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

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

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Abstract

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1 Introduction

Both deep out-of-the-money (DOOM) put 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 DOOM have different pricing structures\(^1\), both products can be converted into a unit recovery claim (URC), which pays $1 if the firm defaults and zero otherwise. If the Law of One Price holds, then a URC written on a given firm should have the same price whether it is traded in the CDS market or in the option market. Any price deviation between CDS and DOOM should eventually converge, except if it is prevented by market frictions (Carr and Wu, 2011).

While the prices of CDS and DOOM are driven by firm’s default probability, non-credit drivers are also intensively studied in the literature. CDSs’ driving factors are actually well studied in recent years. Researchers argue that CDS can be explained substantially by several non-credit drivers such as market illiquidity (e.g. Corò et al., 2013; Tang and Yan, 2007), and also be affected by its relevant markets such as stock and bond market (e.g. Das and Hanouna, 2009; Norden and Weber, 2009). Though, the price of a CDS reflects mostly firm’s probability of default and CDS remains as a mostly used hedging tool for credit risk (Bai and Wu, 2016).

On other hand, the drivers for DOOM as credit protection is comparatively under exploration, although the normal option driving factors are intensively studied. As mentioned before, since DOOM put option can be seen as a financial product of dual role—a credit protection product and a normal option, the question of interest is to what extent a DOOM option acts alike a credit protection product, instead of a option. A groundbreaking work done by Carr and Wu (2011) show the similarity in price between CDS and DOOM; nevertheless the authors show that DOOM is also affected by non-credit pricing factors, e.g., option delta, which drive DOOM price away from CDS. Later studies also investigate on the price deviation between CDS and

\(^1\)The price in a CDS contract is called CDS spread, where buyer pays periodical payments to the seller; while the price for a option contract is called option premium, where buyer pays an one-off premium at the time of the purchase.
DOOM; detailed comparison is provided in later section.

In this study, we provide a new insight on the price convergence between CDS and DOOM. Recently, a new thread of literature studies the systematic drivers for CDS spreads (e.g. Galil et al. 2014; Kolokolova et al. 2016). Our main research question is that whether the CDS systematic driver also affects DOOM option, and that how it influences the CDS-PUT price co-movement. Given that a set of CDS and DOOM written on the same underlying firm, any firm-specific characteristics are less likely to contribute to the price deviation and the subsequent convergence. On the contrary, we conjecture that the systematic force that drives CDS has similar effect on DOOM, and then the systematic information can alleviate or improve the CDS-PUT price deviation. Here, we use firm’s rating as a systematic force, and examine how the rating information explains CDS-PUT price co-movement. A recent work by Kolokolova et al. (2016) show that individual CDSs with more deviation from the rating class of the underlying firm are more likely to move toward the rating-implied value, supporting the argument in Aunon-Nerin et al. (2002) that credit rating of underlying firm, as a systematic information, is an important source of information in the individual CDS spreads. Prior studies, though, criticize the sluggish reflection of firm’s credit rating and argue that firm’s credit rating is less price informative (reflecting past information) in a changing market circumstance (see Chava et al. 2016; Hart and Zingales 2011). Hence, we use market-implied rating provided by Markit, which can reflect the changes of the market circumstance more timely\(^2\) in order to eases the critics about using historical rating classification.

We brief the technical detail in the following. After we recover the CDS- and put-implied hazard rate, we group our CDS- and put-recovered hazard rates by firm’s credit rating, and then fit the Nelson-Siegel (NS) term structure model. This process enables us to separate each recovered hazard rate into two components—a NS model fitted value \((F)\) and a residual term \((R)\). Next, we study the cross-market deviations for the fitted values (i.e. \(F^{CDS}\) and \(F^{PUT}\)) and the residuals (i.e. \(R^{CDS}\) and \(R^{PUT}\)). Specifically, we investigate the drivers that explain the cross-market deviation between components (i.e. \(D^F\) and \(D^R\), where \(D^F = F^{PUT} - F^{CDS}\) and \(D^R = R^{PUT} - R^{CDS}\)). As mentioned before, DOOM may be driven by non-credit option pricing factors; especially, DOOM options are far less popular compared to near- and at-the-money options (Chung and Park 2016; Etling and Miller 2000). The lack of liquidity might contribute to the price deviation. Here, we test option pricing factors such as option delta

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option implied volatility, option open interest and bid-ask spread, and find that the systematic deviation ($D^F$) is more related to market inefficiency proxied by bid-ask spread, while the idiosyncratic deviation ($D^R$) is more related to individual option pricing factor e.g. option delta and option implied volatility.

Further analyses show that the two cross-market deviations are temporary, because both deviations $D^F$ and $D^R$ diminish over time, leading to a time-series price convergence between CDS and DOOM. Hence, we argue that our approach of extracting systematic information is valid to predict the price convergence between CDS and DOOM put options. Consistent with prior studies, we show that the CDS-PUT convergence indeed exists, even after controlling for the mis-pricing factors. However, the convergence in the two deviations is more than just price convergence; in fact, the meaning is twofold. It means the fitted values of CDS and DOOM move toward each other over time. Importantly, it also indicates that CDS and DOOM overall move toward to their rating-based fitted values. For the latter, it shows a systematic force that also contributes to overall CDS-PUT convergence. We also provide additional evidence showing that indeed both CDS and DOOM move toward their fitted NS curves. The findings support our main argument that DOOM, as a substitute for CDS, is also driven by underlying firm’s rating, the same factor that affects CDS spread.

Finally, we build trading signals based on our findings. We use a unique CDS trading data, where the prices are firmly committed by the participants. We carefully consider the plausibility to execute the strategy; each trade has its specific times to enter and unwind the positions. We identify 1,949 trades in our sample, and we compare a simple Benchmark trading strategy, based on the absolute deviation, and a more refined Decomposition strategy, using the two cross-market deviations $D^F$ and $D^R$ as trading signals. We find that our refined Decomposition strategy, on average, outperforms the Benchmark strategy by 0.416% in terms of daily return. Importantly, one can have three times better return when following the trading signals than against the signals.

\[3\] As discussed, although DOOM put option can be used as credit protection product, the pricing factors (which are not directly linked to default risk) for a normal option may still deviate the option price from CDS. Hence, such convergence may be due to these mis-pricing factors, instead of our NS components.
2 Previous Literature

Our study in CDS-DOOM deviation is closely related to studies under Carr-Wu framework. Carr and Wu (2011) argue that CDS and DOOM are used for hedging firm’s default risk, and hence they show that both products indeed 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 DOOM put 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 DOOM, 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-DOOM size (Kim et al., 2013). To further expand the CDS-DOOM 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. They show that their IURC has tighter linkage than Carr-Wu 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 DOOM put option were strongly influenced by macroeconomic variables (e.g. VIX) and the option market became more powerful in prediction. Another concern is about time inconsistency for the put-recovered URC. The CDS-DOOM pair only consider contemporary matching, but it may cause mismatch in time series. For example, two put-recovered URCS, written on the same firm in different period, may be recovered from two different option contracts due to, e.g., different option strikes; hence, our study further matches CDS-DOOEm pairs time-seriesly, to fix the issue. In addition, studies also find that the CDS-DOOM deviation is heteroscedastic in terms of firm’s credit quality, and document that put-implied URC tend to be much more expensive than CDS-implied URC for firms with poor credit quality (Angelopoulos et al., 2013; Park et al., 2014). Our study enriches this increasing strand of literature and provide insight of the CDS-DOOM co-movement with respect to firm’s rating.

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

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

5 Carr and Wu (2011) keep mentioning that they are using “5,276 pairs of URC values” in all their analyses, to remind readers of the potential time-series inconsistency of the CDS-DOOM pairs.
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 research interest focuses on liquidity of the traded securities. Among the first group, researchers usually view CDS as a hedging tool for equities. Hence their focus is more on the comparison on default risk between the risk-neutral (for CDS) and the physical (for equity, e.g. stock) views. Since the pricing kernels of the default risk are different, the link between CDS and equity might be weak. Earlier research examines the link and document strong link between CDS and equity markets. 

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. In addition, studies also show that the pricing of stock include default risk, not merely business or operating risk (Vassalou and Xing, 2004). Particularly, recent studies show the importance of using CDS to gauge equity risk premia. Friewald et al. (2014) 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) also relates to higher moments of equity returns such as volatility and skewness. However, the link can become weaker when CDS market condition changes. 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 risk and equity volatility may be jeopardized due to the deviation between credit risk and equity volatility.

Recently, several studies establish connections between CDS and various other markets. 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). Studies, in general, do not find single dominant market in terms of price discovery, although they find that stock market slightly more often leads the other two markets. However, the linkage between LOP 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 macro-economic or market factors such as VIX systematically affect the individual CDS spreads. Also, Kolokolova et al. (2016) 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 to the NS curve. We explore the systematic drivers in CDS and equity option markets, and understand the potential arbitrage opportunities under LOP. Yet, as there is no valid theoretical argument that explains sector can be a potential systematic force, and the data for macro-economic factors is not granular enough. Here, we focus this study in another yet-explored systematic information: the firm’s credit rating, based on the findings in Kolokolova et al. (2016).

