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Price convergence between credit default swap and put option: New evidence

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ABSTRACT

Credit default swaps and deep out-of-the-money put options can be used for credit protection, but these markets are not perfectly integrated, leading to different implied hazard rates. The differences in the implied hazard rates are linked to deviations between consensus rating-based hazard rate curves in the two markets, and a residual component related to market frictions. We show that both components diminish over time, but their convergence is asynchronous. A trading strategy based on a joint signal from the curve and residual differences outperforms a conventional trading approach that relies on the absolute differences between the implied hazard rates. Hedge funds are likely to exploit within-market inefficiencies and deviations from rating-based curve, but they do not seem to profit from market segmentation.

1. Introduction

Both deep out-of-the-money put (DOOMP) options and credit default swaps (CDS) provide protection against firm default, allowing buyers to recover losses on the underlying stock or bond, respectively. Although CDS and DOOMP option have different pricing structures, both products can be converted into a unit recovery claim (URC), which pays $1 if the firm defaults and zero otherwise. Carr and Wu (2011) suggest that, if the law of one price holds, a URC on a particular firm should have the same price regardless of the market (viz. CDS or option) where the claim is traded; any price deviation, in the absence of market frictions, should eventually converge to zero. The law of one price, however, may not always hold if the markets are segmented or only partially integrated, leading to limited arbitrage, which, together with other market frictions, causes persistent deviations of relative security prices from their theoretical relations. Another important limitation of the original (Carr and Wu, 2011) approach is an implicit assumption of a flat term structure of URC prices. If a non-flat term structure exists, as is the case of CDS (Kolokolova et al., 2019), maturity mismatch between DOOMPs and CDSs would manifest itself in larger differences in URC prices and potentially hamper the inference about future convergence. Hence, it is important to understand the association of the term structure of URCs and their convergence.

Our paper contributes to the discussion of CDS-DOOMP connections along several dimensions. First, building on the evidence that CDS-DOOMP deviations are heterogeneous with respect to firm's credit quality,[2] we characterize each market by the rating-based hazard-rate curves, implied by URCs of the observed CDS and DOOMP prices. These curves capture not only the average levels of the hazard rates, but also the curvature as a function of contract maturity. Second, we show that individual hazard rates

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[2] DOOMP-implied hazard rates tend to be higher than those of CDS for poor credit quality firms (Angelopoulos et al., 2013).

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converge to their respective rating curves, and this convergence cannot be captured merely by the average or median values of the hazard rates. Next, we present evidence on how the term structure of URC-implied hazard rates affects the price discrepancy. The difference between the rating-based hazard-rate fitted curves of the two markets captures systematic price differences and market segmentation. The difference between the individual derivative price and its respective rating-based curve captures the relative idiosyncratic departures from the consensus prices within the markets. We also consider an additional component which is related to maturity mismatch between CDSs and DOOMPs, and it changes with the relative curvature of two rating-based curves. We find that the overall time-series convergence (as implied by the law of one price) in the prices of URCs across the two markets depends on the joint behavior of the differences. The systematic curve difference and the difference in individual deviations from the curves should go in the same direction as a precursor for convergence. Our evidence shows that convergence in URC prices can be observed only in about one third of our sample. We contribute to the discussion on how partial market segmentation affects price difference between the two markets.

CDS market is a perfect laboratory for studying market integration because it is linked to equity, bond, and derivative markets, but its participants are predominantly professional traders (see Aldasoro and Ehlers, 2018, Table 1), who may be able to quickly trade against mispricing. The existing literature largely focuses on relative mispricing across CDS-equity and CDS-bond market pairs.[3] Stocks and bonds, however, are largely investment targets, whereas CDSs are mainly used to trade downside risk. A similar goal can be achieved using DOOMP options, seemingly making these two products close substitutes for one another. Relative mispricing on CDS and DOOMP markets has not yet received sufficient scholarly attention, although it may be of paramount importance for an investor choosing an optimal strategy for downside risk management. Instead, current studies emphasize price similarity between these two markets. Carr and Wu (2011) suggest that URCs derived from DOOMP option and CDS should be the same; any differences between them can be used to predict their future price movements. Their empirical analysis is based on weekly observations for 121 companies between 2005 and 2008, and uses only options with the strike price under $5. Kim et al. (2013) include a broader range of options in their analysis and use an implied URC (IURC).[4] These IURC's are more strongly connected to each other than URCs of Carr and Wu (2011) during the financial crisis of 2007.

Different from those studies, we argue that the law of one price does not perfectly hold as there are a number of fundamental differences in the market characteristics and in the investor type between CDS and DOOMP markets. CDSs are traded over the counter and options are exchange traded. The most common CDS contract has a maturity of 5 years (over 80% of our sample), but the most common DOOMP option has maturity less than six months (77% of our sample). Hence, although CDS and DOOMP option can both be used to hedge firms' credit risk, they attract different types of traders, with different investment horizons, distinct trading strategies, liquidity preferences and risk-aversions. In particular, the DOOMP market is populated by short-term sophisticated institutional investors, such as hedge funds, whereas insurance companies and banks dominate the CDS market (Aldasoro and Ehlers, 2018; Mengle, 2007). In the presence of partial market segmentation, when only a fraction of investors can trade on both markets and rebalance their portfolios gradually, a supply shock in one market causes overreaction in prices of risk and under-reaction in the other market. These discrepancies gradually disappear and the prices of risk across the markets converge over time (Greenwood et al., 2018).

Methodologically, we first recover the CDS- and DOOMP-implied hazard rates from the individual contracts following Carr and Wu (2011). As we recognize that credit rating of the underlying firm is an important determinant of the individual CDS spreads and possibly of the put option prices (Aunon-Nerin et al., 2002), reflecting the firm's default risk (Altman and Rijken, 2004; Löffler, 2004), in the second step we group the hazard rates of CDS and DOOMP option by firm's credit rating, and fit the Nelson-Siegel (NS) term structure curves, following Kolokolova et al. (2019). This process enables us to separate each implied hazard rate into two components – a NS-model fitted value and a residual term. The fitted values represent the consensus prices in each of the two markets based on a particular credit rating, whereas the residuals capture the within-market deviations from the consensus prices.

Next, we show that within-market deviations diminish over time, with both CDS- and DOOMP-implied hazard rates converging to their fitted values on the corresponding NS curves. This finding extends the work of Kolokolova et al. (2019), that shows CDS spread convergence to the corresponding rating-based curve, to the option market. As for the cross-market curve differences, we find evidence of the convergence between curves over time. The cross-market differences, however, increase when the two markets become more disintegrated.

The decomposition of CDS- and DOOMP-implied hazard rates into their fitted and residual components allows us to extract trading signals related to their potential convergence. The pairs of CDSs and DOOMP options are traded only if both differences in their systematic and idiosyncratic components point to the same convergence direction. We use a unique CDS trading data set from GFI to test our strategy. The dataset contains the traded prices, as opposed to composite (average) prices often used in CDS research. Using the actual trades, we are able to construct a realistic trading strategy, in which each position has its own specific time of entering and unwinding, with trading costs also taken into consideration. Our proposed long-short strategy results in significant positive expected returns after transaction costs are deducted, whereas a benchmark trading strategy, based simply on the absolute

[3] For example, CDS illiquidity leads to short-term horizon price discrepancy between a CDS and the underlying stock (Kapadia and Pu, 2012). The cross-hedging strategy between credit and equity markets in five European countries is jeopardized due to insufficient co-movement between credit and equity markets (Fonseca and Gottschalk, 2014). Different margin requirements lead to further price dispersion across markets (Garleanu and Pedersen, 2011; Shen et al., 2014). CDS slope (measured as the difference between 5-year and 1-year CDS spreads) negatively predicts future stock returns and firm fundamentals (He et al., 2017). CDS-bond relative price difference is affected by the interest rate spread between the uncollateralized and collateralized loans (Garleanu and Pedersen, 2011). Recently, Lee et al. (2021) document the CDS return anomalies stemming from the influence of credit ratings, and the effect of anomalies spills over equity and bond markets.

[4] Carr and Wu (2011) use options with put delta smaller than -15% in absolute value, while Kim et al. (2013) include options with put delta up to −70%.

differences between CDS and DOOMP-implied hazard rates following Carr and Wu (2011), delivers negative expected returns. The key reason for such poor performance is that out of 2,930 trades identified based on the absolute differences between CDS- and DOOMP-implied hazard rates, few trades actually led to convergence. Our proposed signals using the systematic and idiosyncratic components substantially improve the identification of profitable trades.

To further test the information content of the within-market and cross-market deviations and its potential effect on performance of arbitrageurs, we construct time series measures of aggregate noise in the CDS and DOOMP markets and an aggregate measure of market segmentation based on curve differences. The noise measures capture the level of potential exploitable arbitrage opportunities in the economy and are positively related to the average returns of hedge funds – institutional investors that are commonly seen as professional arbitrageurs. Market segmentation, however, seems to be harder to exploit, with the high levels of segmentation predicting poorer future performance of hedge funds.

Our paper complements the literature related to the law of one price in financial markets, financial market integration, and cross-market predictability. Studies on the law of one price often investigate foreign exchange rates or commodity prices in different regions or countries (see, e.g., Parsley and Wei, 1996; Goldberg and Verboven, 2005), international trades (Goodwin et al., 1990), and multiple (overseas) stock listings (e.g. Foerster and Karolyi, 1999; Howe and Kelm, 1987). Corporate bond and option markets are found to be relatively well integrated, which allows estimation of bond credit spreads through a combination of a long equity position and a short put option, both with observable market values (Culp et al., 2018). Strong cross-market predictably is found between stock and bond markets (Pitkäjärvi et al., 2020). We contribute to the discussion of the law of one price and market integration across markets that are often used for hedging credit risk, viz. CDS and DOOMP option markets. These two markets are not perfectly integrated and the price of hedging downside risk in these two markets will be in most cases different. From a practical point of view, those investors who conventionally use only one of these markets for hedging downside risk may benefit from continuous monitoring of both markets, in order to choose a more favorably priced instrument at each point in time.

