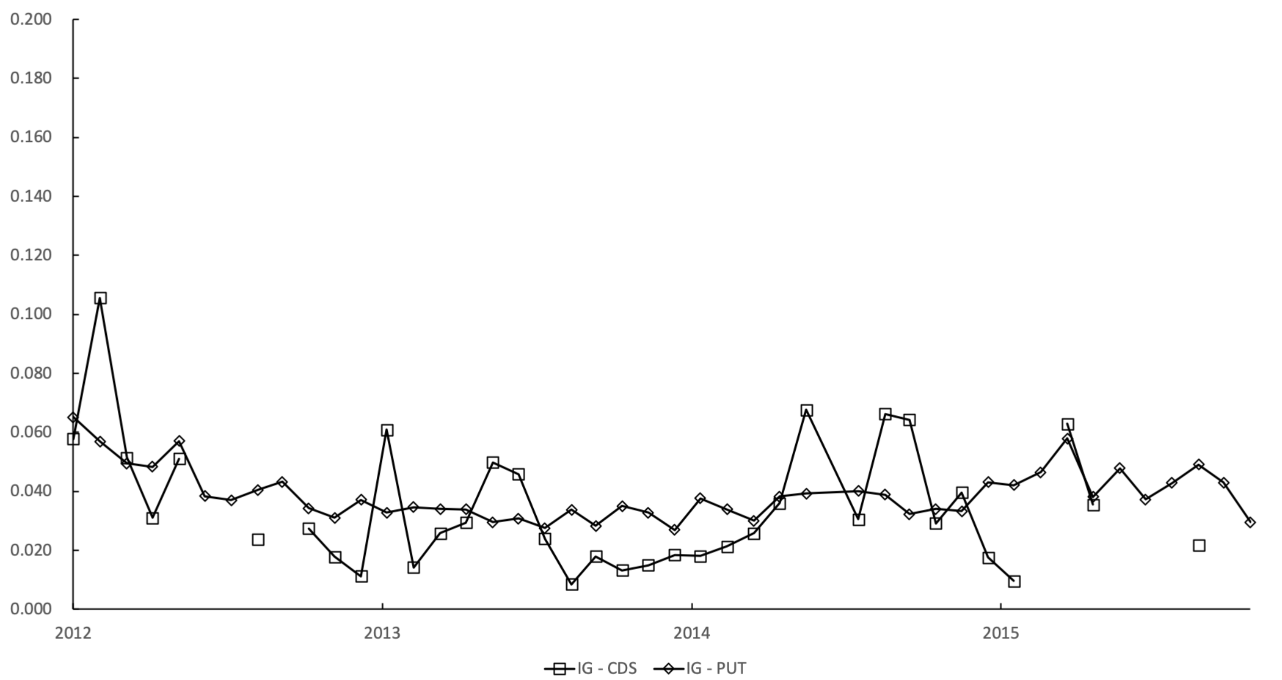
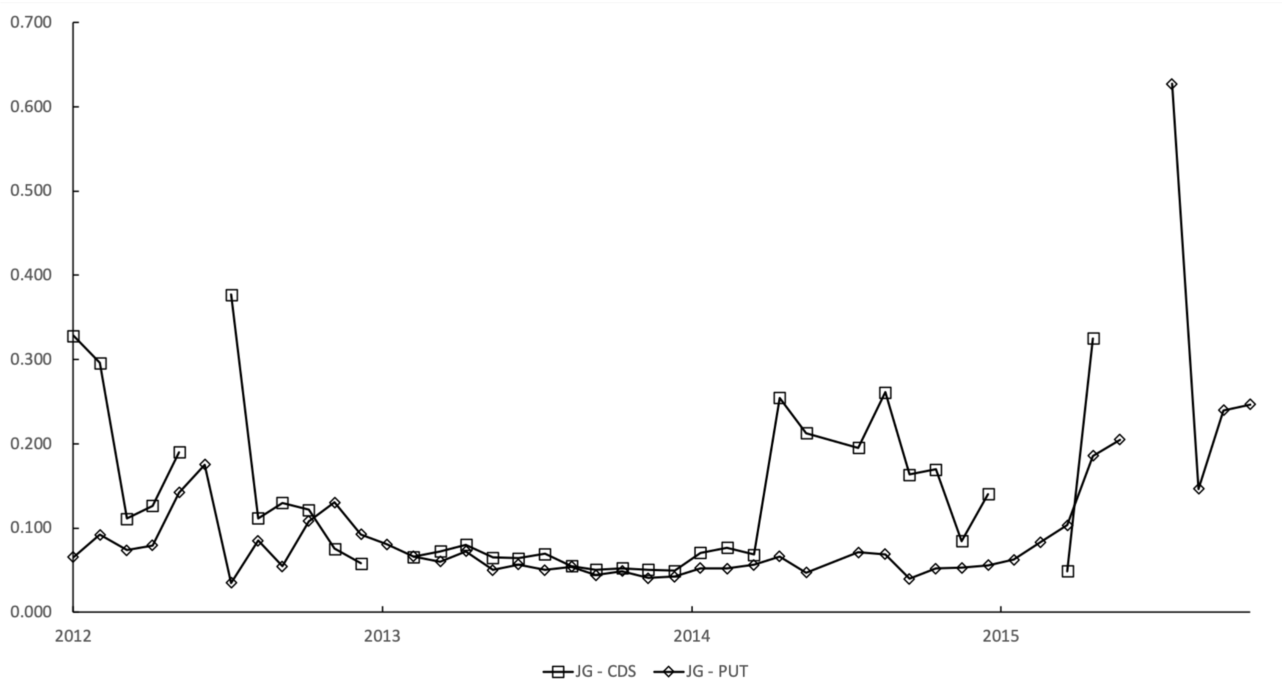