The third and most recent CDS research on cross-market connection investigates the impact of liquidity (and liquidity risk). Compared to CDS liquidity, equity market liquidity is well understood and it is well known that liquidity risk is asymmetric and exhibits stronger market impact during liquidity drain-out. Brunnermeier and Pedersen (2009) argue that liquidity drain-out is the outcome of a vicious circle of market and funding liquidity interaction. Empirically, Brennan et al. (2012) show that liquidity premium for stock increases mainly due to the sell side. Brennan et al. (2013) find negative Amihud illiquidity (i.e. illiquidity measure based only on negative stock returns) has a higher explanatory power for stock returns. On the contrary, conventional wisdom viewed CDS as pure default risk, and hence often CDS spread was used to measure pure credit risk in bond liquidity studies (e.g. Longstaff et al., 2005). However, recent empirical evidence on CDS suggests that CDS liquidity risk matters in explaining CDS spreads. Corò et al. (2013), for example, show that two liquidity factors (daily time-weighted average bid-ask spread, and industry average bid-ask spread) dominate other factors (such as changes in credit rating and macroeconomic conditions) in explaining CDS spread changes. Tang and Yan (2007) study a range of liquidity factors derived from quotes and bid-ask spread, and conclude that the short-term changes in CDS spread are explained by these factors. Moreover, studies find that not only CDS market liquidity affects CDS spreads, but CDS spread is also affected by the illiquidity of other assets. Bühler and Trapp (2010) develop a reduced-form model to separate pure credit risk and pure liquidity risk by calibrating CDS and bond data. They find that credit and liquidity risk in CDS and bond are interwoven, and also that the increased credit risk can further dry up the liquidity in both markets. Das and Hanouna (2009) find that
the equity liquidity measured by Amihud stock illiquidity spills over the CDS market with the
evidence that the quarterly change of CDS spread can be explained by stock illiquidity. Our
proposed method of separating hazard rates, to some extent, bears the liquidity information
(in NS residuals) for CDS and option markets (Hu et al., 2013; Kolokolova et al., 2016); hence,
our study also provides insights on how CDS and equity option illiquidities affect CDS-DOOM
price co-movement.
3 Data

3.1 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 CDS trading—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 no initial value to protection buyer or to protection
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 restricted and 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 prices—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 reality, par spread quote is more popular
than points upfront quote.

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 on 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 are very different. 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.

Mayordomo et al. [2014] pointed out these inconsistencies in the data format and the approaches to construct
CDS quotes cast doubt on the reliability of empirical research findings for CDS market, and the authors provide
detailed discussion and comparison among CDS data sources.
The main CDS quotes used in this study is obtained from GFI credit market data. GFI is 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 includes 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 CDS 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. Note that for some quotes, only bid (or ask) price is available, then 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 with the maturity ranges 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 maturity is 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 (in bars) and of the average daily traded names (in 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 figure indicates that CDS trades cluster in some period, and such clustering is because of GFI’s clients. For example, the recent decline in CDS trades was partly due to, according to the senior manager’s reply in the GFI, its clients’ trading shift to multi-name CDS product (a bundled transaction with more than one single-name CDSs).
As our CDS data is from a single dealer, one might be concerned if the CDS prices in GFI is significantly different from other CDS data providers due to sample bias. To reassure the sample representation in this study, we also have done an analysis by comparing our GFI CDS prices with Markit CDS prices. Based on our analysis, we do not find evidence of the significant difference between GFI and Markit average prices and their dynamics, and therefore conclude that the CDS prices in our GFI sample should provide good price representativeness for the CDS market. The complete analysis is presented in Appendix B.

3.2 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 the matched DOOM put option, which are put options with (1) the absolute value of put option delta is larger than 15%, (2) option bid price is larger than zero, and (3) the trading volume of the corresponding option is larger than zero.

We relax two selection criteria from the original Carr and Wu (2011) study. The first one is to relax restriction on option strike price. We argue in the following that this criterion is not appropriate in market practice: the rationale for restricting strike price comes from the assumption that CDS contracts for underlying names that have greater default risk (and lower stock price) are usually more common and popular in the market, as the objectives for CDS is to hedge default risk. However, recent studies (see Kolokolova et al., 2016; 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 is unlikely to have traded option with strike price under $5, applying this criterion will exclude a large number of CDS trades unnecessarily, and therefore we do not include the strike price restriction criterion.

The other criterion we relax is the one-to-one matching between CDS and 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. Here, we retain all the put options as long as they fit our selection criteria, as we need to use the put options with different maturities to fit the put-implied curve.

Carr and Wu (2011) restrict option strike price to be under $5.
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 rather high bid-ask spread, with the sample average of 0.09. Such high bid-ask spread indicates higher transaction cost for the illiquid put options. In addition, the average time to maturity for the put option is 0.38 years, highlighting that option trades are more popular for short maturity.

Panel B reports the maturity distribution of the matched put options. We find that 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.]
4 Methodology

4.1 URC-implied Hazard Rate

In this section, we briefly explain, following Carr and Wu (2011), how CDS and put option are linked using unit recovery claim. A unit recovery claim (URC) as 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:

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

(1)

where $r$ is the risk-free interest rate, $\tau$ is the default time, and $I$ is an indicator function taking the value of 1 if default happens before $T$ and zero otherwise. If default events follow a Poisson distribution with constant hazard rate $H$, then

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

(2)

Based on Equation (2), the CDS-implied URC (denoted as $U^C$) can be written as

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

(3)

where $\zeta$ is the inverse of loss-given-default (i.e. $1/(1-rr)$, with the bond recovery rate $rr$) and $k$ is the CDS spread. Equation (3) holds when the default arriving rate has a flat term-structure with $H = k/(1 - rr)$.

Next, consider the put-implied URC. An American put option allows investors to sell the underlying security at the pre-determined strike price. In terms of credit protection, the protection buyer decides to exercise the put option when stock price is below a certain threshold value

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

(4)

where $K$ is strike price and $S_\tau$ is the asset value at the time when the firm defaults.

Apart from firms that are “too big to fail”, the price of the DOOM put is entirely driven by the default probability and not by the stock price or the stock volatility. The authors 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, then any two American puts (with the same underlying) whose strike prices are within the default corridor $[A, B]$ replicate a pure credit insurance that pays off if and only if the company defaults prior to the option expiry. In particular, the put option has an analytic value:

$$P(t, T) = K \left[ H \left( \frac{1 - e^{-(r+H)(T-t)}}{r + H} \right) - Ae^{-rT} \left[ 1 - e^{-H(T-t)} \right] \right].$$  \hfill (5)

Combining Equations (2) and (5), the put-recovered URC (denoted as $U^P$) can be valued as a scaled difference between the two put option prices

$$U^P = \frac{P(K_2, T) - P(K_1, T)}{K_2 - K_1}.$$  \hfill (6)

For the special case in which stock price falls to zero at default time (i.e. $A = 0$), $K_1 = 0$. Equation (6) is re-written as

$$U^P = P(K, T)/K.$$  \hfill (7)

After we obtain $U^C$ and $U^P$ following Carr-Wu 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 (2) and (7). The CDS-implied hazard rate (denoted as $H^C$) is computed as $H^C = k/(1 - rr)$; here, we set $rr$ as 0.4 for all our CDSs. Wuse the recovered hazard rates to build a term structure of hazard rates.

4.2 Rating-based URC Curves

In [Hu et al. (2013)], the authors measure the “noise” in U.S. Treasury bonds as the difference between the fitted and the observed yields, and use it as a measure for the shortage of arbitrage capital in the economy. Following the same spirit, we estimate the residual term in the URC-implied hazard rates as the difference between the observed hazard rates and their fitted values as follows:

$$H(\tau) = F(\tau) + R(\tau)$$  \hfill (8)
where $H$ is the URC-implied hazard rate obtained from a put or CDS with maturity $\tau$, $F$ is the fitted value specific to the credit rating class, and $R$ is the residual.\footnote{There may be other factors in addition to the shortage of arbitrage capital that affect the sign and/or the magnitude of $R$. Some of the factors are market specific (since bonds are underlying for CDSs and stocks are underlying for put options), others are firm specific or are related to the general market conditions. Carr and Wu (2011) find, for example, that $U^P$ is greater than $U^C$. Empirically, $U^P$ increases as stock price moves closer to the strike price and as stock volatility increases, but it decreases as put open interest increases.} 

We obtain the daily fitted values $F(\tau)$ for each rating class based on the Nelson and Siegel (1987) model, which allows for a humped shape term structure:

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

where $\beta_0$ and $\beta_1$ are parameters reflecting the long-term and short-term hazard rates, $\beta_2$ captures a hump at the medium term, and $m$ determines the shape and the position of the hump.

Equation (9) is estimated separately for put option and CDS. In addition, we set $\beta_0 > 0$, $\beta_0 + \beta_1 > 0$, $\beta_0 + \beta_1 + \beta_2 > 0$ and $m > 0$ to avoid negative hazard rates.

4.3 Implementation and Analyses

Following the above-mentioned procedure, we form our rating curves for the CDS and put samples, separately. The curve-fitting procedure is performed each trading day. The observations are grouped according to the underlying rating information when fitting Nelson-Siegel (NS) curves. The underlying rating information is obtained from Markit. In this study, we use Markit implied rating, where the underlying firm’s rating is determined by comparing the corresponding CDS spread to nearest preset rating boundaries.\footnote{The explanation for determining the market-implied rating can be found in 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. Our actual rating information\footnote{Firm’s actual rating is the average of the Moody’s and S&P ratings adjusted to the seniority of the CDS and rounded to not include the ‘+’ and ‘-’ levels.} in Markit database is available only from 2002 to 2012, when we compare the actual rating and implied rating for the limited sub-sample, we find rather high correlation coefficient (66.03% over the period from 2002 to 2012, but even higher (70.79%) over the period from 2010 to 2012). Since the implied rating does not deviate from the actual rating, but reflects more promptly for market conditions, we use the implied rating information as our grouping criterion.