2. Research design and hypotheses

To study the relation between CDS and DOOMP markets, we first calculate the implied hazard rates from CDSs (H^C) and DOOMP options (H^P), following Carr and Wu (2011). If the law of one price holds, one would expect the implied hazard rates derived from the CDS and DOOMP markets to be the same, thus $H^P = H^C$; any difference in the hazard rates is therefore a white noise.[5] At the same time, these two markets are substantially different from one another. CDSs are traded OTC, while options are exchange traded contracts. Typical contract maturity of CDSs is much longer than that of DOOMPs. The CDS market is less liquid and exhibits higher transaction costs. All these differences are likely to attract different types of investors into these markets, with, for example, different risk aversions, investment horizons and possibly different expectations about firms' credit risk. These investors may be unwilling or unable to trade across the markets, making the markets partly segmented. Thus, consensus hazard rates prevailing in each of the markets may be different from each other, and the differences in observed hazard rates may be more persistent than implied by the law of one price as suggested by Carr and Wu (2011).

In order to filter out consensus hazard rates in each of the markets, in the next step, following Kolokolova et al. (2019), we fit Nelson–Siegel (NS) model to the implied hazard rates. We then split the hazard rates into the rating-based fitted values (F^C and F^P for CDS and DOOMP markets, respectively) and the residual components (R^C and R^P). The rating-based fitted values capture the consensus level of hazard rates, while the residual components capture contract-specific noise. The technical details of the decomposition are discussed in Section 3.

Another important issue that arises when comparing the two markets, which is not explicitly dealt with in Carr and Wu (2011), is the maturity mismatch between the most common CDSs and DOOMPs. The most liquid CDSs have a maturity of five years, while the most liquid DOOMPs usually have a maturity shorter than three months. If the term structure of hazard rates is flat, the maturity of the contracts does not matter, and the rating-based fitted values of the hazard rates can be compared as extracted from CDSs and DOOMPs without any adjustments. However, as we show later in the paper, the term structure of hazard rates is on average concave for both CDS and DOOMP markets. Hence, the difference in the implied hazard rate also depends on the slope and curvature of the fitted hazard rate curves.

In this paper we propose to decompose the difference between CDS- and DOOMP-implied hazard rates into the difference in the fitted rating-based curves, the difference in residual components, and a slope adjustment as follows:

$$\begin{aligned}\underbrace{H^P_{\tau_P} - H^C_{\tau_C}}_{\text{Total difference}} &= (F^P_{\tau_P} + R^P_{\tau_P}) - (F^C_{\tau_C} + R^C_{\tau_C}) \\ &= \underbrace{(F^P_{\tau_P} - F^C_{\tau_C})}_{\text{Difference in fitted values at actual maturities}} + \underbrace{(R^P_{\tau_P} - R^C_{\tau_C})}_{\text{Difference in residuals}} \\ &= \underbrace{(F^P_{\tau_C} - F^C_{\tau_C})}_{\text{Curve difference}} + \underbrace{(F^P_{\tau_P} - F^P_{\tau_C})}_{\text{Slope adjustment}} + \underbrace{(R^P_{\tau_P} - R^C_{\tau_C})}_{\text{Difference in residuals}},\end{aligned} \tag{1}$$

where τ_P and τ_C denote maturities of the DOOMP and CDS contracts respectively.

The difference between the two NS-fitted curves ($F^P_{\tau_C} - F^C_{\tau_C}$) is likely to be linked to market segmentation, leading to our first research hypothesis.

[5] Carr and Wu (2011) explain how option factors may impact the total difference.

Hypothesis H1. DOOMP-CDS cross-market curve difference is positively related to factors segmenting the two markets.

Since residuals relative to their respective curves capture additional contract-specific noise, their difference ($R^P_{\tau_P} - R^C_{\tau_C}$) is likely to be related to the relative market inefficiency of the two markets, and hence, we formulate the accompanying hypothesis:

Hypothesis H1a. DOOMP-CDS cross-market residual difference is positively related to factors capturing relative inefficiency of the two markets.

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

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

where D is either a curve ($F^P_{\tau_C} - F^C_{\tau_C}$) or residual ($R^P_{\tau_P} - R^C_{\tau_C}$) cross-market difference in hazard rates for firm i. X is a set of explanatory variables, and d is the error term of the regression. We also include calendar day and rating fixed effects in all the regressions. Since we always compute the residuals relative to the their rating curve at the actual maturity of the contract in question, in what follows we suppress sub-indices for residuals.

To create a complete picture of the drivers of the components of the difference in hazard rates, we also use the difference in fitted values at actual maturities ($F^P_{\tau_P} - F^C_{\tau_C}$), and the slope adjustment ($F^P_{\tau_P} - F^P_{\tau_C}$) as D.

Following prior literature, we identify a set of potential explanatory variables. We classify them according to their relationship to DOOMP-CDS market integration and market efficiency, and explain how they may impact the cross-market differences. Note that since curve difference will be the same for all DOOMP-CDS pairs of the same rating on the same day, the loadings on each factor will capture the effect of the *average* characteristic of all contracts on the day of curve fitting.

The first two factors are the level of credit risk and option delta; they capture the investors' motivation to trade in the two markets.

(1) $0.5\times(H^P + H^C)$: The average of the implied hazard rates reflects the credit risk of a firm. Higher hazard rates indicate higher credit risk; thus DOOMP options are more likely to be used as credit protection instruments, making them more aligned with CDSs. We expect the curve difference to reduce as credit risk increases. At the same time, higher credit risk may reduce market liquidity. Some studies (e.g. Tang and Yan, 2007) find that credit risk is negatively related to trading liquidity. Assuming that the liquidity of exchange-traded put option market is less sensitive to credit risk than that of the CDS market, residual difference is likely to increase with the level of credit risk.

(2) |Delta|: Option delta represents the moneyness of option. A trader who hedges credit risk is likely to prefer to buy a put option with a lower strike price (i.e. more deep out-of-the-money), because such option is cheaper. Hence, when |Delta| is larger, the put option behaves more like a traditional option, and is less likely to be traded for the purpose of credit risk protection. Therefore, we expect a positive relationship between the curve difference and the |Delta|. At the same time, when |Delta| of a put option is larger, the connection between the put option and its rating curve weakens; as a result we expect the residual difference to increase too.

The next three factors are put option maturity, bid–ask spread (BAS) for put option, and the BAS for CDS; these three factors capture structural similarity between the two markets.

(3) Put Maturity: Most exchange-traded options have maturities shorter than one year, whereas most CDSs have a maturity of 5 years. As put maturity increases[6] the two contracts become more similar. Hence, we expect a negative relationship between put maturity and curve difference. Similarly, the residual difference is likely to be smaller for a put option with a longer maturity, as its implied hazard rate is likely to be more aligned with its corresponding rating curve, due to its application as a credit protection tool. In our regressions, put maturity is calculated by taking natural logarithm of the put maturity expressed in days.

(4) Put BAS: Put option bid–ask spread measures the level of put option illiquidity. Less liquid put options narrow the difference in liquidity levels between the two markets, and these put options are more likely to be used for credit protection than for the speculation on stock price movements. Thus, a larger option BAS is expected to be negatively related to the curve difference. Yet, low liquidity makes the option market less efficient. The put option price is more likely to deviate from its fundamental value, and hence the option BAS is expected to be positively related to the residual difference.

(5) CDS BAS: CDS bid–ask spread measures the level of CDS illiquidity. Less liquid CDSs widen the difference in liquidity level between the two markets; therefore a larger CDS BAS is expected to be positively related to the curve difference. Similar to put option, low liquidity also makes the CDS market less efficient; when CDS price deviates further from its fundamental value due to illiquidity, the residual difference ($R^P - R^C$) is expected to decrease due to the increase in R^C.

The next two factors are option open interest and the number of CDS intra-day trades; they capture the depth of market and, thus, the ease for an investor to switch between the two markets.

(6) Open Interest: Higher option open interest indicates higher demand for the DOOMP options. Given the conjecture that the DOOMP option is used mainly for credit risk protection, a higher demand implies that more investors use DOOMP options as a substitute for CDSs. Therefore, higher open interest should reduce the curve difference.

(7) CDS Trade: The number of CDS intra-day trades captures the depth and liquidity of CDS market. More intra-day trades allow investors to easily switch between the two markets for credit protection. Therefore, we expect the curve difference to be negatively related to the number of CDS trades.

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

[6] This discussion here focuses only on put option maturity, as only the 5-year CDSs are included in our samples.

(8) Implied Vol: Option-implied volatility reflects investor's risk aversion as well as the expectation of the underlying stock price. Under the classical Black and Scholes (1973) option pricing framework, higher implied volatility corresponds to a higher put option price. If the increase in implied volatility is due to a higher level of risk aversion of put option investors, the higher put option price should discourage credit protection buyers to use DOOMP option as a substitute of CDS; therefore, the curve difference is expected to increase. However, if the increase in implied volatility is due to a higher objective expectation of stock price volatility (reflecting a higher probability for the underlying firm to hit the default barrier), the curve difference may not change, as the CDS price and CDS implied hazard rate should also increase due to the same market expectation. Wang et al. (2013) find evidence that option variance risk premium (calculated as option implied volatility minus the expected realized volatility) increases the CDS spread. As a result, the expected sign of the effect of the implied volatility on the curve difference cannot be determined ex-ante, as it depends on the reasons for changes of implied volatility.

2.1. Within-market convergence to the rating curve

Hypothesis H1a tests if the residual difference in hazard rates is linked to short-term within-market inefficiencies. If the residuals (R^P and R^C) are only driven by these inefficiencies, they are likely to diminish over time, leading to the convergence of individual hazard rates to their corresponding NS fitted curves. Kolokolova et al. (2019) have shown that this is true for the CDS market, and CDS-implied hazard rates tend to converge towards the NS rating curves, especially if the deviations are substantial. Here, we extend this work to test if such convergence is also present in the DOOMP option market.

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

To test this hypothesis, we estimate the following model:

$$\Delta H(i,t_1,t_2) = \beta_0 + \beta_1\ \Delta F(i,t_1,t_2) + \beta_2\ R(i,t_1) + e(i,t_2), \tag{3}$$

where $\Delta H(i,t_1,t_2)$ is the change in the hazard rate between times t_1 and t_2, $\Delta F(i,t_1,t_2)$ is the corresponding change in the NS-fitted value, and $R(i,t_1)$ is the residual at time t_1. We estimate Eq. (3) for CDS and put option separately, using the actual maturities of the contracts when computing the fitted values. We also control for calendar day and rating fixed effects in the regression.

Negative and significant β_2 coefficients would suggest an error correction mechanism where hazard rates H converge to their respective fitted values F over time.

2.2. Cross-market convergence of the rating curves

The convergence of individual implied hazard rates to their respective rating curves, suggested in the previous section, implies that the residual cross-market difference $R^P - R^C$ should tend to zero, when both $R^P \to 0$ and $R^C \to 0$. If the two markets are segmented, each of them could have its own rating-based fitted curve. Carr and Wu (2011) show that the total difference between hazard rates implied by CDSs and DOOMPs narrows over time. We refine this general finding in our final hypothesis, suggesting that diminishing difference has two main drivers: convergence of hazard rates to their curves and the convergence between curves.