Figure 2: Time Series Plot for Fitted NS Hazard Rate

This figure plots the Nelson-Siegel fitted value for CDS and put option in different grades from July 2012 to April 2016.



(i) Investment Grade



(ii) Junk Grade

Appendix

A Points Upfront and Par Spread Conversion

Points upfront indicates the proportion of the upfront payment that CDS buyer pays to the seller at the beginning of the CDS contract. Hence,

$$\begin{aligned} PVP &= c \times PVE + u \\ \Leftrightarrow u &= PVP - c \times PVE \end{aligned} \tag{20}$$

where u is the points upfront, c is the fixed coupon, PVP is the present value of protection leg, and PVE is the present value of premium leg.

On the other hand, for a par spread CDS contract, the spread is determined such that:

$$PVP = k \times PVE \tag{21}$$

where k is the par spread. Combining Equation (21) and (20), we can convert between points upfront and par spread by:

$$u = (k - c) \times PVE. \tag{22}$$

Here, we assume the firm's default intensity (H) is constant, thus, the calculation of the PVE is equal to

$$PVE = \int_0^t e^{-(r+H)s} ds = \frac{1 - e^{-(r+H)t}}{r + H},$$

with $H = \frac{k}{1-RR}$, discount rate r, and recovery rate RR. We set the recovery rate as 40% and use U.S. swap rate as discount rate.

B CDS Price Comparison

Previous literature has discussed similar concerns on on how representative CDS quotes supplied by different data providers are. As there is no standardized and universal CDS database in the market, CDS prices may differ among data providers. Yet, several studies have found that the GFI data has relatively accurate price representation. Mayordomo et al. (2014) compare the mainstream CDS databases and find that the price difference among the databases reduces when a corresponding trade was observed in the GFI. Tang and Yan (2017) compare the GFI CDS prices with the CDS transaction data in the OCC (Comptroller of the Currency) and the ISDA (International Swaps and Derivatives Association) reports, and they show that the GFI data can be used to represent the market prices. Therefore, we collect data from the GFI as it has fewer concerns on price representation and on sample bias.

Markit calculates daily CDS prices by averaging the CDS prices from fifferent contributors. Table 12 reports the descriptive statistics for Markit CDS daily price for the same period as in our GFI sample.

As the price in the two databases are on different basis, we need to first convert the intra-day CDS price in the GFI to a daily CDS price, similar to the Markit. The conversion is done by averaging the GFI intra-day prices on the same CDS contract to create a single daily price. After the conversion, the GFI observations reduce only slightly from 46,495 to 33,008. This indicates that the concentration of daily trades on certain underlying names is not obvious. The average GFI daily CDS spread is 222.02 bps with the standard deviation of 614.83 bps. Panel B reports the observation distribution of CDS maturity, and we find that the distribution of the daily observations are not obviously different from the intra-day observations.