There may be other factors in addition to the shortage of arbitrage capital that affect the sign and/or the magnitude of $R$. Some of the factors are market specific (since bonds are underlying for CDSs and stocks are underlying for put options), others are firm specific or are related to the general market conditions. Carr and Wu (2011) find, for example, that $U^P$ is greater than $U^C$. Empirically, $U^P$ increases as stock price moves closer to the strike price and as stock volatility increases, but it decreases as put open interest increases.
We store our daily set of NS parameters $[\beta_0, \beta_1, \beta_2, m]$ in Equation (9) for different rating classes of our CDSs and put options. Hence, for a given CDS (or put option), one can calculate the NS-fitted value for the CDS (or the put option) as long as the rating and the corresponding time to maturity information is provided. Note that, since the parameters are calibrated for a group of CDS (or put option) with the same rating, two CDSs (or put options) will have the same NS-fitted values if they have the same rating of the underlying asset and time to maturity. In order to understand the time-series trend of our NS-fitted values, we use our daily set of parameters and calculate their 5-year fitted value (i.e. set $\tau = 5$ in Equation (9)). Each month, we further average the fitted values, in order to have a more general view of the time-series trend. Figure 2 illustrates the time-series NS-fitted values from CDSs for rating classes. It shows that the CDS-implied values presented in “layers” by rating classes: poor rating class has higher NS-fitted values, while good rating class tends to have lower NS-fitted values. Since the NS-fitted value reflect the default risk (hazard rate) to the rating class, higher value indicates higher default risk. We also observe that C rating class is more volatile than other rating classes, especially in 2014 and at the end of 2015. It may be because the scarce of observations. The NS calibration is affected by the quantity of the observation. Since we have much fewer observation for C rating firms, the parameters are likely to be driven by some outliers. Also, for some days, we cannot perform the NS calibration because there is no traded CDSs written on C rating firms.

[Figure 2 is about here.]

Similarly, Figure 3 illustrate the time-series trend of NS-implied values for put options. Although the NS-fitted values for put options, in general, is in line with its rating class (i.e. higher or lower NS-fitted value means poor or good rating class), we find many occurrences of crossover between rating classes. This reflects the fact that the price of put option, empirically, is also affected by option-specific factors (option pricing factor, option market conditions, etc). Another possible explanation for the crossover is because of the properties of our put sample. Recall that all our put observations are within 3 years, the NS-fitted value for 5-year may be more volatile using near-maturity observations. Also, C rating class has fewer NS-fitted values and the NS-fitted values are potentially driven by few outliers.

[Figure 3 is about here.]

Table 3 reports the descriptive statistics of the daily NS-fitted values for CDS and put
options used in Figure 2 and 3. For CDSs (reported in Panel A), the NS-fitted value increases as rating becomes poor, and the standard deviation is also increasing with rating classes. For put options, poor rating classes in general have higher NS-fitted values than good rating classes, but the increase is not strictly monotonic. We observe that BBB and BB rating classes have higher sample average than B rating. This is due to some peaks happened in these two rating classes (see breakdown for rating classes in Figure 3iv and 3v), and these high peaks increase the sample average as well as the sample standard deviation. If we compare the sample median, then the NS-fitted values for the put options are in line with the rating classes. The sample medians for [AA, A, BBB, BB, B, C] are [0.020, 0.022, 0.029, 0.032, 0.049, 0.017]. In addition, the NS-fitted values for put option (the sample average across rating is 0.07) is in general larger than for CDS (the sample average across rating is 0.05). The deviation between put option and CDS can be attribute to the different market conditions. We will explore this aspect and discover some applications from our proposed curve components in later sections.

[Table 3 is about here.]
5 Hypotheses and Research Design

After we obtain the Nelson-Siegel (NS) components of fitted value \((F)\) and residual \((R)\) using Equation (8) and (9), we then study the characteristics and the potential applications of these components. Particularly, we focus more on the “cross-market” behavior of the components, instead of the individual markets. Hence, we try to answer two main research questions in this study: (1) what can explain the cross-market deviation between CDS and put option, and (2) what is the time-series movement for the cross-market deviation.

To begin with, we introduce three deviation measures, which are mainly tested in this study:

\[
\begin{align*}
\text{Total Deviation: } D_H &= H_P - H_C, \\
\text{Systematic Deviation: } D_F &= F_P - F_C, \\
\text{Idiosyncratic Deviation: } D_R &= R_P - R_C.
\end{align*}
\]

where \(H\) is the recovered hazard rate from CDS or put option, using Carr-Wu framework, and \(F\) (or \(R\)) is the fitted value (or residual) of the hazard rate, further derived from NS term structure model. \(C\) (or \(P\)) indicates that the value is derived from CDS (or put option). Mathematically, \(D_H = D_F + D_R\). In addition, these deviation measures are all calculated by put option value deducted by CDS value, to reflect our descriptive statistics that the values in option are on average larger than in CDS. Also, our definition of these deviation measures is in line with previous studies (e.g. Carr and Wu, 2011; Kim et al., 2013). However, different from these previous studies (they only study the total deviation), our study further explore the deviation in “components”.

5.1 Determinants of Cross-market Deviation

In theory, DOOM put options reflect only pure default risk and hence the pricing of DOOM put option is irrelevant to the underlying stock prices. However, the pay-off of a DOOM put still follows an option’s pay-off (i.e. Strike – Stock); put option, in reality, may still be affected by factors linked to normal option pricing. Hence, these factors can potentially deviate put option price from CDS price, and our deviation measures \(D_H, D_F,\) and \(D_R\) are expected to capture the effect, not just random values. We also conjecture that option market conditions (e.g. price effectiveness) can be another reason to pull the put option away from CDS. Hence,
we formulate our first hypothesis:

**Hypothesis 1:** CDS-PUT cross-market deviations can be explained by the option-related factors.

Moreover, our study focuses on the deviation in the NS components (i.e. $D^F$ and $D^R$), instead of on the total deviation ($D^H$). Therefore, we formulate additional hypothesis as follows:

**Hypothesis 1a:** The systematic and idiosyncratic cross-market deviations can be explained by the option-related factors.

Recall that our systematic deviation ($D^F$) is calculated from the fitted value of the rating-based curves; the deviation supposedly be less related to the factors linked to the individual option pricing but be more related to option market conditions. On the contrary, the idiosyncratic deviation ($D^R$) is more related to the option pricing factors. Namely, we conjecture that these two deviation measures to capture different aspects of the driving factors. Therefore, a related corollary is formulated as follows:

**Corollary 1:** Two deviations are related to different aspects of the driving factors.

*In particular, the systematic deviation is more related to option market conditions, while the idiosyncratic deviation is more related to option pricing factors.*

To test our hypotheses regarding the causing of the cross-market deviations, we perform a contemporaneous pooled panel regression as follows:

$$D(i,t) = \beta_0 + \beta_1 X(i,t) + d(i,t)$$  \hspace{1cm} (13)

where $D$ is one of the three deviation measures ($D^H$, $D^F$, or $D^R$), $X$ is the option-related driving factors, and $d$ is the residual term of the regression. We also add calendar dummies and rating dummies to control for time and group fixed effect when we perform the panel regression. We choose, e.g., the average of recovered hazard rates, option delta, option implied volatility, option open interest, and option bid-ask spread for $X$. The first three factors are based on Carr and Wu (2011). The latter two are chosen based on our conjecture on option market conditions. In the following, we explain the rationale and our expected results one by one.

1. $0.5 \times (H^P + H^C)$: We use the average of the URC-implied hazard rate to test whether
the level of the hazard rate affects the level of cross-market deviation. Usually, higher level of average hazard rate has greater level of deviation; hence we expect to observe a positive relationship.

(2) Option delta: Option delta represents the option price sensitivity to the underlying stock. 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 $|\text{delta}|$ is larger, put option is expected to be closer to the in-the-money condition, and the put option should behave more like a traditional option, instead of a credit risk protection. Therefore, we expect a positive relationship between the deviation and the the $|\text{delta}|$.

(3) Implied volatility: Option-implied volatility is a crucial pricing factor and it reflects investor’s expectation regarding underlying stock price risk. Under the traditional option pricing framework, higher implied volatility is expected to have higher (put) option price, leading to higher put-implied hazard rate. Given other things equal, higher option implied volatility is supposed to increase the cross-market deviation. However, the classic Merton (1974) model hints that underlying stock’s volatility also affects CDS spread, because higher stock volatility increases the probability of hitting the default barrier of the underlying firm. Especially for recent years, during which many studies find that the equity market and CDS market are more connected. Such deepened connection implies that implied volatility may also affect CDS spread. Indeed, several studies (e.g. 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. As discussed so far, the impact of option implied volatility on the deviation depends on the magnitude of the price sensitivity to the implied volatility in the individual CDS and option markets. Hence the sign of the effect is inconclusive.

(4) Maturity: There is maturity mismatch between CDS and put option; also, option maturity on average is shorter than CDS maturity. If the mismatch is narrowed (or put maturity is increasing)\footnote{We use 5-year CDS in our test; therefore, we focus only on put option maturity.} then the cross-market deviation is expected to be alleviated. Hence, we expect a negative relation between put maturity and deviation. In addition, we conjecture that there is a non-linear effect on the deviation, so we use logarithm of the put maturity.

(5) Open interest: Option open interest indicates the demand for the put options. Higher open interest means the put option is more popular. Here, we hypothesize that it is easier to buy a put option than a CDS, as put option is exchanged-traded product, while CDS is
traded over the counter. If a potential protection buyer cannot buy a CDS over the counter, then he may alternatively turn to put option market for substitute product. Therefore, we hypothesize that higher open interest can reduce the cross-market deviation, as put is more likely to converge to the CDS prices.

(6) Bid-ask spread: Option bid-ask spread measures the level of the illiquidity of the put option. A larger spread between option bid and ask prices is expected to drive put option away from its fundamental price for default risk. Therefore, we expect positive effect on the CDS-PUT deviation.

Significant coefficients imply that the chosen option-related factor can explain why put option deviates from CDS. In addition, when we test for Corollary 1, we expect factors (1) to (4) are more related to idiosyncratic deviation, while factors (5) and (6) are more related to systematic deviation.