Hypothesis H3. Convergence between CDS and DOOMP implied hazard rates is driven by diminishing fitted-curve difference and simultaneous reduction in residual difference between these markets.

To test this hypothesis, we regress the change in the difference of the individual implied hazard rates on the residuals from Eq. (2) that capture curve difference, residual difference, and DOOMP-curve slope adjustment:

$$\Delta D^H(i,t_1,t_2) = \beta_0 + \beta_1\ d^F(i,t_1) + \beta_2\ d^R(i,t_1) + \beta_3\ d^S(i,t_1) + e(i,t_2) \tag{4}$$

where d^F, d^R and d^S are regression residuals obtained from Eq. (2) for the curve difference, residual difference, and DOOMP slope adjustment, respectively. We also control for calendar day fixed effect. $\Delta D^H(i,t_1,t_2)$ is the change in the difference between DOOMP- and CDS-implied hazard rate between times t_1 and t_2, computed at their actual maturities. That is:

$$\Delta D^H(i,t_1,t_2) = \left[H^P_{\tau_P}(i,t_2) - H^C_{\tau_C}(i,t_2)\right] - \left[H^P_{\tau_P}(i,t_1) - H^C_{\tau_C}(i,t_1)\right]. \tag{5}$$

Using the residual term from Eq. (2), instead of using the original differences, allows us to control for the known drivers of cross-market differences. Moreover, we also estimate the regression in Eq. (4) replacing d^F, d^R, and d^S by original values of the curve difference, residual difference, and DOOMP slope for comparison and robustness check.

A negative value of β_1 implies convergence of the hazard rates due to curve convergence. Similarly, a negative value of β_2 implies convergence of the hazard rates due to diminishing residual difference. Hence, the convergence of H^P and H^C will be the strongest if d^F and d^R share the same sign (both positive or both negative). In other words, we expect a stronger convergence between CDS and DOOMP option if both curve and residual cross-market differences deviate in the same direction, and a weaker convergence when their directions are different ($d^F > 0$ and $d^R < 0$, for example). We remain agnostic about the direction of the effect of the DOOMP-curve slope adjustment (β_3) on the convergence between H^P and H^C, and let the data suggest the effect, if any.

3. Hazard rate construction and deviation decomposition

3.1. URC-implied hazard rate

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

For the special case in which stock price falls to zero at default time (i.e. $A = 0$), $K_1 = 0$, and $K_2 = K < B$, Eq. (11) simplifies to:

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

We calculate the put-implied hazard rate (denoted as H^P) based on Eqs. (7) and (12). 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 (Friewald et al., 2014).

3.2. Rating-based hazard rate curves

Hazard rates recovered in the previous section capture the credit risk of the firms. Kolokolova et al. (2019) show that rating-based hazard rate curves serve as a benchmark to which investors anchor the CDS prices. Hence, we fit the Nelson and Siegel (1987) term structure separately to hazard rates $H(\tau)$ for each maturity τ and for each rating class, to construct the daily rating-based hazard rate curves for the two markets.[7]

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

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

where β_0 and β_1 are parameters reflecting the long-term and short-term hazard rates, β_2 captures a hump at the medium term, and m determines the shape and the position of the hump. Eq. (13) is estimated separately for put option and CDS. The estimation steps are detailed in Kolokolova et al. (2019).

[7] Note that the hazard rates implied by CDSs and DOOMPs can be seen as the average hazard of the underlying over the lifetime of the contract. They resemble in their spirit the yields to maturity of corporate bonds. While fitting the Nelson–Siegel curves, we construct a type of hazard rate "yield curves" for each type of contracts, similar to the approach adopted in Kolokolova et al. (2019).

We next decompose the CDS and DOOMP implied hazard rates into their fitted and residual components:

$$H_\tau = F_\tau + R_\tau \quad (14)$$

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

4. Data

4.1. CDS data

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

In points upfront quote, the periodic payments of a CDS are restricted to a standardized coupon value (denoted as c). The common fixed coupon is 25, 100, 300, or 500 bps. Since the coupon value is unlikely to equate the premium leg with the protection leg, one party of the CDS contract may have advantage over the other. To compensate for this advantage, a one-off upfront payment (denoted as u) is made to the disadvantaged party. As a result, a points upfront quote contains two pieces of information – upfront payment (u) and periodic fixed coupon (c). For example, if the fixed coupon c is smaller than the par spread k, then the protection buyer pays less than the fair value of the contract. In this case, the protection buyer is asked to pay an upfront payment to the protection seller. In practice, par spread quote is more popular than points upfront quote.[8]

A number of data providers supply market CDS quotes. The major ones include GFI, Markit, CMA, Reuters, and Bloomberg. Yet, there is a concern about the consistency and price representativeness of the CDS data provided by these sources, because none of these data providers cover all the CDS trades; also, the approaches for constructing CDS prices used by data providers vary substantially. For example, Reuters provides CDS data in the form of a daily 'composite price' which is computed from the quotes taken from a group of contributors; some of these quotes can be doubtful as they neither represent an actual trading price nor a firm commitment to trade. CMA uses an aggregation methodology which is based on intra-day prices and the application of different weights to the contributions.[9]

The main CDS quotes used in this study are 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. The CDS quotes in GFI data are actual prices with trading commitments from protection buyers and sellers. The GFI CDS data contains 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 U.S. single-name CDSs on senior debt with non-restructure type. The sample contains both types of quotes. Of the total 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 the supplementary Online Appendix.

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

We further explore the time-series pattern of CDS trades over our sample period. Fig. 1 plots the number of monthly trades (presented by a bar chart) and the average number of traded names per day (the line graph) over the period from July 2012 to April 2016. CDS contracts 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. According to the senior manager at GFI, the recent decline in CDS trades was partly due to its clients' trading preference shifting to multi-name CDS products (i.e. a bundled transaction with several single-name CDSs).

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

8 In our dataset, over 95% of quotes are expressed as par spreads.

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

Table 1
CDS intra-day observation descriptive statistics.

Panel A: CDS Intraday Descriptive Statistics

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

Panel B: Maturity Distribution

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

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, median, 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 descriptive statistics of the spreads and the number of observations split according to maturity.

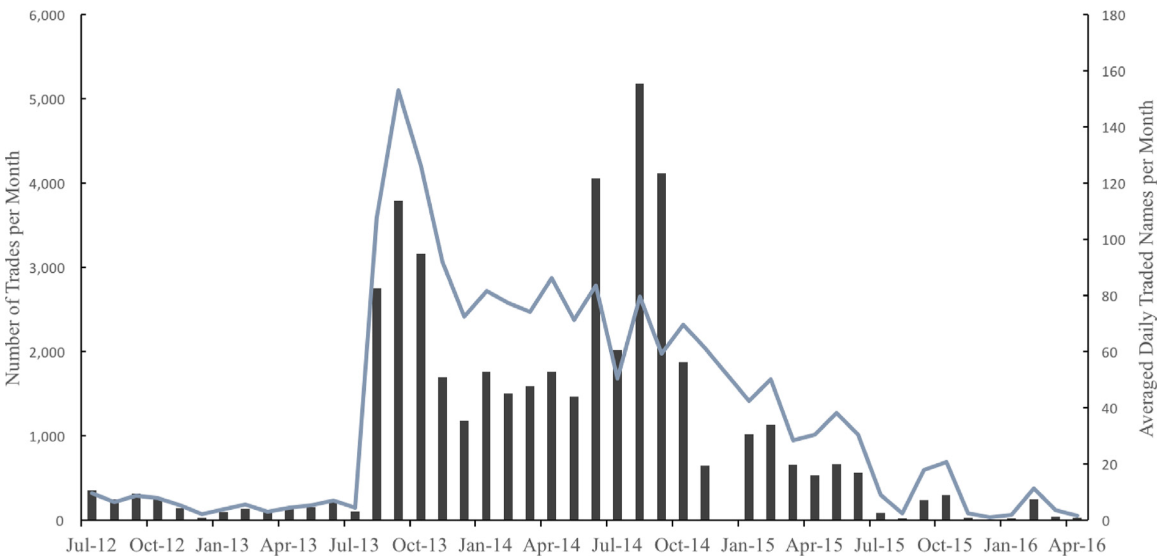

Fig. 1. Number of trades and traded names.
This figure plots the number of CDS trades per month (in bar graph) and the averaged daily traded names per month (in line graph) over the sample period from July 2012 to April 2016.

4.2. 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 matching DOOMP options for the CDSs. We use put options with (1) absolute put delta less than 0.15, (2) option bid price larger than zero, and (3) trading volume larger than zero.

We relax the last two selection criteria from the original Carr and Wu (2011) study. Unlike Carr and Wu (2011), we do not restrict option strike price to be under $5. Allowing for a wider range of strike prices accounts for heterogeneity of potentially endogenous default boundaries of different firms. Many factors, for example, bond liquidity (Feldhütter and Schaefer, 2018) and corporate debt policy (Feldhütter and Schaefer, 2021) contribute to firm's default. In a related study, Davydenko (2012) shows that empirically corporate default boundaries have a wide range from 30% to 122% of the face value of debt. Other studies (e.g. Kolokolova et al., 2019; Yu, 2006) suggest that the popular traded names are not always those with greater default risks. In fact, CDS contracts for investment grade firms are more popular than those for junk grade firms. Since the investment grade firms are unlikely to have

Table 2
Put option daily observation descriptive statistics.

Panel A: Put option descriptive statistics

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

Panel B: Maturity Distribution

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

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, median, STD, maximum, and minimum for the DOOMP option (mid-price), bid–ask spreads (BAS), time to maturity, option open interest, implied volatility, and option delta (in absolute value, $|Delta|$) of the sample. Panel B reports the descriptive statistics of the options and the number of observations split according to maturity.

traded option with strike price under $5, applying this criterion would exclude a large number of CDS trades unnecessarily (see Kim et al., 2013).[10]

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

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

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

4.3. Pairing CDS and DOOMP option

Before proceeding with our analysis, to properly measure cross-market deviations, we construct pairs of CDS and DOOMP option. Every day and for every firm we choose a 5-year CDS contract and match it to a put option with the maturity nearest to the CDS, which in this case will be the longest DOOMP maturity available. We fix the time to maturity for CDSs as 5 years since the 5-year CDSs are the most popular contracts (in general and in our sample) and are the most liquid. 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. This results in 4,268 pairs of CDS and put options over the sample period from July 2012 to April 2016. This forms the sample we use for the trading analysis later.