[Table 12 is about here.]

With the converted data, we then compare the CDS data from GFI and Markit by focusing on the price comparison of 5-year CDSs. Using the GFI-Markit matching code programmed by GFI, we matched 26,522 pairs of observations in the two databases. Table 13 reports the descriptive statistics for the 5-year CDSs. We find rather similar sample averages in the two data-sets. The sample averages for our matched sample are 140.05 bps (GFI) and 137.69 bps

(Markit). However, it is clear that GFI sample has higher standard deviation than Markit sample. Yet, when we further test the difference in sample average (by Student's t-test) and in standard deviation (by Chi-square test), we do not find any evidence on the statistically significant difference between GFI and Markit. Finally, we check the correlation of the matched pairs. The pair-wise correlation coefficient is 93.92%, and the scatter plot (Figure 3) shows that the two samples align with the diagonal line, indicating that our choice of GFI prices does not introduce any bias with respect to Markit – a larger but less detailed database.

[Table 13 and Figure 3 are about here.]

Table 12: CDS Daily Observation Descriptive Statistics

This table reports the descriptive statistics for the GFI daily CDS prices over the sample period from July 2012 to April 2016. The daily price is the average price of the trade for the same maturity and written on the same entity. Panel A reports the mean, STD, maximum, and minimum for the CDS spreads (mid-price), bid-ask spreads (BAS), and the time to maturity of the sample. Panel B reports the number of observations in CDS time to maturity.

Panel A: CDS Daily Price Descriptive Statistics

	Mean	STD	Max	Min	N
Spread (bp)	222.02	614.83	9,900.00	0.00	33,008
BAS (bp)	0.13	1.48	50.00	0.00	32,916
Maturity (yr)	4.69	1.51	10.00	0.00	33,008

Panel B: Maturity Distribution

		> 1Y	> 2Y	> 3Y	> 4Y	> 5Y	> 6Y	> 7Y	> 8Y	> 9Y
	≤ 1Y	≤ 2Y	≤ 3Y	≤ 4Y	≤ 5Y	≤ 6Y	≤ 7Y	≤ 8Y	≤ 9Y	≤ 10Y
Count	2,477	747	820	751	26,553	283	691	1	0	685
Percent	7.50%	2.26%	2.48%	2.28%	80.44%	0.86%	2.09%	0.00%	0.00%	2.08%