5.2 Cross-market Reversion Test

Our second research question is related to the time-series movements of our recovered hazard rates, in relation to our two deviation measures. If Carr-Wu framework holds, then the deviation between the recovered hazard rates is expected to vanish over a period of time under the Law of One Price. For this regard, Carr and Wu (2011) have partly proved that the deviation between CDS and put option is going to be narrowed over a period of time, after controlling for deviation drivers. But the diminishing in total deviation does not automatically indicate that our two deviation measures will both diminish over time. Recall that the systematic deviation captures the (signed) distance between the CDS and option curves, while the idiosyncratic deviation captures the (signed) distance between the recovered hazard rate and their corresponding curves. We conjecture that both deviation measures diminish over time. Our conjecture on the systematic deviation is based on Carr-Wu framework, because the systematic deviation is related to the price movement between CDS and put option.

On the other hand, our conjecture on the idiosyncratic deviation is based on Kolokolova et al. (2016), in which CDS prices have a tendency to move toward their rating-grouped estimated values. If put option acts alike CDS, then we expect the idiosyncratic deviation also to diminish over time. Notably, the time-series convergence in idiosyncratic deviation provides additional insight on the CDS-PUT co-movement, implying that CDS and put option also tend to move toward their NS curves. Here, we provide mathematical explanation about our conjecture on the
idiosyncratic deviation. Recall that the definition of the idiosyncratic deviation \( D^R = R^P - R^C \), if \( D^R \to 0 \), then the value of \( R^P \) is close to \( R^C \) (i.e. \( R^P \to R^C \)). Therefore, the interpretation of the diminishing in \( D^R \) depends on the behavior of \( R^C \). If CDS moves toward their NS curve, then we argue that the diminishing in \( D^R \) means that put option also moves toward their corresponding NS curve, and vise versa. Empirical evidence (Kolokolova et al., 2016) shows that CDS indeed move toward to their NS curve, supporting our interpretation regarding the diminishing in \( D^R \). Here, we formulate our second hypothesis:

**Hypothesis 2:** Both systematic and idiosyncratic deviations vanish over time. Notably, the diminishing in idiosyncratic deviation also indicates that CDS and put option overall converge to their NS curves.

To test our \( H2 \) hypothesis, we regress the time-series movement of the recovered hazard rate on our deviation measures by:

\[
\Delta H^P(i,t_1,t_2) = \beta_0^P + \beta_1^P d^F(i,t_1) + \beta_2^P d^R(i,t_1) + e^P(i,t_1) \tag{14}
\]
\[
\Delta H^C(i,t_1,t_2) = \beta_0^C + \beta_1^C d^F(i,t_1) + \beta_2^C d^R(i,t_1) + e^C(i,t_1) \tag{15}
\]

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 previous Equation (13). We also add calendar dummies to control for time fixed effect. We do not include rating dummies because the effect has been already captured in \( d^F \). In short, a negative \( \beta_1^P \) (\( \beta_2^P \)) and a positive \( \beta_1^C \) (\( \beta_2^C \)) suggest NS-fitted value \( F \) (NS residual \( R \)) contribute to the convergence between \( H^P \) and \( H^C \) over time.

Here, we use the residual term from Equation (13), instead of their original deviations \( (D^F \) or \( D^R) \). We then control for the known cross-market drivers. These drivers, from the discussion in the previous section, are related to temporary market shock (e.g. bid-ask spread) or to structural difference of the products (e.g. \(|\Delta| \)). After we control for these drivers, then the unexplained part of the deviations is supposed to be temporary or random.

The rationale of the set of the regressions is explained in more detail. Hypothetically, the unexplained deviations \( (d^H, d^F, \) and \( d^R) \) do not hinder the CDS-PUT convergence, if the CDS-PUT convergence indeed exists; these unexplained deviations supposedly contain (mostly) white noise. The negative coefficient of \( \beta_1^P \) (\( \beta_2^P \)) indicates that, when one observes positive estimated deviations \( d^F \) (\( d^R \)) at time \( t_1 \), \( H^P \) decreases from time \( t_1 \) to \( t_2 \). Similarly, positive coefficient of
\( \beta_1 \) (\( \beta_2 \)) indicates that, when one observes the same positive estimated deviations \( d_F \) (\( d_R \)) at time \( t_1 \), \( H^C \) decreases from time \( t_1 \) to \( t_2 \). Recall that our deviation measure is the put-implied value subtracted by CDS-implied value (see Equations (10) to (12)), negative \( \beta_1^P \) (\( \beta_2^P \)) and positive \( \beta_1^C \) (\( \beta_2^C \)), together, indicates a smaller observed cross-market deviation \( H^P - H^C \) at time \( t_2 \) than at time \( t_1 \).

Importantly, our set of regressions for reversion test provides another implication in relation to the deviations of the NS components \( F \) and \( R \). From our previous discussions, we hypothesize that both NS components contribute to the price convergence between CDS and put option. We expect the \( \beta \) coefficients in Equation (14) are negative, while the \( \beta \) coefficients in Equation (15) are positive. As the sign of the \( \beta \) coefficients is the same in the equation, we then expect the magnitude of time-series price change in \( H \) to be more obvious, if \( d_F \) and \( d_R \) share the same sign. Namely, we expect a stronger price convergence in CDS and put option in this case. Likewise, we expect a weaker price convergence when the directions of deviations are different (\( d_F > 0 \) and \( d_R < 0 \), for example), because the effects on price change are canceling out each other. Implicitly, \( d_F \) and \( d_R \) provide refined information for predicting for price convergence.

In addition, we use only unexplained deviations of the NS components, so that we can clearly isolate the individual component’s impact on the cross-market deviation. We do not include \( d_H \) in the regression due to the nature of the perfect linear relationship \( D^H = D^F + D^R \). Also note that the set of \( d_F \) and \( d_R \) is obtained using the same factor in \( X \), when we test for the reversion.

We also attempt to test the time convergence under the original deviation measures. If we can still observe the convergence without controlling for our known drivers, it indicates that the deviations are just temporary. Hence, we formulate our corollary related to our \( H2 \) hypotheses:

**Corollary 2**: The systematic and idiosyncratic deviations are both temporary in time.

To test **Corollary 2**, we repeat the regressions in (14) and (15), but replace \( d_F \) and \( d_R \) by \( D_F \) and \( D_R \), respectively. Significant coefficients suggest temporary deviation between the recovered hazard rate.
Within-market Reversion Test

Finally, we test the characteristics of the NS residual $R$. Recall that the residual term $R$ in our study refers the deviation between the actual hazard rate $H$ and the NS-fitted hazard $F$ in a given rating class. Our $H2$ hypothesis tests the overall effect of the convergence to their NS curves. To explore whether the individual convergences contribute to the overall convergence, we formulate our last hypothesis:

**Hypothesis 3**: CDS and put option converge to its market-specific NS curves.

If the individual convergence holds, then the overall convergence to the NS curves come from both effects of the convergence. To test this hypothesis, we perform an error correction model:

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

(16)

where $\Delta H(i, t_1, t_2)$ (or $\Delta F(i, t_1, t_2)$) is the time-series changes in the hazard rate (or NS-fitted value) from time $t_1$ to $t_2$, and $R(i, t_1)$ is the residual at time $t_1$. We run two sets of error correction model for CDS and put option separately. If there is significant negative $\beta_2$ coefficient, then the result indicates that the our recovered hazard rates converge to its NS curves over time. We also include calendar day and rating dummies in the regressions to control for fixed effects.
6 Results

In this section, we present our results based on our testable hypotheses in Section 5. However, before we conduct our proposed regression, we need to construct paired CDS and put option. Recall that, in our Methodology, the NS curves are generated using CDS (or put option) with the same rating. There is no need to pair CDS and put option. Now, if we test their cross-market deviations and the time-series innovation of the deviations, we need pair CDS and DOOM put option together. In the following, we detail the pairing procedure and then report the results.

6.1 Pairing CDS and Put Option

The main criterion when we pair the CDSs and put options is that we choose 5-year CDS, then we match the put option with the nearest maturity for that CDS. We fix the time to maturity in the CDS side, for (1) 5-year CDS is the largest group in our sample, and (2) it is widely known that 5-year CDS is the most popular contract, and the price should encounter minimal impact due to illiquidity. 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 5,265 pairs of CDS and put options over the sample period from July 2012 to April 2016. These 5,265 CDS-PUT pairs also indicate the plausible trading opportunities where one can trade on both CDS and put option on a given day.

After the cross-sectional matching for the CDS and put option, we further match these pairs time-seriesly. The purpose of time-series consistency is twofold: (1) we need a consistent time-series innovation on CDS and put option, required in our proposed regression, and (2) with time-series matching, we provide a plausible trading strategy, i.e. specific time to engage in securities and time to unwind the portfolio. Besides, consider that CDS and put option are relatively illiquid products, it is possible that one would not be able to unwind his CDS-PUT positions before, e.g., 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. As discussed, one prefers not to have very long holding period, to avoid the increased uncertainty in the cross-market situations. On the contrary, if the holding period is too short, then the trading profit may be consumed by the transaction cost. Based on
previous studies (Carr and Wu, 2011; Kolokolova et al., 2016), we further restrict the holding period between 7 and 30 calendar days. We further pair among our 5,265 CDS-PUT pairs for 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. We compare option ID, provided in OptionMetrics, to make sure we do not mismatch the option. Finally, we identify 1,949 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-PUT pair of prices for building 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 trade is performed on a daily basis. The average holding period is 13.42 days and more than 80% of our identified trades can be unwound with three weeks (see Table 4).

[Table 4 is about here.]