After the cross-sectional matching of CDSs and put options, we further match the pairs along the time-series dimension. The purpose of time-series consistency is twofold: (1) we need the time-series changes in CDS and DOOMP option prices for our proposed regressions, and (2) with the time-series matching, we are able to further develop a feasible trading strategy with an appropriate time to unwind or close the positions.

For a feasible trading strategy, one should take into consideration that CDSs and DOOMP options are relatively illiquid products. It is possible that one may not be able to unwind the CDS-put positions before the option contract expires. Therefore, holding period is an important factor for the time-series matching. A long holding period can increase the uncertainty of strategy implementation;

[10] In our sample, less than 1% of put options have a strike price below $5, rendering the number of paired CDS-DOOMP contracts too small for meaningful empirical analysis. To check for sensitivity of our results to the DOOMP option strike price, as a robustness check we repeat the analysis using only those CDS-DOOMP pairs in which the strike price is smaller than the 10th percentile ($12) and smaller than 25th percentile ($22.5) in our sample. The results reported in Online Appendix Tables S8 to S10 are qualitatively similar compared to the ones reported in the paper.

yet, a holding period that is too short may close the positions prematurely before the majority of price convergence takes place and as a result the trading profit is largely consumed by the transaction costs. Based on previous studies (Carr and Wu, 2011; Kolokolova et al., 2019), we restrict the holding period to be between 7 and 30 calendar days to determine the opportunity to unwind the position of our 4,268 CDS-put pairs. If multiple opportunities exist during the holding period of 7 and 30 days, we choose the earliest opportunity to unwind.[11] Overall, we identify 2,134 possible trades in our sample. Each trade consists of two trading opportunities $\{[k(t_1), Price^P(t_1)], [k(t_2), Price^P(t_2)]\}$, where $[k(t_1), Price^P(t_1)]$ is the pair of CDS spread and DOOMP option price for building a trading strategy at time t_1 and $[k(t_2), Price^P(t_2)]$ is the CDS-DOOMP pair of values 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, when we test the trading strategies.

5. Results

The CDS and DOOMP-implied hazard rates are computed as described in Section 3.1. Fig. 2 presents the scatter plots for the implied hazard rates for all paired CDS-DOOMP contracts and three subsamples based on the magnitude of maturity mismatch. On average, the hazard rates implied by these two markets are reasonably well aligned, with the correlation coefficient of 58%. The quality of alignment, however, depends substantially on the degree of maturity mismatch between the CDS and the DOOMP contracts. This correlation decreases to 47% for the subsample with the largest maturity mismatch (Subfigure (ii)) and increases to 85% for the subsample with the smallest maturity mismatched (Subfigure (iv)). This result further highlights the importance of the maturity adjustment when analyzing the difference between CDS and DOOMP-implied hazard rates.

5.1. Nelson–Siegel (NS) fitted curves

We fit the NS rating curves to the CDS and DOOMP option implied hazard rates every trading day. Since almost all the GFI CDS contracts are traded on the 5-year tenor, we find that there are insufficient tenors to form a stable curve. Therefore, for CDS curves, we match GFI CDSs to Markit CDSs, and include the Markit CDS spreads for the other tenors.[12] Since the composite prices in Markit are reported largely on daily basis, the numbers of CDS contracts with different maturities from 6 months to 10 years are approximately equal, and the fitted curves are not driven by only one maturity. At the same time, the longest maturity of DOOMP options is 2.5 years. Thus, the parameters of the NS-fitted curves for DOOMPs are determined by the observed dynamics of short-term contracts. The observations are grouped according to the Markit implied rating when fitting the Nelson–Siegel (NS) curves.[13] Having estimated the daily sets of NS parameters $[\beta_0, \beta_1, \beta_2, m]$ in Eq. (13) for different rating classes of the CDSs and DOOMP options, we calculate the NS-fitted values of hazard rates for each security using their ratings and times to maturity.[14] Table S3 in the Online Appendix reports the mean, median and standard deviation of the fitted values of the NS curves and the corresponding residuals for all CDS and DOOMP observations. The average residuals are virtually zero for both CDS and DOOMP curves. The coefficients of correlation between the residuals and the fitted values are close to zero and not statistically significant.

Fig. 3 plots the average NS-fitted curves for CDS and DOOMP markets for investment grade and junk grade underlyings, together with the 90% empirical confidence bounds. Fitted average hazard rates are always higher for junk grade underlying for both CDS and DOOMP market, reflecting their high credit risk. Remarkably, average DOOMP-implied curves are always higher than CDS-implied ones. The difference is especially persistence for investment-grade underlying. The 90% confidence bounds for the curves do not overlap for maturities up to 7 years. Even though the average difference in the DOOMP- and CDS-implied curves for junk-grade underlying is higher, it seems to be much more volatile over time, and two confidence intervals subsume one another, suggesting that two curves are not significantly different from one another, due to their high volatility.[15]

We now move to the analysis of the actually traded CDS and DOOMP contracts. We use the matched pairs of CDS and DOOMP contracts (as discussed in Section 4.3) and report the corresponding fitted values of hazard rates and residuals relative to the corresponding NS-fitted curves in Table 3. The fitted values and the residuals are computed using the actual maturities of the corresponding contracts. Thus, the fitted values reflect both the differences between the curves across the two markets as well as differences in maturities of the contracts. The mean and median fitted hazard rates monotonically increase as the rating worsens, and the standard deviations of the hazard rates also tend to go up for poorer rating classes. In our sample of CDS-DOOMP paired contracts, DOOMPs exhibit higher average fitted values of hazard rates than CDSs for all rating classes, except for the riskiest one, which contains a relatively small number of contracts (30 pairs of contracts).

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

[12] We did not use Markit CDS in the trading tests as Markit CDS data does not include bid or ask prices.

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

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

[15] Figure S2 in the Online Appendix further illustrates the time-series dynamics of the NS-fitted values.

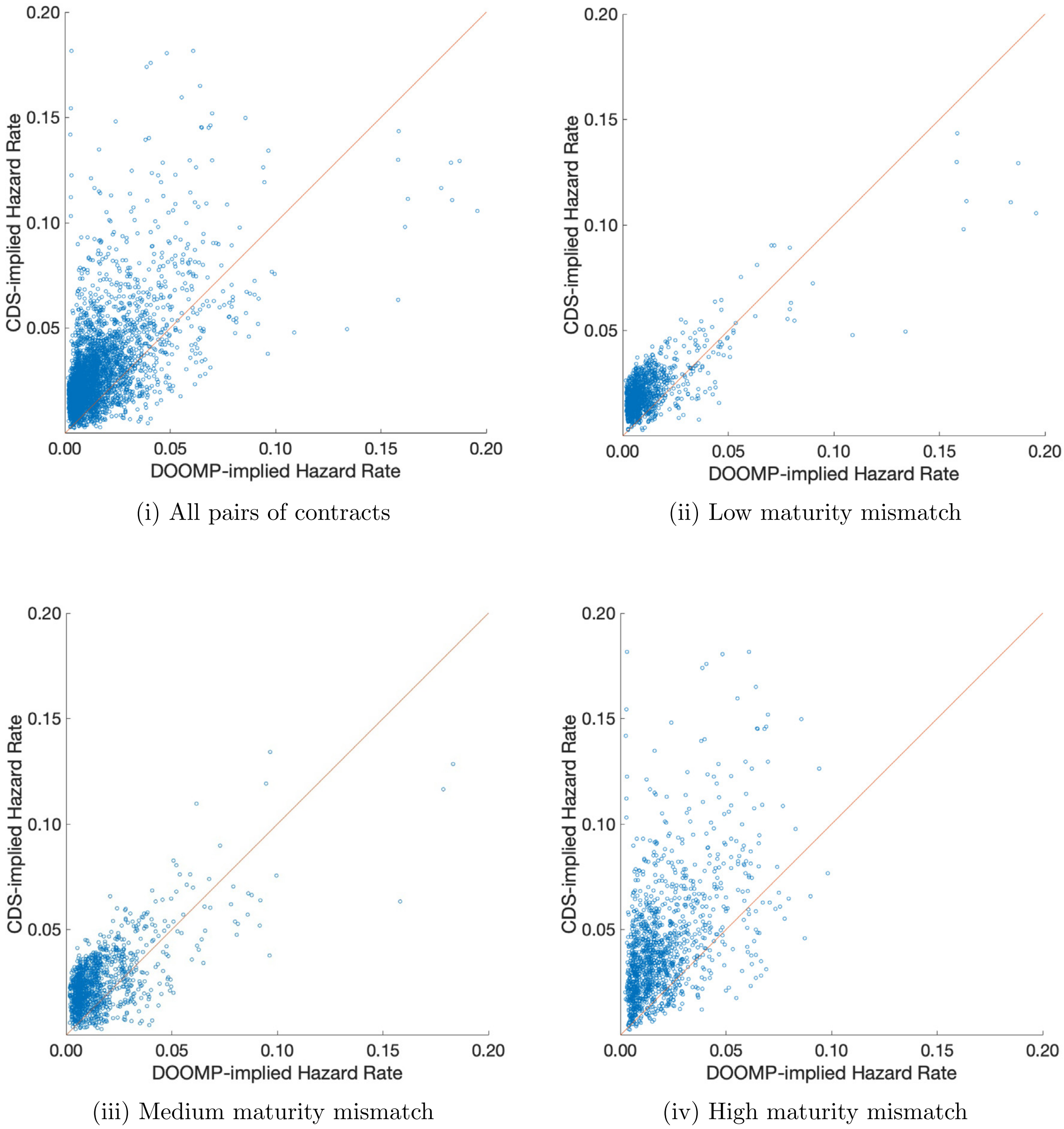
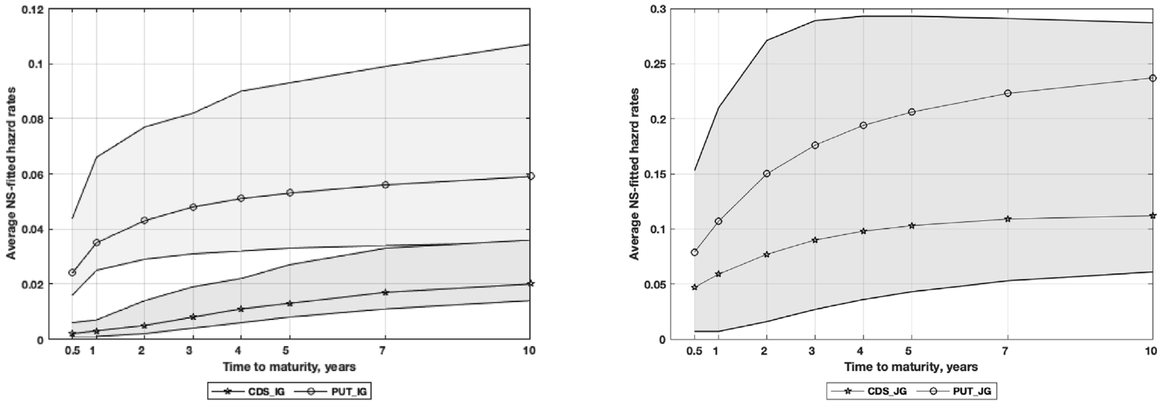


Fig. 2. CDS and DOOMP-implied hazard rates.
This figure presents the scatter plot for the implied hazard rates from the paired CDS (H^C) and DOOMP (H^P) contracts over the sample period from July 2012 to April 2016. Subfigure (i) uses all pairs. Subfigure (ii) uses one third of pairs with the smallest maturity mismatch between CDS and DOOMP contracts, subfigure (iii) uses one third the pairs with the moderate mismatch, but subfigure (iv) uses one third of pairs with the largest maturity mismatch.