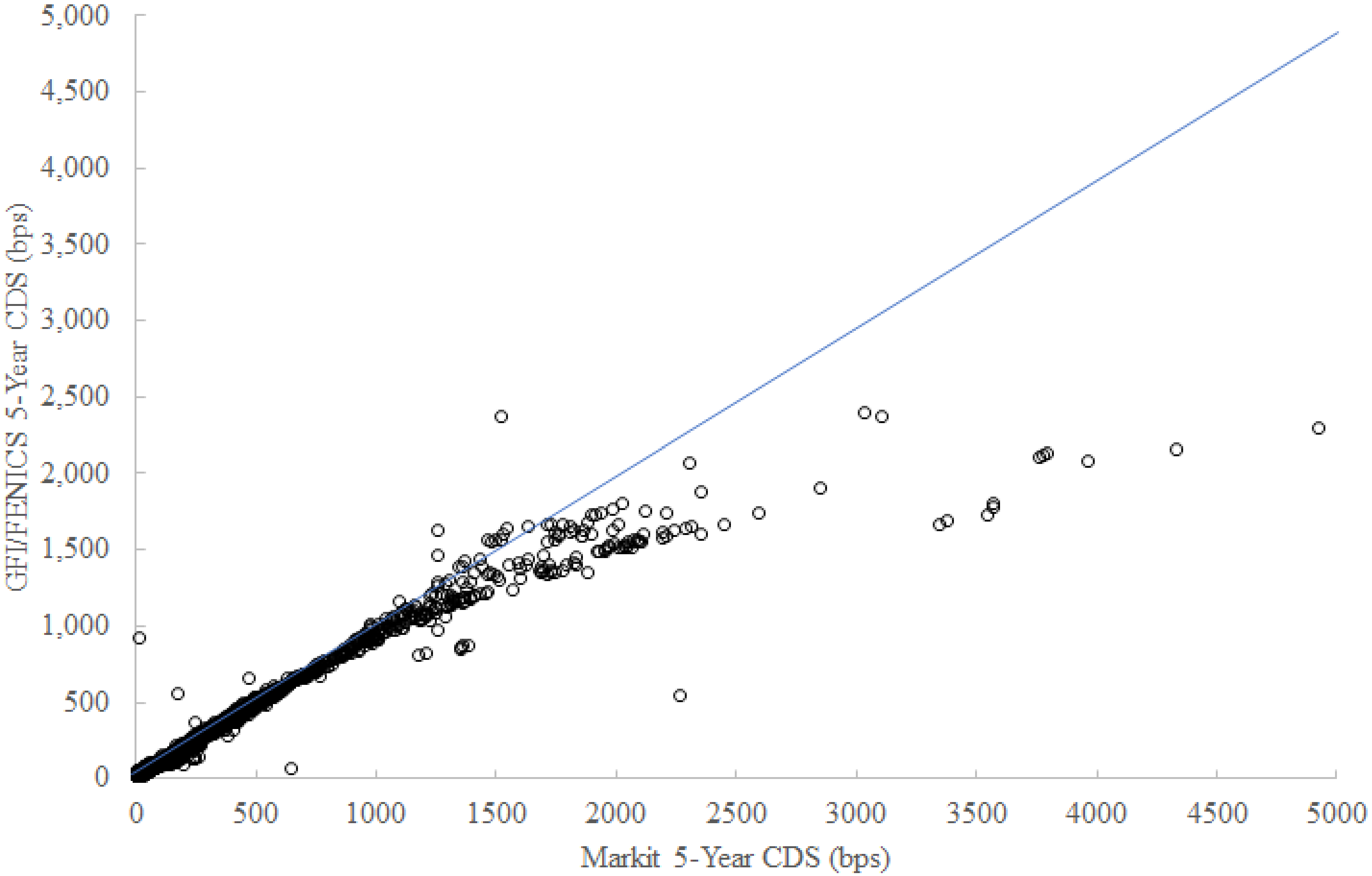
Table 13: GFI and Markit Comparison

This table reports the comparison for 5-year CDS spreads between GFI and Markit. The sample period is from July 2012 to April 2016. For each database, we report their descriptive statistics, including sample mean, STD, maximum, and minimum, respecitvely. We also report the results for the paired t-test and Chi-square test. The respective stats are reported in [ ]. ***, **, and * represents the significance in 1%, 5%, and 10% levels, respectively.

	Mean	STD	Max	Min	N
Markit 5-year CDS (bp)	137.69	180.73	5,325.25	10.68	26,522
GFI 5-year CDS (bp)	140.05	225.67	8,366.53	9.00	26,522
				Mean Diff (t-test)	-2.36
					[-1.33]
				STD Ratio (Chi2 test)	0.80***
					[0.64]

Figure 3: GFI and Markit CDS Scatter Plot

This figure plots the scatter plot of the Markit 5-year CDS and the GFI 5-year CDS from July 2012 to April 2016.



C Derivation of Hedge Ratio

This section provides the derivation for hedge ratio ($dPrice^P/dPrice^C$). Since put option and CDS prices are not in a linear relation, we compute the hedge ratio using the Carr and Wu (2011) URC formula ($U^P = U^C$). The price of a put option and a CDS spread in the same underlying firm is linked by the following relation:

$$Price^P = K\zeta Price^C \frac{1 - e^{-(r+\zeta Price^C)\tau^C}}{r + \zeta Price^C}, \tag{23}$$

where $Price^P$ is the put option price, $Price^C$ is the CDS spread, and τ^C is the time to maturity of the CDS. Taking the first derivative of the put option price with respect to a CDS spread, we then obtain the following hedge ratio:

$$\frac{dPrice^P}{dPrice^C} = K\left[\frac{1}{Price^C} + \zeta\tau^C - \zeta\left(r + \zeta\frac{1}{Price^C}\right)\right]U^C. \tag{24}$$