### 6.2 Results for Determinants of Cross-market Deviation

Table 5 reports the results for the cross-market deviation, using the Equation (13) specification of \(D_H = \beta_0^H + \beta_1^H X + d^H\), where \(X\) is one of the above-mentioned option related factors. We find that the \(\beta_1^H\) loading on \(0.5 \times (H_P + H_C)\) is 0.269, significantly at the 1% level. The result supports our hypothesis that higher level of average hazard rate has greater level of cross-market deviation. The loading on \(|\Delta|\) is 0.278, significantly at the 1% level, indicating that, when a put option becomes more in the money, the pricing of such option behaves more like a normal option, leading to a larger cross-market deviation. On the contrary, we find a negative \(\beta_1^H\) loading on option-implied volatility. Originally, option-implied volatility is supposed to pose a positive impact on the cross-market deviation. However, this factor also affects CDS prices (Wang et al., 2013), leading to an indecisive sign of the impact. The negative and significant coefficient means that the impact on CDS is larger than put option, in terms of hazard rate. The result can be explained by the type of the product transaction. Since CDS is traded over the counter, and the illiquidity is usually more concerned in an OTC product than an exchange-traded product, such larger magnitude of reaction in CDS due to implied volatility is expected.

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12For example, we observe ad-hoc that one CDS-PUT pair can be unwound after 9, 10, and 12 days. Consider that both CDS and put option are illiquid, one naturally unwind the position on the ninth day. To reflect this behavior, we also unwind the positions at the earliest opportunity when we construct our trades, instead of choosing the most profitable opportunity.
Also we find negative $\beta_1^H$ loading on option open interest, significantly at the 1% level. As expected, higher demand on put option decreases the cross-market deviation. We do not find significance on option bid-ask spread. Finally, we find negative loading on option maturity, indicating that the mismatch in CDS-PUT maturity increases the cross-market deviation. For a robustness check, we include all the deviation drivers in one regression, reported in Model (7) and (8), and we find the significance and signs are largely consistent.

[Table 5 is about here.]

Similarly, we use the Equation (13) specification for $D^F$ and $D^R$, respectively, to understand what drives our two systematic and idiosyncratic deviations. The regression results for components deviation are reported in Table 6. Panel A reports the specification of $D^F = \beta_0^F + \beta_1^F X + d^F$, and Panel B reports the specification of $D^R = \beta_0^R + \beta_1^R X + d^R$. We find that the drivers, in most of the cases, are not significant in explaining the NF-fitted value deviation ($D^F$), except for the option bid-ask spread. However, we observe positive loading on the option bid-ask spread, indicating that option illiquidity can reinforce the cross-market deviation in terms of NS-fitted value $F$. On the contrary, the significance of the deviation drivers for the $D^R$ deviation is more in line with that for the $D^H$ deviation, implying that $D^R$ is more related to $D^H$. In addition, we find negative $\beta_1^R$ loading on the option bid-ask spread. Recall that $\beta_1^H$ loading is insignificant and $\beta_1^F$ is positively significant, leading to a negatively significant force on $\beta_1^R$ to compensate the effect for $D^F$. For a robustness check, we include all the deviation drivers in one regression, reported in Model (6), and we find the significance and sign are consistent with the results from individual regressions.

[Table 6 is about here.]

Overall, we find almost all our option-related factors can explain the cross-market deviation and the signs for the effect are in line with our expectation. It indicates that option pricing factors and market conditions have an impact on the cross-market deviations ($H1$ and $H1a$). Moreover, we further explore the drivers on the systematic and idiosyncratic deviations, we indeed find that idiosyncratic deviation is related to individual option pricing factor, while the systematic deviation is more related to option market condition, supporting our $C1$. 

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6.3 Results for Cross-market Reversion

We further test if our systematic and idiosyncratic deviations are temporary, after controlling for known deviation drivers. To this end, we calculate $d^F$ and $d^R$, respectively, at time $t_1$. Both $d^F$ and $d^R$ are the estimated regression residual terms, controlling for one of our known deviation drivers at one time. In addition, $d^F$ and $d^R$ are estimated using the same driver. We then perform the regression specification in Equation (14) and (15), and the results are reported in Table 7. The left-hand side of the table reports the CDS results for the $\beta^C_1$ and $\beta^C_2$. We find that, after controlling for our known deviation drivers, both coefficients $\beta^C_1$ and $\beta^C_2$ are significantly positive. The coefficient itself means that a positive (or negative) current estimated deviation predicts a positive (or negative) future change in the CDS-implied hazard rate. We also include all drivers together (reported in the last row), and the results are consistent with the previous models. Recall that the interpretation of the trend means that CDS moves toward put option. More importantly, we find that both NS-fitted value $F^C$ and residual $R^P$ contribute to the CDS movement, providing strong evidence that the NS components are valid predictors for CDS.

[Table 7 is about here.]

The right-hand side of the table reports the put option results for the $\beta^P_1$ and $\beta^P_2$, after controlling for our known deviation drivers. All the coefficients are significantly negative, except that the loading for $|\Delta|$ is insignificant. Analogue of our previous interpretation, negative $\beta^P_1$ and $\beta^P_2$ coefficients predicts the future put option’s movement toward CDS, and both NS components, $F^P$ and $R^P$, contribute to the convergence between CDS and put option.

Combining together both sides of the table, the evidence supports our $H2$ hypothesis. Positive $\beta^C_1$ and negative $\beta^P_1$ together shows that CDS and put option move toward each other, i.e. their NS curves move to each other over time. Meanwhile, positive $\beta^C_2$ and negative $\beta^P_2$ together indicates that CDS and put option also move toward their corresponding NS curves. And both contribute to the overall CDS-PUT convergence.

For a robustness check, we regress unconditional deviation ($D^F$ and $D^R$) using Equations (14) and (15), and we find that the CDS-PUT convergence still holds, supporting our conjecture that these known drivers are just temporary ($C2$). It also implies that one can construct a trading strategy by exploiting the systematic and idiosyncratic deviation without controlling for these deviation drivers.
6.4 Results for NS Curve Convergence

Table 8 reports the results for the error correction model specification of Equation (16). Panel A reports the results for error correction model on CDS. $\beta^C_1$ is 0.049 and $\beta^C_2$ is -0.060, both significantly at the 1% level. The result indicates that the time-series movement of CDS-implied hazard rate is mainly captured by the NS-fitted value $F$. Since our NS-fitted value is constructed by grouping underlying firm’s rating, it also highlights the importance of rating as a systematic factor. At the same time, the loading on the NS residual $R^C$ is significantly negative, supporting our argument that the CDS-implied hazard rate converges to the rating-based URC curves.

Table 8 is about here.

Panel B reports the results for error correction model on put option. Both $\beta^P_1$ and $\beta^P_2$ are not significant, although negative $\beta^P_2$ implies a potential convergence to the rating-based URC curves. Recall in Figure 3 that there are several occasions of crossover in the rating-based URC curves for the put option, such results therefore are not surprising. From our previous analyses, it supports the results here that these known drivers (e.g. $|\Delta|$ and BAS) indeed hinder the potential convergence of put option to its NS curves. In addition, the error correction model also gives us more insights on our $C2$ hypothesis. Recall that we find our idiosyncratic deviation still diminishes over time without controlling for known driving factors. The additional results reported in Table 8 imply that the main force of the diminishing in the idiosyncratic deviations come from CDS part, while put option has sluggish movement toward their NS curves.

To further explore the NS curve convergence in option part, we modify the variables in the error correction model. Recall that we have obtained the explained deviations for our total, systematic, and idiosyncratic deviation measures. We then are able to remove those effect from our option values. Namely, we calculate a modified recovered hazard rate for put option by $H^{P*} = H^P - X\beta$, where $X\beta$ is the fitted value from $D^H = \alpha + X\beta + d^H$ (Equation (13)). Similarly, we calculate the modified $F^{P*}$ and $R^{P*}$ from $D^F = \alpha + X\beta + d^F$ and $D^R = \alpha + X\beta + d^R$, respectively. Hence the modified values supposedly reflect underlying firm’s default risk more. Here we include all the drivers when we estimated the explained deviation $X\beta$.

The results are reported in Panel C. After we control for known drivers, we find some evidence that put option indeed behaves alike CDS, moving toward to their NS curves, with $\beta_2$ loading of -0.004 at the 5% level. The results, combined together with CDS, support our $H3$
hypothesis that both CDS and put option move toward to their NS curves, contributing to the diminishing in $d^R$ over time ($H2$).
7 Simulated Trading Opportunities

7.1 Strategy Description

Theoretically, CDS and put option can substitute each other for a credit protection of the underlying firm. If one observes a price deviation between these two products, he can construct an arbitrage strategy based on the cross-market deviation, because the prices of CDS and put option are expected to return to their fundamental URC prices. In other words, one can trade at time $t_1$ on the signal of $D^H$, taking a long position in the security (CDS or put option) with a lower $H$ (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 to be unwound after the two $H$s are converged at some time $T$ (or practically, at the earliest unwound opportunity time $t_2$). The arbitrage return (denoted as $r^A$) on this strategy can be calculated by

$$r^A = r^L - r^S$$

$$r^L \text{ or } r^S = \frac{\log U(t_2) - \log U(t_1)}{t_2 - t_1},$$

where $U$ is the URC price of the instrument of interest and the holding period is from $t_1$ to $t_2$. Here we use the converted $U^P$ or $U^C$ price as these two values refer to the same pay-off where the URC seller pays $1$ if the underlying firm defaults. Therefore, we can ignore hedge ratio between $U^P$ and $U^C$ in this case. But, as a robust check, we also use their raw price to check the validity of our argument.

As a Benchmark strategy, one can follow our above-mentioned strategy. Namely, if $D^H$ is positive (negative), we long (short) CDS and short (long) put option at the same time at time $t_1$, and we unwound the position at time $t_2$, as theoretically $D^H \to 0$ over time.