The implied hazard rate curves fit the CDS term structure well. The average residuals for CDSs are zero for all rating classes apart from the C rating class. For DOOMP option, the rating curves seem to overestimate the implied hazard rates on average, as the mean residuals are negative for all rating classes, apart from the B rating class. At the same time, DOOMP option residuals are much more volatile than those implied by CDSs. For example, for the BBB rating class, the standard deviation of R^C is just 0.004, whereas that of R^P is 0.027.

5.2. Results: Cross-market differences

Table 4 reports the results for the panel regression in Eq. (2) for the determinants of the different components of the cross-market difference in hazard rates. Consistent with our Hypothesis H1, the curve difference increases when CDS and put markets



(i) IG NS-curves (ii) JG NS-curves

Fig. 3. Average fitted NS hazard rate curves.
This figure plots the average Nelson–Siegel fitted curves of hazard rates based on CDS and DOOMP option markets with investment grade (IG) and junk grade (JG) rating from July 2012 to April 2016. The shaded area represents 90% confidence bounds around the average NS curves. In (ii) only CDS-curve confidence bounds are plotted for the ease or depiction.

become more heterogeneous and is reduced when the two markets become more homogeneous (column [1]). The residual difference increases with higher levels of market frictions, which is consistent with our Hypothesis H1a (column [3]). As for the slope adjustment of DOOMP-curve (column [4]), it increases if DOOMP options have riskier underlyings, longer maturities, and larger bid–ask spread. At the same time, it reduces if DOOMP options have, on average, higher option deltas and higher implied volatilities.

Notably, many factors have the opposite effect on the curve difference, residual difference and the DOOMP slope adjustment. For example, the curve difference is smaller for riskier underlyings; yet, both residual difference and the DOOMP slope adjustment increase for riskier underlyings. Put bid–ask spread is negatively related to the curve difference, but positively related to the slope adjustment, and it has no significant relation with residual difference. Also, when the average maturity of traded DOOMP options is higher, the curve difference and the residual differences both reduce, but the slope adjustment increases.

The resulting effects of these factors on the total deviation in hazard rates are milder in absolute values, as reported in column [5] of Table 4, albeit still statistically significant. As a robustness check, we repeat the analysis for different sub-samples: sub-periods, sectors, and underlying credit ratings. The results reported in the supplementary Online Appendix indicate that the signs and significance of the determinants for the components of hazard rate differences are consistent across the sub-samples, although they are more volatile compared with the full-sample results.

We additionally test if shocks in prime dealers' equity capital ratio are related to cross-market differences. The relevant results are reported in the Online Appendix, Table S7. DOOMP option and CDS market attract different types of investors. In particular, large financial intermediaries – primary dealers – actively participate in these markets. Following He et al. (2017), we construct a variable capturing innovations in the capital ratio[16] and include this additional variable in Eq. (2). Shocks to the primary dealers' capital ratio have only marginal effects in our regressions, and that the effects of the previously discussed key variables remain qualitatively unchanged after controlling for the capital ratio shocks.

5.3. Results: Within-market convergence to the rating curve

Table 5 reports the results for hazard rate convergence to the rating-based curve, as specified in Eq. (3), for the CDS market. Based on the complete sample (Panel A) we find that the loading on the change in the fitted values β_1^C is 0.158 and the loading on past residuals β_2^C is −0.063, both significant at the 1% level. The results indicate that the time-series movement of CDS-implied hazard rate is mainly captured by the NS-fitted value F^C. The negative loading on the NS residual R^C further supports convergence of CDS-implied hazard rates to the rating-based curves, consistent with Kolokolova et al. (2019). Panels B to D further report the results for different sub-samples. The convergence results are robust, pronounced in all sub-periods, for most industries, and for both investment grade and junk grade underlyings. This further highlights the importance of credit rating in the CDS market as a driver of the consensus prices.

[16] We first compute the intermediary capital ratio for the sector as the ratio of total market equity to total market assets (the sum of the book value of debt and the market value of equity) of primary dealer holding companies. Next we estimate the shocks in the capital ratio as the innovations in its fitted AR(1) process, scaled by its lagged value.

Table 3
Implied hazard rates: Fitted and residual values for CDS-DOOMP paired contracts.

	AA	A	BBB	BB	B	C
A: Fitted values F						
Panel A1: CDS implied F^C						
Mean	0.006	0.010	0.016	0.030	0.055	0.144
Median	0.006	0.010	0.016	0.029	0.056	0.127
STD	0.001	0.003	0.003	0.004	0.009	0.068
N	1434	1104	964	484	252	30
Panel A2: DOOMP option implied F^P						
Mean	0.025	0.028	0.038	0.041	0.064	0.120
Median	0.024	0.027	0.033	0.037	0.055	0.108
STD	0.007	0.010	0.023	0.019	0.031	0.051
N	1434	1104	964	484	252	30
Panel A3: Difference in DOOMP option and CDS implied fitted values $F^P - F^C$						
Mean	0.019	0.018	0.022	0.011	0.009	−0.024
Median	0.018	0.017	0.016	0.007	0.000	0.000
STD	0.007	0.009	0.023	0.019	0.032	0.076
N	1434	1104	964	484	252	30
B: Residuals R						
Panel B1: CDS implied R^C						
Mean	0.000	0.000	0.000	0.000	0.000	0.004
Median	−0.001	−0.001	0.000	−0.001	−0.002	0.008
STD	0.002	0.003	0.004	0.005	0.011	0.062
N	1434	1104	964	484	252	30
Panel B2: DOOMP option implied R^P						
Mean	−0.004	−0.005	−0.004	−0.001	0.003	−0.013
Median	−0.006	−0.006	−0.003	−0.002	0.003	−0.011
STD	0.014	0.013	0.027	0.023	0.036	0.032
N	1434	1104	964	484	252	30
Panel B3: Differences in DOOMP option and CDS implied residuals $R^P - R^C$						
Mean	−0.004	−0.005	−0.004	−0.001	0.004	−0.018
Median	−0.005	−0.005	−0.004	−0.002	0.002	−0.028
STD	0.014	0.014	0.027	0.023	0.036	0.066
N	1434	1104	964	484	252	30

Panels A1–A3 report the descriptive statistics for the fitted values of implied hazard rates from the Nelson–Siegel rating based curves for matched pairs of individual CDS and DOOMP option contracts, and their differences. Panels B1–B3 report the descriptive statistics of the corresponding residuals. The fitted values are computed using the actual maturities of each contract. The sample period is from July 2012 to April 2016.

Convergence of DOOMP options to their rating curve is similarly strong (Table 6). β_1^P is positive and highly significant for the complete sample and for most of the sub-samples, indicating that changes in the rating-implied consensus values of hazard rates do drive changes of individual put-implied hazard rates. The only exception is the sector Industrials, where the coefficient is negative but not statistically significant. The coefficient β_2^P is negative and highly statistically significant in all specifications, confirming strong convergence of individual DOOMP-implied hazard rates to their corresponding rating curves.

We now assess the marginal benefits of the NS curve fitting compared to, for example, approximating them by the average or median hazard rate in each rating class. We repeat the estimation of the convergence regressions (Tables 5 and 6), but together with the changes in the fitted values ΔF and the levels of residuals R relative to the NS-fitted curves, we also introduce the changes in the average (median) hazard rates implied by the corresponding contracts $Mean^C$ ($Median^C$) and $Mean^P$ ($Median^P$), as well as the differences between the CDS and DOOMP-implied hazard rates of individual contracts and the mean/median values. The results reported in Table 7 indicate that changes in the mean (median) values of the hazard rates within each rating class are strong predictors of the individual changes in the hazard rates. At the same time, the changes in the fitted values of the NS curves remain highly statistically significant. Hence, while the changes in the mean/median hazard rates seem to be capturing well the parallel shift of the hazard rate curves, the changes in the NS-fitted values further capture the changes in the curvature. Most importantly, however, we cannot detect any convergence of CDS and DOOMP-implied hazard rates to their mean/median values. For CDSs, the coefficients on $H^C - Mean^C$ and $H^C - Median^C$ are virtually zero and not statistically significant, while those for DOOMP are positive and statistically significant, suggesting possible divergence from the mean/median values. The deviations from the NS-curves R^C and R^P remain negative and highly significant, supporting convergence of the implied hazard rates to the NS-curves, which in turn highlights the effectiveness of the NS-curve fitting approach in the case of CDS- and DOOMP-implied hazard rates.

5.4. Results: Cross-market convergence of the rating curves

The estimation results for the cross-market curve convergence (Eq. (4)) are reported in Table 8. We use the residuals d^F, d^R and d^S computed from Eq. (2), for all results in Table 8 except for the second row in Panel A, in which we use unconditional raw differences ($F^P_{\tau_C} - F^C_{\tau_C}$, $R^P_{\tau_P} - R^C_{\tau_C}$, and $F^P_{\tau_P} - F^P_{\tau_C}$) in Eq. (4) instead for comparison and robustness check.

Table 4
Determinants of the CDS-DOOMP hazard rate differences.