Here, we propose a refined strategy (Decomposition strategy, hereafter) using information from our NS components. Recall that $D^H = D^F + D^R$, we argue that the magnitude of the convergence in $H$ becomes stronger, if $D^F$ and $D^R$ have the same sign. The rationale behind is that we expect $D^F$ and $D^R$ both to explain the price convergence in the same direction. If $D^F$ and $D^R$ do not have the same sign, then the effect on price convergence will be canceled out.\[13\] 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 the same time at time

\[13\]More detailed discussion can be found in our previous Section 6.3.
only when $D^F$ and $D^R$ are both positive (negative); and we unwound the position at time $t_2$. This strategy is more stringent because the potential trading opportunities are reduced, but the additional information is expected to enhance the prediction in convergence in $H$. Figure 4 provides some examples of our Decomposition strategy, using the coefficients in Table 7 (Model 1). It shows that, when $D^F$ and $D^R$ have the same sign, the future price movements of the CDS and put option are more likely to be predicted.

To implement this trading strategy, we make several additional assumptions. We use the put options and CDS spreads in our paired sample and assume that they are traded at the quoted prices with zero transaction cost. The securities are perfectly divisible and there is no trading limits. Since we consider short trading periods (between 7 and 30 days), we can ignore the impact from maturity mismatch between CDS and put option. In addition, since CDS and put option have different product structure (e.g. different pay-off pattern and different payment frequency), we use CDS- and option-implied URC prices in our simulated trades. After conversion, both prices refer the same product structure, namely, protection sellers pay $1 if the firm defaults and zero otherwise.

### 7.2 Performance Comparison

We follow the trading algorithm for our 1,949 trades. Recall that, for Benchmark strategy, we long a CDS position and short the matched put option at time $t_1$, if we observe a positive cross-market deviation $D^H$; and we unwound the positions at time $t_2$. We operate the opposite for a negative $D^H$. Recall that, for our Decomposition strategy, we add additional restriction: we trade only when $D^F$ and $D^R$ have the same sign. For example, we long a CDS position and short the corresponding put option at time $t_1$ if we observe both $D^F$ and $D^R$ are positive (remember that such condition guarantees a positive $D^H$), and we operate the opposite for both negative $D^F$ and $D^R$. The additional restriction reduces the number of our 1,949 trades to 1,002 trades, because not all the trades fulfill the criteria. We report the strategy performance in Table 9. Panel A reports the arbitrage performance in terms of daily return, using the URC prices. We find positive average return for our Benchmark strategy. The average return ($Ret^B$) is 0.927%, significantly greater than zero at the 1% level under $t$ test. For our Decomposition strategy, we observe even higher average return of 1.343% ($Ret^D$), with fewer number of trade than our Benchmark strategy. In specific, $Ret^D$ is higher than $Ret^B$ by 0.416%, again significantly at the
1% level under our two sample $t$ test. The results combined together provide strong evidence that NS-implied components indeed provide refined signal for the convergence between CDS and put option. On the other hand, we group the rest of the trades that are not included in our Decomposition strategy, we find that, if the signs of $D^F$ and $D^R$ differ, the propensity of convergence indeed is much weaker; the average return (denoted as $Ret^O$) is merely 0.487%.

To further confirm that our results are not affected by the URC conversion, as a robustness check, we repeat our analyses using the raw CDS spreads and put option premiums, and the results hold.

[Table 9 is about here.]
8 Conclusion

Since prices of CDS and DOOM are primarily driven by the default of probability (DP) of the underlying firms, the implied DP from these two securities should be very close, if not identical, if they are written on the same firm. In this study, we investigate the cross-market divergence and time-series convergence of the hazard rates recovered from CDS and DOOM, over the sample period from July 2012 to April 2016. We fit the Nelson-Siegel (NS) term structure model to recovered hazard rates of firms with the same ratings, and use the fitted values as the systematic component and the residuals as the idiosyncratic component. Hence, each CDS-PUT pair provides a set of systematic and idiosyncratic deviations. We find that the average hazard rate, option delta, implied volatility, option open interest, option bid-ask spread, and option maturity can explain the total CDS-PUT deviation. Furthermore, the deviations of the systematic components relates to market inefficiency measured as bid-ask spread, while the deviation of the idiosyncratic components relates to option pricing factors. More importantly, we find that the NS components can be used to predict future price changes in CDS and DOOM put option, because we find both deviations diminish over time. Our results imply that there exists a systematic force that drives the price convergence between CDS and DOOM put option, because we also find evidence that both CDS and DOOM move to their NS curves time-seriesly.

To exploit the divergence and convergence patterns of the hazard rates recovered from CDS and DOOM, we test two trading strategies. The first strategy, Benchmark, trades on the divergence of implied hazard rates. While, the second strategy, Decomposition, adds an extra condition, by requiring that both systematic and idiosyncratic deviations have the same direction. We find both strategies produce statistically significant positive returns. Our more refined Decomposition strategy, on average, significantly outperforms Benchmark in terms of daily return. This indicates that using systematic and idiosyncratic deviations as trading signals can better predict the future convergence between CDS and DOOM.
References


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

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>STD</th>
<th>Max</th>
<th>Min</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spread (bp)</td>
<td>278.50</td>
<td>856.77</td>
<td>9,966.40</td>
<td>0.00</td>
<td>46,495</td>
</tr>
<tr>
<td>BAS (bp)</td>
<td>0.13</td>
<td>1.47</td>
<td>60.00</td>
<td>0.00</td>
<td>46,056</td>
</tr>
<tr>
<td>Maturity (yr)</td>
<td>4.70</td>
<td>1.48</td>
<td>10.00</td>
<td>0.00</td>
<td>46,495</td>
</tr>
</tbody>
</table>

Panel B: Maturity Distribution

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<th>≤ 2Y</th>
<th>≤ 3Y</th>
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<th>≤ 7Y</th>
<th>≤ 8Y</th>
<th>≤ 9Y</th>
<th>≤ 10Y</th>
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</thead>
<tbody>
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<td>Count</td>
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<td>994</td>
<td>1,212</td>
<td>968</td>
<td>37,723</td>
<td>334</td>
<td>954</td>
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<td>0</td>
<td>942</td>
</tr>
<tr>
<td>Percent</td>
<td>7.24%</td>
<td>2.14%</td>
<td>2.61%</td>
<td>2.08%</td>
<td>81.13%</td>
<td>0.72%</td>
<td>2.05%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>2.03%</td>
</tr>
</tbody>
</table>
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 DOOM put 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

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>STD</th>
<th>Max</th>
<th>Min</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Premium</td>
<td>0.44</td>
<td>0.61</td>
<td>11.65</td>
<td>0.01</td>
<td>82,623</td>
</tr>
<tr>
<td>BAS</td>
<td>0.09</td>
<td>0.15</td>
<td>4.29</td>
<td>0.00</td>
<td>82,623</td>
</tr>
<tr>
<td>Maturity (yr)</td>
<td>0.38</td>
<td>0.50</td>
<td>2.38</td>
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<td>82,623</td>
</tr>
<tr>
<td>Open Interest</td>
<td>2,964</td>
<td>11,045</td>
<td>344,233</td>
<td>1</td>
<td>82,623</td>
</tr>
<tr>
<td>Implied Vol</td>
<td>0.34</td>
<td>0.15</td>
<td>2.91</td>
<td>0.09</td>
<td>82,623</td>
</tr>
<tr>
<td></td>
<td>\Delta</td>
<td></td>
<td>0.08</td>
<td>0.04</td>
<td>0.15</td>
</tr>
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</table>

Panel B: Maturity Distribution

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<th>\leq 1Y</th>
<th>&gt; 1Y</th>
<th>\leq 1.5Y</th>
<th>&gt; 1.5Y</th>
<th>\leq 2Y</th>
<th>&gt; 2Y</th>
<th>\leq 2.5Y</th>
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<tbody>
<tr>
<td>Count</td>
<td>63,328</td>
<td>9,295</td>
<td>5,770</td>
<td>2,879</td>
<td>1,351</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent</td>
<td>76.65%</td>
<td>11.25%</td>
<td>6.98%</td>
<td>3.48%</td>
<td>1.64%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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 prices with parameter $\tau$ set to 5 year. Panel B reports the fitted value for the option prices with the parameter $\tau$ set to 5 year. Each panel reports the sample mean, STD, maximum, and minimum for different rating classes.

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

<table>
<thead>
<tr>
<th></th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.006</td>
<td>0.011</td>
<td>0.018</td>
<td>0.032</td>
<td>0.061</td>
<td>0.210</td>
</tr>
<tr>
<td>STD</td>
<td>0.003</td>
<td>0.005</td>
<td>0.006</td>
<td>0.007</td>
<td>0.016</td>
<td>0.215</td>
</tr>
<tr>
<td>Max</td>
<td>0.023</td>
<td>0.041</td>
<td>0.047</td>
<td>0.073</td>
<td>0.217</td>
<td>2.079</td>
</tr>
<tr>
<td>Min</td>
<td>0.002</td>
<td>0.002</td>
<td>0.002</td>
<td>0.004</td>
<td>0.021</td>
<td>0.014</td>
</tr>
<tr>
<td>N</td>
<td>492</td>
<td>561</td>
<td>608</td>
<td>563</td>
<td>528</td>
<td>378</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.028</td>
<td>0.043</td>
<td>0.080</td>
<td>0.070</td>
<td>0.057</td>
<td>0.181</td>
</tr>
<tr>
<td>STD</td>
<td>0.075</td>
<td>0.140</td>
<td>0.270</td>
<td>0.233</td>
<td>0.068</td>
<td>0.261</td>
</tr>
<tr>
<td>Max</td>
<td>1.522</td>
<td>1.475</td>
<td>3.024</td>
<td>2.598</td>
<td>1.039</td>
<td>2.430</td>
</tr>
<tr>
<td>Min</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>N</td>
<td>474</td>
<td>541</td>
<td>588</td>
<td>510</td>
<td>467</td>
<td>210</td>
</tr>
</tbody>
</table>
Table 4: Holding Period Distribution

This table reports the counts of holding period for our identified 1,949 trades. The sample period is from July 2012 to April 2016. The sample average and the standard deviation (STD) are reported in the last two rows.

<table>
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<th></th>
<th>≥ 7D</th>
<th>&gt; 14D</th>
<th>&gt; 21D</th>
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</thead>
<tbody>
<tr>
<td>Count</td>
<td>1179</td>
<td>439</td>
<td>331</td>
</tr>
<tr>
<td>Percent</td>
<td>60.49%</td>
<td>22.52%</td>
<td>16.98%</td>
</tr>
</tbody>
</table>

Mean 13.42
STD 6.36
Table 5: CDS-PUT Deviation

This table reports the results for the CDS-PUT deviation drivers for our identified 1,949 trades. The sample period is from July 2012 to April 2016. For each deviation driver, we test the regression specification of \( D^H = H^P - H^C = \beta_0^H + \beta_1^H X + d^H \). We include one of our deviation drivers at one time in our regression (1) to (6), including the average hazard rate, option delta in absolute value (\(|\text{Delta}|\)), implied volatility, option open interest, option bid-ask spread (BAS), and logarithm of option maturity. We include all the deviation drivers in our regression (7) and (8). The coefficient \( t\)-stat is reported in [ ].

<table>
<thead>
<tr>
<th>Dependent Variable: ( D^H = H^P - H^C )</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
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</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.015</td>
<td>-0.023</td>
<td>0.007</td>
<td>-0.000</td>
<td>-0.000</td>
<td>-0.006</td>
<td>-0.038</td>
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</tr>
<tr>
<td></td>
<td>[-0.86]</td>
<td>[-1.46]</td>
<td>[0.39]</td>
<td>[-0.02]</td>
<td>[-0.02]</td>
<td>[-0.36]</td>
<td>[-2.71]</td>
<td>[-5.45]</td>
</tr>
<tr>
<td>(0.5 \times (H^C + H^P))</td>
<td>0.269</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.150</td>
<td>0.760</td>
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<tr>
<td></td>
<td>[11.34]</td>
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<td></td>
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<tr>
<td>(</td>
<td>\text{Delta}</td>
<td>)</td>
<td></td>
<td>0.278</td>
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<td>0.027</td>
<td>0.033</td>
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<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
<td>-0.000</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[-3.65]</td>
<td></td>
<td></td>
<td></td>
<td>[-4.10]</td>
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<tr>
<td>Put BAS</td>
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<td>No</td>
<td>No</td>
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<td>No</td>
<td>No</td>
<td>Yes</td>
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<tr>
<td>Adj. R-sqr</td>
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<td>0.34</td>
<td>0.11</td>
<td>0.12</td>
<td>0.11</td>
<td>0.27</td>
<td>0.50</td>
<td>0.74</td>
</tr>
</tbody>
</table>
This table reports the results for the CDS-PUT deviation drivers for our identified 1,949 trades. The sample period is from July 2012 to April 2016. In Panel A, we test the regression specification of $D^F = F^P - F^C = \beta_0^F + \beta_1^F X + d^F$. The regression specification in Panel B is $D^R = R^P - R^C = \beta_0^R + \beta_1^R X + d^R$. We include one of our deviation drivers at one time in our regression (1) to (6), including the average hazard rate, option delta in absolute value ($|\text{Delta}|$), implied volatility, option open interest, option bid-ask spread (BAS), and logarithm of option maturity. We include all the deviation drivers in our regression (7) and (8). The coefficient $t$-stat is reported in $[\cdot]$.  

### Panel A: Fitted Value $F$ Deviation

<table>
<thead>
<tr>
<th>Dependent Variable: $D^F = F^P - F^C$</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.015</td>
<td>0.015</td>
<td>0.000</td>
<td>0.002</td>
<td>0.000</td>
<td>0.004</td>
<td>-0.008</td>
<td>0.002</td>
</tr>
<tr>
<td>$0.5*(H^C+H^P)$</td>
<td>-0.239</td>
<td>-0.591</td>
<td>-0.055</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$</td>
<td>\text{Delta}</td>
<td>$</td>
<td>-0.157</td>
<td>-0.056</td>
<td>-0.165</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Implied Vol</td>
<td>0.004</td>
<td>0.076</td>
<td>0.033</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Open Interest</td>
<td>-0.000</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Put BAS</td>
<td>0.052</td>
<td>0.055</td>
<td>0.048</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Put Maturity</td>
<td>0.003</td>
<td>-0.005</td>
<td>0.003</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Rating FE</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Adj. R-sqr</td>
<td>0.28</td>
<td>0.28</td>
<td>0.28</td>
<td>0.28</td>
<td>0.28</td>
<td>0.28</td>
<td>0.28</td>
<td>0.30</td>
</tr>
</tbody>
</table>

### Panel B: Residual $R$ Deviation

<table>
<thead>
<tr>
<th>Dependent Variable: $D^R = R^P - R^C$</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.031</td>
<td>-0.038</td>
<td>0.007</td>
<td>-0.003</td>
<td>-0.001</td>
<td>-0.010</td>
<td>-0.030</td>
<td>-0.058</td>
</tr>
<tr>
<td>$0.5*(H^C+H^P)$</td>
<td>0.508</td>
<td>0.442</td>
<td>0.815</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$</td>
<td>\text{Delta}</td>
<td>$</td>
<td>0.435</td>
<td>0.363</td>
<td>0.356</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Implied Vol</td>
<td>-0.018</td>
<td>-0.048</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Open Interest</td>
<td>-0.000</td>
<td>-0.000</td>
<td>-0.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Put BAS</td>
<td>-0.053</td>
<td>-0.052</td>
<td>-0.045</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Put Maturity</td>
<td>-0.011</td>
<td>-0.005</td>
<td>-0.010</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Rating FE</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Adj. R-sqr</td>
<td>0.27</td>
<td>0.28</td>
<td>0.27</td>
<td>0.27</td>
<td>0.27</td>
<td>0.27</td>
<td>0.28</td>
<td>0.30</td>
</tr>
</tbody>
</table>
Table 7: CDS-PUT Convergence

This table reports the results for the CDS-PUT convergence for our identified 1,949 trades. The sample period is from July 2012 to April 2016. The right-hand side of the table reports the regression specification of Equation (14) and the left-hand side of the table reports the regression specification of Equation (15). $d^F$ and $d^R$ are the estimated deviation using Equation (13) with $D^F$ and $D^R$, respectively. We include one of our deviation drivers at one time in our regression, including the average hazard rate, option delta in absolute value (|$\text{Delta}$|), implied volatility, option open interest, option bid-ask spread (BAS), and logarithm of option maturity. The coefficient $t$-stat is reported in $[\ ]$.

Panel A: Controlling for option-related factors

<table>
<thead>
<tr>
<th></th>
<th>Model: $\Delta H^C = \beta_0^C + \beta_1^C d^F + \beta_2^C d^R + e$</th>
<th>Model: $\Delta H^P = \beta_0^P + \beta_1^P d^F + \beta_2^P d^R + e$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta_1^C$ $\beta_2^C$ Time FE Adj. R-sqr</td>
<td>$\beta_1^P$ $\beta_2^P$ Time FE Adj. R-sqr</td>
</tr>
<tr>
<td>$0.5 \times (H^P + H^C)$</td>
<td>0.009 0.009 Yes 0.13</td>
<td>-0.084 -0.086 Yes 0.22</td>
</tr>
<tr>
<td></td>
<td>[2.57] [2.72]</td>
<td>[-3.89] [-4.05]</td>
</tr>
<tr>
<td></td>
<td>Delta</td>
<td>0.016 0.016 Yes 0.14</td>
</tr>
<tr>
<td></td>
<td>[4.28] [4.44]</td>
<td>[-0.39] [-0.49]</td>
</tr>
<tr>
<td>Implied Vol</td>
<td>0.007 0.008 Yes 0.13</td>
<td>-0.055 -0.058 Yes 0.22</td>
</tr>
<tr>
<td></td>
<td>[2.24] [2.40]</td>
<td>[-2.65] [-2.80]</td>
</tr>
<tr>
<td>Open Interest</td>
<td>0.006 0.006 Yes 0.13</td>
<td>-0.058 -0.061 Yes 0.22</td>
</tr>
<tr>
<td></td>
<td>[1.78] [1.94]</td>
<td>[-2.80] [-2.95]</td>
</tr>
<tr>
<td>Put BAS</td>
<td>0.007 0.007 Yes 0.13</td>
<td>-0.059 -0.062 Yes 0.22</td>
</tr>
<tr>
<td></td>
<td>[2.12] [2.27]</td>
<td>[-2.86] [-3.02]</td>
</tr>
<tr>
<td>Put Maturity</td>
<td>0.006 0.007 Yes 0.13</td>
<td>-0.115 -0.117 Yes 0.23</td>
</tr>
<tr>
<td></td>
<td>[1.71] [1.84]</td>
<td>[-5.03] [-5.18]</td>
</tr>
<tr>
<td>ALL Factors</td>
<td>0.014 0.015 Yes 0.13</td>
<td>-0.063 -0.066 Yes 0.13</td>
</tr>
<tr>
<td></td>
<td>[3.28] [3.42]</td>
<td>[-2.29] [-2.40]</td>
</tr>
</tbody>
</table>