	Dependent variable				
	[1] Diff. in Curve $F^P_{\tau C} - F^C_{\tau C}$	[2] Diff. in Fitted Values $F^P_{\tau P} - F^C_{\tau C}$	[3] Diff. in Residuals $R^P_{\tau P} - R^C_{\tau C}$	[4] Slope Adjustment $F^P_{\tau P} - F^P_{\tau C}$	[5] Diff. in Hazard Rates $H^P_{\tau P} - H^C_{\tau C}$
Constant	0.037	0.009	−0.070**	−0.028	−0.061***
	[0.51]	[0.32]	[−2.55]	[−0.38]	[−3.55]
$0.5 \times (H^C + H^P)$	−0.274**	0.576***	0.282***	0.851***	0.858***
	[−2.54]	[14.49]	[6.95]	[7.69]	[33.64]
$\|Delta\|$	0.091***	−0.072***	0.246***	−0.164***	0.173***
	[2.89]	[−6.21]	[20.64]	[−5.05]	[23.16]
Implied Vol	0.050***	−0.035***	0.062***	−0.085***	0.027***
	[3.10]	[−5.94]	[10.30]	[−5.16]	[7.13]
Open Interest	−0.000***	−0.000***	0.000**	0.000	−0.000***
	[−3.74]	[−5.76]	[2.51]	[1.57]	[−4.99]
CDS BAS	−4.660	3.511	−1.818	8.171	1.693
	[−0.16]	[0.33]	[−0.17]	[0.27]	[0.25]
Put BAS	−0.009**	0.002	0.000	0.011***	0.002***
	[−2.36]	[1.44]	[0.29]	[2.82]	[2.71]
CDS Trade	−0.000	0.000	−0.000	0.000	−0.000
	[−0.15]	[0.53]	[−0.59]	[0.33]	[−0.11]
Put Maturity	−0.003***	0.001**	−0.008***	0.004***	−0.007***
	[−3.27]	[2.51]	[−19.80]	[4.09]	[−27.60]
Time FE	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes
Adj. R-sqr	0.22	0.23	0.41	0.22	0.74
N	4268	4268	4268	4268	4268

This table reports the results for the determinants of different components of the difference between DOOMP and CDS implied hazard rates. The sample period is from July 2012 to April 2016. The control variables include the average hazard rate, the absolute value of option delta ($|Delta|$), implied volatility, option open interest, bid–ask spread for CDS or DOOMP, the number of CDS trades and the logarithm of option maturity. The t-statistics are reported in brackets. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

In Panel A, the estimated values of both β_1 and β_2 are negative and statistically significant at the 1% level, implying strong convergence in DOOMP- and CDS-implied hazard rates. Importantly, the coefficients remain negative and significant also when unconditional raw differences are used. Thus, positive curve difference between DOOMP- and CDS-implied hazard rates predicts an increase in the CDS-implied hazard rate and a decrease in the put-implied hazard rates, supporting our Hypothesis H2, i.e., convergence of the NS-curves over time. Remarkably, the DOOMP-curve slope adjustment does not seem to be strongly related to hazard rate convergence; it is not statistically significant for both specifications.

The convergence results discussed above imply that it may be possible to construct a trading strategy exploiting this cross-market convergence in hazard rates, using as a signal the curve differences and residual differences obtained directly from the implied hazard rates.

The convergence results are overall robust across different sub-samples as shown in Panels B to D. The only exception is the Technology sector, for which curve difference seems to predict further divergence in implied hazard rates, and DOOMP slope adjustment is also positively related to future change hazard rate difference.

In the Online Appendix E, we provide further robustness checks on DOOMP-CDS convergence. Our convergence results are shown to be robust with respect to different contract maturities, portfolio holding periods, as well as variations in recovery rates. The CDS data we use in these robustness checks are obtained from Markit.

6. Exploiting convergence in trading strategy

The documented convergence between DOOMP- and CDS-implied hazard rates suggests that it may be possible to exploit the information on relative mispricing of these two products to construct a profitable trading strategy. In particular, time series convergence can be predicted by the difference in fitted NS-curve values (computed at a CDS maturity for both contracts), capturing convergence of the curves, and the difference in residuals (relative to the NS-fitted values at actual maturity of each of the contracts), capturing convergence of individual contracts to their respective NS-curves. These two differences constitute a signal at time t_1 for future relative change of the DOOMP- and CDS-implied hazard rates and, thus, relative change in the prices of these contracts. According to the signal, one takes a long position in the relatively underpriced security (a CDS or a DOOMP) and a short position in the relatively overpriced security. The positions are unwound at time t_2, when convergence is realized.

The challenge in assessing the DOOMP-CDS trading return is that DOOMP option and CDS contracts have different payoff patterns. Even though the trades are conducted between times t_1 and t_2 (the initial positions are taken at t_1 and the offsetting positions are taken at t_2), the resulting cash flows are generated even after t_2 on the CDS part. Taking an offsetting position in DOOMP at t_2 is equivalent to not having any DOOMPs in the portfolio after that. Taking an offsetting position in CDS, however, results in

Table 5
CDS convergence to rating curves.

Model: $\Delta H_t^C = \beta_0^C + \beta_1^C \Delta F_t^C + \beta_2^C R_t^C + e_t$							
	β_0^C	β_1^C	β_2^C	Time FE	Rating FE	Adj. R^2	N
Panel A: Complete Sample							
Coef.	0.002	0.158***	−0.063***	Yes	Yes	0.29	2134
	[0.80]	[14.29]	[−6.38]				
Panel B: Period							
2012–13	0.002	0.191***	−0.066***	Yes	Yes	0.26	790
	[0.75]	[8.91]	[−4.06]				
2014	0.001	0.095***	−0.153***	Yes	Yes	0.53	945
	[1.42]	[7.17]	[−9.70]				
2015–16	0.005***	0.212***	−0.122***	Yes	Yes	0.52	399
	[3.04]	[7.00]	[−5.70]				
Panel C: Sector							
Consumer	0.006**	0.066***	−0.007	Yes	Yes	0.61	534
	[2.18]	[3.14]	[−0.37]				
Material	−0.002	0.145***	−0.090***	Yes	Yes	0.66	503
	[−1.23]	[6.37]	[−3.86]				
Financials	0.007**	0.393***	−0.236***	Yes	Yes	0.41	332
	[2.08]	[9.66]	[−4.71]				
Industrials	0.002	−1.103**	0.138	Yes	Yes	0.41	399
	[0.15]	[−2.08]	[0.32]				
Technology	0.003***	0.178***	−0.046	Yes	Yes	0.49	366
	[3.26]	[6.49]	[−1.43]				
Panel D: Grade							
Investment	0.002**	0.180***	−0.110***	Yes	Yes	0.35	1751
	[2.45]	[12.98]	[−12.83]				
Junk	0.004	0.117***	−0.051*	Yes	Yes	0.55	383
	[0.93]	[3.84]	[−1.89]				

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

having two distinct CDS contracts in the portfolio, both having the same underlying and maturing in 5 years, but likely different spreads. Thus, the total profit/loss of the trade consists of a one-off cash flow of the price difference in DOOMPs purchased/sold between t_1 and t_2, and a stream of future cash flows equal to the difference in the t_1- and t_2- CDS spreads. This stream is generated up until CDS maturity of 5 years or firm default. Hence, when evaluating performance of trades between DOOMP option and CDS, one should consider the exact timing of the future cashflows, and not only a nominal difference in the spot prices between t_1 and t_2. To illustrate, in the following we provide an example for the calculation of trading strategy returns.

Consider, for example, a long-CDS and short-DOOMP option case, and build the following strategy.

At the initial time $t = t_1$, the signal is evaluated:

(1) Short-sell one DOOMP option, and generate a positive cashflow of $\$Price^P(t_1)$.
(2) Buy $\frac{Price^P(t_1)}{N \cdot k(t_1)}$ units of CDS contracts, written on the same underlying firm. $k(t_1)$ is the CDS spread, thus, $\$k(t_1)$ is the dollar-price of CDS contract with the par value of \$1, paid every year. N stands for the CDS maturity, that is the maximum number of years the CDS contract remains active. The intuition behind the choice of N is that the initial cash flow received from selling the put option $\$Price^P(t_1)$ should be sufficient to cover maximum cash flows from buying CDS. In this study we use the most liquid 5-year CDS contracts, hence, $N = 5$ in our analysis.

At time $t = t_2$, the positions are closed:

(3) Buy back one DOOMP option at price $\$Price^P(t_2)$.
(4) Short $\frac{Price^P(t_1)}{N \cdot k(t_1)}$ units of CDS contract at $\$k(t_2)$ price. Since the trading positions are closed within days after time t_1, the future CDS cash flows will be netted. The overall netting the CDS leg of the strategy can generate is:

$$\$ \left[\frac{Price^P(t_1)}{N \cdot k(t_1)} \times (k(t_2) - k(t_1)) \times \alpha N \right], \tag{15}$$

where α ($0 \leq \alpha \leq 1$) is the adjustment factor for early termination of the CDS contracts due to firm's default. It equals to the ratio of the actual surviving time of the underlying firm to the CDS maturity, and it captures the length of the period after the put position is closed and the trader receives the difference in CDS spreads from the short and long positions in CDS contracts.

Table 6
DOOMP convergence to rating curves.

Model: $\Delta H_t^P = \beta_0^P + \beta_1^P \Delta F_t^P + \beta_2^P R_t^P + e_t$							
	β_0^P	β_1^P	β_2^P	Time FE	Rating FE	Adj. R^2	N
Panel A: Full sample							
Coef.	0.001	0.342***	−0.340***	Yes	Yes	0.28	2134
	[0.11]	[19.23]	[−18.51]				
Panel B: Period							
2012–13	0.003	0.344***	−0.172***	Yes	Yes	0.22	790
	[0.22]	[8.97]	[−6.05]				
2014	−0.001	0.423***	−0.513***	Yes	Yes	0.43	945
	[−0.13]	[17.92]	[−17.97]				
2015–16	0.030*	0.161***	−0.247***	Yes	Yes	0.17	399
	[1.96]	[4.17]	[−5.98]				
Panel C: Sector							
Consumer	−0.020	0.160***	−0.170***	Yes	Yes	0.29	534
	[−1.29]	[4.76]	[−3.84]				
Material	−0.001	0.235***	−0.337***	Yes	Yes	0.40	503
	[−0.13]	[6.87]	[−11.06]				
Financials	−0.003	0.455***	−0.424***	Yes	Yes	0.50	332
	[−0.26]	[8.46]	[−7.53]				
Industrials	0.004	−0.025	−0.292***	Yes	Yes	0.24	399
	[0.49]	[−0.48]	[−7.70]				
Technology	0.004	0.772***	−0.505***	Yes	Yes	0.30	366
	[0.19]	[11.02]	[−7.86]				
Panel D: Grade							
Investment	0.002	0.317***	−0.299***	Yes	Yes	0.21	1751
	[0.15]	[15.41]	[−15.25]				
Junk	0.018	0.318***	−0.247***	Yes	Yes	0.22	383
	[0.72]	[5.07]	[−3.42]				

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

Table 7
CDS and DOOMP convergence to rating curves: Controlling for mean and median.

	Dep.: ΔH^C			Dep.: ΔH^P	
	[1]	[2]		[1]	[2]
Constant	0.012	−0.025	Constant	−0.001	−0.001
	[0.00]	[−0.00]		[−0.11]	[−0.06]
ΔF^C	0.037***	0.033***	ΔF^P	0.238***	0.212***
	[6.02]	[4.41]		[15.22]	[13.97]
R^C	−0.020***	−0.021***	R^P	−0.315***	−0.298***
	[−3.52]	[−2.92]		[−16.85]	[−16.42]
$\Delta Median^C$	0.947***		$\Delta Median^P$	0.727***	
	[69.30]			[24.24]	
$H^C - Median^C$	−0.000		$H^P - Median^P$	0.222***	
	[−0.00]			[8.51]	
$\Delta Mean^C$		0.983***	$\Delta Mean^P$		0.797***
		[58.69]			[27.68]
$H^C - Mean^C$		0.000	$H^P - Mean^P$		0.233***
		[0.00]			[9.01]
Time FE	Yes	Yes	Time FE	Yes	Yes
Rating FE	Yes	Yes	Rating FE	Yes	Yes
Adj. R-sqr	0.81	0.72	Adj. R-sqr	0.49	0.53
N	2134	2134	N	2134	2134

This table reports the results for CDS and DOOMP option convergence to their respective rating curves. The sample period is from July 2012 to April 2016. H^C and H^P are the URC-implied hazard rates for a CDS and put option respectively; F^C and F^P are the NS-fitted values; R^C and R^P are the NS residual. $Mean$ and $Median$ are the mean and median values of the corresponding hazard rates across the contracts with the same rating as that of the contract of interest and all possible maturities. The coefficient t-statistics are reported in brackets. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels.

Table 8
CDS-DOOMP convergence.

	Model: $\Delta D^H = \beta_0 + \beta_1 d^F + \beta_2 d^R + \beta_3 d^S + e$				
	$\beta_1(d^F)$	$\beta_2(d^R)$	$\beta_3(d^S)$	Time FE	Adj. R-sqr
Panel A: Full sample					
The Model	−0.069***	−0.208***	−0.035	Yes	0.17
	[−3.35]	[−8.98]	[−1.63]		
Raw Diff	−0.040**	−0.165***	−0.012	Yes	0.18
	[−2.14]	[−10.79]	[−0.61]		
Panel B: Period					
2012–2013	−0.054	−0.222***	−0.047	Yes	0.14
	[−1.34]	[−5.76]	[−1.16]		
2014	−0.072***	−0.230***	−0.016	Yes	0.28
	[−2.67]	[−6.85]	[−0.59]		
2015–2016	−0.156*	−0.252***	−0.003	Yes	0.07
	[−1.67]	[−2.98]	[−0.04]		
Panel C: Sector					
Consumer	−0.049	−0.159***	−0.004	Yes	0.20
	[−0.94]	[−2.61]	[−0.08]		
Material	−0.222***	−0.273***	−0.197***	Yes	0.27
	[−3.96]	[−5.35]	[−3.97]		
Financials	−0.165	−0.329***	−0.146	Yes	0.20
	[−1.44]	[−2.89]	[−1.26]		
Industrials	−0.194**	−0.582***	−0.312***	Yes	0.27
	[−2.22]	[−7.54]	[−4.09]		
Technology	0.160**	−0.054	0.290***	Yes	0.27
	[2.14]	[−0.68]	[3.69]		
Panel D: Grade					
Investment	−0.030	−0.140***	0.007	Yes	0.19
	[−0.93]	[−5.10]	[0.26]		
Junk	−0.084	−0.241**	−0.054	Yes	0.08
	[−0.81]	[−2.11]	[−0.52]		

This table reports the results for the CDS-DOOMP convergence. The sample period is from July 2012 to April 2016. The number of observations is 2,134. D^H is the difference in DOOMP- and CDS-implied hazard rates. d^F, d^R, and d^S are residuals from Eq. (2), where curve difference $F^P_{\tau_C} - F^C_{\tau_C}$, residual difference $R^P_{\tau_P} - R^C_{\tau_C}$, and DOOMP slope adjustment $F^P_{\tau_P} - F^P_{\tau_C}$ are regressed on the set of control variables. In Panel A, the full sample is used. "The Model" denotes regression using the residuals d^F, d^R, and d^S, while "Raw Diff" denotes the regression where the residuals are replaces with the actual raw differences. Panels B to D report the results based on sub-samples. The coefficient t-statistics are reported in brackets. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels.

If the underlying firm survives until maturity, $\alpha = 1$. In case of early default, there is no extra cash inflow or outflow generated, since both CDSs have the same underlying. Note that this amount of cash flow covers the whole protection period of the two CDS contracts.

The total profit and loss (PnL) realized of such strategy over N years can be calculated as:

$$PnL = \underbrace{\left(\frac{Price^P(t_1)}{N \cdot k(t_1)} \times (k(t_2) - k(t_1)) \times \alpha N\right)}_{\text{netting of the two CDSs}} \underbrace{-Price^P(t_2)}_{\text{DOOMP buy-back}} \underbrace{+Price^P(t_1)}_{\text{DOOMP short-sell}}$$
$$= \alpha \frac{Price^P(t_1)}{k(t_1)}(k(t_2) - k(t_1)) - (Price^P(t_2) - Price^P(t_1)).$$

Relative to the initial DOOMP price of $\$Price^P(t_1)$, the total return (over N years) of the trading strategy will be

$$r = \frac{\text{PnL}}{\text{Initial Input}} = \left[\alpha \frac{Price^P(t_1)}{k(t_1)}(k(t_2) - k(t_1)) - (Price^P(t_2) - Price^P(t_1))\right] / Price^P(t_1)$$
$$= \alpha \left(\frac{k(t_2)}{k(t_1)} - 1\right) - \left(\frac{Price^P(t_2)}{Price^P(t_1)} - 1\right) = \alpha \cdot r^{CDS} - r^{Put}.$$

Approximating the returns on the individual assets using continuously compounded rates, we obtain the following return of the trading strategy:

$$r = \begin{cases} \alpha \cdot \log \frac{k(t_2)}{k(t_1)} - \log \frac{Price^P(t_2)}{Price^P(t_1)}, \text{ if long/short CDS/DOOMP at } t_1, \\ -\alpha \cdot \log \frac{k(t_2)}{k(t_1)} + \log \frac{Price^P(t_2)}{Price^P(t_1)}, \text{ if short/long CDS/DOOMP at } t_1. \end{cases} \tag{16}$$

Eq. (16) illustrates how the realized return can be computed for this trading strategy. The parameter α is not known ex-ante; thus, in order to evaluate the expected return of the strategy, it needs to be estimated. One way to do so would be to infer it from the CDS spreads and hazard rates themselves, with the expected time to default being inverse of the hazard rate. In our analysis, however, we do not rely on expected returns and, instead, compute the realized returns. The CDS contracts are either held until maturity or until the default of the underlying, automatically adjusting the total return to the time at CDS maturity/default.

The trading returns in Eq. (16) do not consider the transaction costs, which are likely to be substantial in DOOMP and CDS markets. We adjust the returns for transaction costs using the reported bid–ask spreads (BAS). The adjusted returns r' are computed by substituting the actual put prices and CDS spreads by transaction-cost adjusted ones. The purchasing prices increase by $\frac{1}{2} \times BAS$, while selling prices decrease by the same amount, thus, resulting in smaller realized returns.[17]

The most important decision related to the trading strategy is the choice of a trading signal. First, as a *Benchmark* strategy, we use the total difference between DOOMP option and CDS hazard rates $H^P - H^C$, as a signal. If it is positive, that is, DOOMP option is relatively overpriced, we long a CDS and short a DOOMP option at time t_1. If the difference is negative, we short a relatively overpriced CDS and long a DOOMP option at time t_1. This strategy would be purely based on the arguments discussed in Carr and Wu (2011). Second, we propose a *Decomposition* strategy, based on the NS-components of the hazard rate. Recall that the magnitude of the convergence in hazard rates is stronger, if both differences in rating-based hazard rate curves and residuals have the same sign (due to the β_1 and β_2 having the same sign in Table 8). Thus, in our *Decomposition* strategy, we trade only when both differences ($F^P_{\tau_C} - F^C_{\tau_C}$ and $R^P_{\tau_P} - R^C_{\tau_C}$) have the same sign. Specifically, when both differences are positive, we long a CDS and short a DOOMP at time t_1; when both differences are negative, we short a CDS and long a DOOMP. This strategy is more stringent and therefore the number of potential trades is lower, but the additional constraint is expected to increase the likelihood of convergence. To further evaluate the benefits of the *Decomposition* strategy, we also include an *Excluded* trading strategy for reference. This strategy consists of those trades, which are included in the *Benchmark* strategy, but not in the *Decomposition* strategy; in other words, we trade based on the sign of $H^P - H^C$, but only if two components ($F^P_{\tau_C} - F^C_{\tau_C}$ and $R^P_{\tau_P} - R^C_{\tau_C}$) have different signs. When computing fitted hazard rates and residuals, we use the NS-curves estimated as of the date of decision (i.e. t_1); thus, the strategy relies only on past information and can be implemented in real time. As for the holding period, we choose the time t_2 to unwind the position at the first opportunity after 7 trading days.[18]

At the same time, convergence, if any, may be stronger for the cases with larger absolute deviations (Carr and Wu, 2011; Kolokolova et al., 2019). In order to evaluate the relative importance of the size of the total deviation in hazard rates vs. directions of the components of the deviation, we consider the same strategies – *Benchmark*, *Decomposition*, and *Excluded* – but require the absolute size of the total deviation in the implied hazard rates to be higher than the historical median absolute deviation.

6.1. Trading strategy performance

For the *Benchmark* strategy, we identify 2,930 trades with the holding periods ranging from 7 days to more than 1 year. Our *Decomposition* strategy reduces the number of valid trading signals to 1,037, as it requires the same sign of the differences in rating-based fitted values and residuals. Table 9 reports the distribution of holding periods for all trades, as well as for the trades with the same or different signs for the two differences. The average duration of trades with the same sign is 28.53 days, whereas the average duration of trades with different signs is 36.93 days; this means that the trading horizons are shorter for the *Decomposition* strategy due to stronger convergence upon the joint signal.