Panel B: Without controlling for option-related factors

<table>
<thead>
<tr>
<th></th>
<th>Model: $\Delta H^C = \beta_0^C + \beta_1^C d^F + \beta_2^C d^R + e$</th>
<th>Model: $\Delta H^P = \beta_0^P + \beta_1^P d^F + \beta_2^P d^R + e$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta_1^C$ $\beta_2^C$ Time FE Adj. R-sqr</td>
<td>$\beta_1^P$ $\beta_2^P$ Time FE Adj. R-sqr</td>
</tr>
<tr>
<td>Model (1)</td>
<td>0.007 0.007 No 0.003</td>
<td>-0.082 -0.080 No 0.01</td>
</tr>
<tr>
<td></td>
<td>[2.31] [2.47]</td>
<td>[-4.10] [-4.05]</td>
</tr>
<tr>
<td>Model (2)</td>
<td>0.007 0.007 Yes 0.13</td>
<td>-0.059 -0.062 Yes 0.22</td>
</tr>
<tr>
<td></td>
<td>[2.11] [2.27]</td>
<td>[-2.86] [-3.01]</td>
</tr>
</tbody>
</table>
Table 8: Error Correction to Rating Curves

This table reports the results for the error correction model. The sample period is from July 2012 to April 2016. Panel A reports the descriptive statistics for the URC-implied hazard rates and their Nelson-Siegel (NS) components. $H$ is the URC-implied hazard rate for CDS ($H^C$) and put option ($H^P$); $F$ is the NS-fitted value for CDS ($F^C$) and put option ($F^P$); and $R$ is the NS residual for CDS ($R^C$) and put option ($R^P$). Panel B reports the error correction model results for CDS. Panel C reports the error correction model results for put option. The coefficient $t$-stat is reported in [ ].

Panel A: $\Delta H^C_t = \beta_0 + \beta_1 \Delta F^C_t + \beta_2 R^C_t + \epsilon_t$

<table>
<thead>
<tr>
<th>$\beta_0$</th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>Time FE</th>
<th>Rating FE</th>
<th>Adj. R-sqr</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coef.</td>
<td>-0.001</td>
<td>0.049</td>
<td>0.060</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>[-0.49]</td>
<td>[8.91]</td>
<td>[-7.44]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B: $\Delta H^P_t = \beta_0 + \beta_1 \Delta F^P_t + \beta_2 R^P_t + \epsilon_t$

<table>
<thead>
<tr>
<th>$\beta_0$</th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>Time FE</th>
<th>Rating FE</th>
<th>Adj. R-sqr</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coef.</td>
<td>-0.006</td>
<td>-0.001</td>
<td>-0.003</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>[-0.43]</td>
<td>[-0.72]</td>
<td>[-1.04]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel C: $\Delta H^{P*}_t = \beta_0 + \beta_1 \Delta F^{P*}_t + \beta_2 R^{P*}_t + \epsilon_t$

<table>
<thead>
<tr>
<th>$\beta_0$</th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>Time FE</th>
<th>Rating FE</th>
<th>Adj. R-sqr</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coef.</td>
<td>0.028</td>
<td>0.001</td>
<td>-0.004</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>[2.85]</td>
<td>[0.82]</td>
<td>[-2.14]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 9: Arbitrage on CDS-PUT Convergence

This table reports the arbitrage performance in daily return for our identified 1,949 trades. The sample period is from July 2012 to April 2016. \( Ret^B \) is the return for the Carr-Wu Benchmark strategy, \( Ret^D \) is the return for our Decomposition strategy, and \( Ret^O \) is the return for the trades that are not included in the Decomposition strategy. Panel A reports the returns using URC implied prices, and Panel B reports the returns using their CDS (put option) raw prices. ***, **, and ** represents the significance of one sample or two sample \( t \)-test at the 1%, 5%, and 10% level, respectively.

Panel A: Simulated return using URC prices

<table>
<thead>
<tr>
<th></th>
<th>( Ret^B )</th>
<th>( Ret^D )</th>
<th>( Ret^O )</th>
<th>( Ret^D - Ret^B )</th>
<th>( Ret^D - Ret^O )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (%)</td>
<td>0.927***</td>
<td>1.343***</td>
<td>0.487***</td>
<td>0.416***</td>
<td>0.856***</td>
</tr>
<tr>
<td>STD (%)</td>
<td>2.645</td>
<td>2.730</td>
<td>2.479</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N Trades</td>
<td>1949</td>
<td>1002</td>
<td>947</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B: Simulated return using raw prices

<table>
<thead>
<tr>
<th></th>
<th>( Ret^B )</th>
<th>( Ret^D )</th>
<th>( Ret^O )</th>
<th>( Ret^D - Ret^B )</th>
<th>( Ret^D - Ret^O )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (%)</td>
<td>0.926***</td>
<td>1.344***</td>
<td>0.483***</td>
<td>0.418***</td>
<td>0.860***</td>
</tr>
<tr>
<td>STD (%)</td>
<td>2.642</td>
<td>2.725</td>
<td>2.476</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N Trades</td>
<td>1949</td>
<td>1002</td>
<td>947</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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: Fitted NS Curves for 5-year CDS

This figure plots the Nelson-Siegel fitted value for CDS in different rating classes from July 2012 to April 2016.

(ii) AA

(iii) A

(iv) BBB

(v) BB

(vi) B

(vii) C
Figure 3: Fitted NS Curves for 5-year DOOM Put Option

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

(ii) AA

(iii) A

(iv) BBB

(v) BB

(vi) B

(vii) C
Figure 4: Examples of Trading on $D^F$ and $D^R$ signals

(i) Trade on Decomposition Strategy

Example 1: (Trade)

\begin{align*}
D^P &= F^P - F^C > 0 \\
D^R &= R^P(>0) - R^C(<0) > 0 \\
\end{align*}

$D^P$ and $D^R$ are positive
→ long CDS and short PUT at time $t_1$

\begin{align*}
R^P &= H^P - F^P \\
R^C &= H^C - F^C \\
\end{align*}

Prediction: PUT ↓
\[
\frac{\Delta H^P}{\Delta t} = -0.082 \times D^P - 0.080 \times D^R
\]

Prediction: CDS ↑
\[
\frac{\Delta H^C}{\Delta t} = 0.007 \times D^P + 0.007 \times D^R
\]

(ii) No Trade

Example 2: (No trade)

\begin{align*}
D^P &= F^P - F^C > 0 \\
D^R &= R^P(<0) - R^C(>0) < 0 \\
\end{align*}

$D^P$ and $D^R$ have different sign
→ Weaker or no convergence
→ No trade at time $t_1$

\begin{align*}
R^P &= H^P - F^P \\
R^C &= H^C - F^C \\
\end{align*}

Prediction: PUT?
\[
\frac{\Delta H^P}{\Delta t} = -0.082 \times D^P - 0.080 \times D^R
\]

Prediction: CDS?
\[
\frac{\Delta H^C}{\Delta t} = 0.007 \times D^P + 0.007 \times D^R
\]
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,

\[ PVP = c \times PVE + u \]
\[ \Leftrightarrow u = PVP - c \times PVE \]  
(19)

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:

\[ PVP = k \times PVE \]  
(20)

where \( k \) is the par spread. Combining Equation (20) and (19), we can convert between points upfront and par spread by:

\[ u = (k - c) \times PVE. \]  
(21)

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 price representation of CDS quotes supplied by different data providers. As there is no standardized and universal CDS database in the market, CDS prices 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 becomes less 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 the price contributors. Table 10 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 10 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 11 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
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 evidence on the 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 (shown in Figure 5) shows that the two samples align with the diagonal line, indicating our choice of GFI prices do not deviate from Markit.

[Table 11 and Figure 5 are about here.]
Table 10: 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

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>STD</th>
<th>Max</th>
<th>Min</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spread (bp)</td>
<td>222.02</td>
<td>614.83</td>
<td>9,900.00</td>
<td>0.00</td>
<td>33,008</td>
</tr>
<tr>
<td>BAS (bp)</td>
<td>0.13</td>
<td>1.48</td>
<td>50.00</td>
<td>0.00</td>
<td>32,916</td>
</tr>
<tr>
<td>Maturity (yr)</td>
<td>4.69</td>
<td>1.51</td>
<td>10.00</td>
<td>0.00</td>
<td>33,008</td>
</tr>
</tbody>
</table>

Panel B: Maturity Distribution

<table>
<thead>
<tr>
<th></th>
<th>≤ 1Y</th>
<th>≤ 2Y</th>
<th>≤ 3Y</th>
<th>≤ 4Y</th>
<th>≤ 5Y</th>
<th>≤ 6Y</th>
<th>≤ 7Y</th>
<th>≤ 8Y</th>
<th>≤ 9Y</th>
<th>≤ 10Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>Count</td>
<td>2,477</td>
<td>747</td>
<td>820</td>
<td>751</td>
<td>26,553</td>
<td>283</td>
<td>691</td>
<td>1</td>
<td>0</td>
<td>685</td>
</tr>
<tr>
<td>Percent</td>
<td>7.50%</td>
<td>2.26%</td>
<td>2.48%</td>
<td>2.28%</td>
<td>0.86%</td>
<td>2.09%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>2.08%</td>
<td></td>
</tr>
</tbody>
</table>
Table 11: 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, respectively. 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.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>STD</th>
<th>Max</th>
<th>Min</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Markit 5-year CDS (bp)</td>
<td>137.69</td>
<td>180.73</td>
<td>5,325.25</td>
<td>10.68</td>
<td>26,522</td>
</tr>
<tr>
<td>GFI 5-year CDS (bp)</td>
<td>140.05</td>
<td>225.67</td>
<td>8,366.53</td>
<td>9.00</td>
<td>26,522</td>
</tr>
</tbody>
</table>

- Mean Diff ($t$-test)  -2.36
  \[-1.33\]

- STD Ratio (Chi2 test) 0.80***
  \[0.64\]
Figure 5: 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.