Table 10 reports the descriptive statistics of the fitted hazard rates (at maturity of 5-years, $F^C_{\tau_C}$ and $F^P_{\tau_C}$) and residuals (at actual contract maturities, $R^C_{\tau_C}$ and $R^P_{\tau_P}$) for the pairs of contracts included in the *Decomposition* strategy and the *Excluded* strategy – those not included into the *Decomposition* strategy, but still used in the *Benchmark* strategy. The DOOMP-implied fitted hazard rates are generally higher than those of CDSs. The average fitted values of hazard rates for CDSs in the *Decomposition* strategy are somewhat higher than in the *Excluded* strategy, indicating that CDS market participants view these firms as a bit riskier. The values of the residuals on the DOOMP side are on average positive for the *Decomposition* strategy, and they are negative for the *Excluded* strategy. The *Decomposition* strategy, thus, includes pairs of CDS and DOOMP which have more similar fitted hazard rates.

Table 11 reports the strategy performance in terms of total returns per trade, as well as risk-adjusted performance measured as the alpha relative to the Fama–French 5 factors.[19] For the case without transaction costs (Panel A), the average return for the *Benchmark* strategy (Ret^B) is 18.3%, significantly greater than zero at the 1% level. The *Decomposition* strategy delivers fewer trades but has a

[17] For regulated traders such as banks, the final realized return may be further impacted by the need to mark-to-market their positions in derivatives. Such traders would be required to hold additional capital against these instruments, which reduces the total return (He et al., 2017).

[18] In our regression results, we restrict the holding period between 7 and 30 days. Here, to avoid any selection bias and to make the strategy implementable, we relax this restriction.

[19] The alphas are estimated by running a pooled regressions of excess returns on Fama–French 5 factors. The factors are obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 9
Holding period distribution.

	≥7D ≤14D	>14D ≤21D	>21D ≤30D	>30D ≤6M	>6M ≤1Y	>1Y
Panel A: *Benchmark* strategy, all trades						
Count	1440	392	302	713	75	8
Percentage	49.15%	13.38%	10.31%	24.33%	2.56%	0.27%
					Mean	33.96
					STD	51.65
Panel B: *Decomposition* strategy, $F^P - F^C$ and $R^P - R^C$ with the same sign						
Count	529	151	107	231	19	0
Percent	51.01%	14.56%	10.32%	22.28%	1.83%	0.00%
					Mean	28.53
					STD	39.17
Panel C: *Excluded* strategy, $F^P - F^C$ and $R^P - R^C$ with different signs						
Count	911	241	195	482	56	8
Percent	48.12%	12.73%	10.30%	25.46%	2.96%	0.42%
					Mean	36.93
					STD	57.13

This table reports the number and the percentage of trades with different holding periods. Panel A is based on all trades, included in the *Benchamrk* strategy, Panel B uses trades from the *Decomposition* strategy with the same sign of systematic and idiosyncratic differences ($F^P - F^C$ and $R^P - R^C$), and Panel C is based on trades from the *Excluded* strategy with different signs of the two differences.

Table 10
Fitted and residual hazard rates of traded pairs of CDSs and DOOMPs.

	F^C	R^C	F^P	R^P	$F^P - F^C$	$R^P - R^C$
Panel A: *Decomposition* strategy						
Mean	0.0175	−0.0002	0.0458	0.0109	0.0284	0.0111
Median	0.0123	−0.0006	0.0341	0.0075	0.0202	0.0074
STD	0.0168	0.0053	0.0674	0.0154	0.0639	0.0150
Max	0.2701	0.0609	1.2938	0.1308	1.2432	0.1346
Min	0.0036	−0.0451	0.0031	−0.0863	−0.0460	−0.0829
N	1037	1037	1037	1037	1037	1037
Panel B: *Excluded* strategy						
Mean	0.0155	−0.0001	0.0443	−0.0122	0.0288	−0.0122
Median	0.0104	−0.0004	0.0352	−0.0098	0.0242	−0.0096
STD	0.0203	0.0078	0.0433	0.0157	0.0397	0.0170
Max	0.3500	0.0961	0.7648	0.1631	0.6115	0.2185
Min	0.0034	−0.2161	0.0055	−0.1776	−0.3022	−0.1794
N	1893	1893	1893	1893	1893	1893

This table reports the descriptive statistics of the fitted values of the hazard rate curves (F) and individual contracts' residuals (R) for CDSs (C) and DOOMPs (P) included in the *Decomposition* strategy (Panel A) and those in the *Excluded* strategy, that is, the traded pairs included in the *Benchmark* but not in the *Decomposition* strategy (Panel B).

much higher average return of 30% (Ret^D) as compared to the *Benchmark* strategy. The return difference of 11.7% is positive and significant at the 1% level. Those trades which are excluded from the *Decomposition* strategy clearly exhibit weaker convergence and their average return (Ret^E) is 12%, lower than both *Benchmark* strategy and *Decomposition* strategy. Since DOOMP-CDS trading strategy relies on a relative mispricing of individual credit risk, the equity market factors do not contribute to the performance. Hence, the results based on the 5-factor alphas are very close to those based on total returns discussed above.

Most importantly, the *Decomposition* strategy is the only strategy that produces positive returns after transaction costs (Panel B). In general, transaction costs severely reduce the returns. The *Benchmark* strategy results in a negative return of −8% significant at the 1% level, whereas the return for the *Decomposition* strategy is 3.8%, still significant at the 5% level. Trades excluded from the *Decomposition* strategy result in the losses of −14.3%, significant at the 1% level.

The performance of the *Benchmark* based on large absolute differences of the implied hazard rates improves considerably compared to the unrestricted *Benchmark strategy* both pre- and post-transaction cost (Panels C and D). The mean return increases from 18.3% to 26.3% pre-transaction cost, while after transaction cost it increases from −8% to 3.1%. Despite such an improvement in performance, the mean returns are still lower than that of *Decomposition* strategy from Panels A and B. The performance of *Decomposition* strategy further improves to mean returns of 32% and 7.6% in Panels C and D respectively, when the total absolute difference is required to be above historical median. Overall, this suggests that although the absolute size of the difference between

Table 11
Trading performance on CDS-DOOMP convergence.

	Ret^B	Ret^D	Ret^E	$Ret^D - Ret^B$	$Ret^D - Ret^E$
Panel A: Raw Returns					
Mean	0.183***	0.300***	0.120***	0.117***	0.180***
STD	0.445	0.455	0.426		
t-stat	22.188	21.221	12.256	7.174	10.459
FF5 Alpha	0.181***	0.305***	0.116***	0.104***	0.184***
t-stat	21.752	21.229	11.801	6.266	7.255
N Trades	2930	1037	1893		
Panel B: Transaction Cost Adjusted Returns					
Mean	−0.080***	0.038**	−0.143***	0.118***	0.181***
STD	0.501	0.485	0.498		
t-stat	−8.657	2.525	−12.519	6.684	9.587
FF5 Alpha	−0.082***	0.041***	−0.147***	0.094***	0.170***
t-stat	−8.768	2.702	−12.711	5.070	6.028
N Trades	2930	1037	1893		
Panel C: $\lvert D^H \rvert > Median(\lvert D^H \rvert)$ & Raw Returns					
Mean	0.263***	0.320***	0.182***	0.057***	0.138***
STD	0.450	0.455	0.429		
t-stat	22.405	20.648	10.398	2.926	5.929
FF5 Alpha	0.262***	0.324***	0.169***	0.048***	0.147***
t-stat	21.810	20.534	9.470	4.039	4.555
N Trades	1465	863	602		
Panel D: $\lvert D^H \rvert > Median(\lvert D^H \rvert)$ & Cost-Adj. Returns					
Mean	0.031**	0.076***	−0.034*	0.045**	0.110***
STD	0.474	0.467	0.478		
t-stat	2.486	4.793	−1.757	2.251	4.391
FF5 Alpha	0.028**	0.078***	−0.046**	0.028**	0.093***
t-stat	2.237	4.842	−2.312	2.323	2.765
N Trades	1465	863	602		

This table reports the strategy performance over the sample period from July 2012 to April 2016. Ret^B is the return for the *Benchmark* strategy, based on a total difference in hazard rates signal, Ret^D is the return for our *Decomposition* strategy, based on the both systematic and idiosyncratic differences, and Ret^E is the return for the trades that are excluded from the *Decomposition* strategy. Panel A uses raw returns, and Panel B uses the returns adjusted for transaction costs. Panels C and D use a sub-sample of trades for which the absolute deviation in hazard rates between CDS and DOOMP is above the median. ***, **, and * represent the significance of one sample or two sample t-test at the 1%, 5%, and 10% levels, respectively.

implied hazard rates is an important determinant of convergence, the relative position of rating-based fitted components of the hazard rates and the residuals complements the effect of the deviation size.

We further check how differences in maturities between DOOMP and CDS affect the performance of the strategies. We evaluate the performance of the *Benchmark*, *Decomposition*, and *Excluded* strategies using only those trades that include DOOMPs with maturities less than 6 months, or 6 months and above. Table 12 indicates that the *Decomposition* strategy statistically significantly outperforms the *Benchmark* strategy for both shorter- and longer-maturity DOOMP options. Remarkably, the largest trading profits are associated with trades based on shorter-term DOOMPs. Here, the total average returns reach 42.5% per trade before transaction costs and 6.9% after the costs. Trades involving longer maturity DOOMPs generate a significantly negative average return post-transaction cost for the *Benchmark* strategy, and a not statistically significant return for the *Decomposition* strategy.

We also compare the performance of the strategies for different lengths of holding periods. We evaluate the performance of the *Benchmark*, *Decomposition*, and *Excluded* strategies using only those trades that are closed within the first 14 days after origination (which roughly corresponds to the median of holding periods), and those that are closed after a longer holding period. Table 13 indicates that the *Decomposition* strategy statistically significantly outperforms the *Benchmark* strategy for both holding period sub-samples. The largest trading profits are associated with longer holding periods. This may suggest that over longer periods of time convergence between DOOMP- and CDS-implied hazard rates is more likely. Post-transaction cost returns of both the *Benchmark* strategy and the *Decomposition* strategy are negative for short holding periods, although the *Decomposition* strategy still delivers statistically significantly higher returns than the *Benchmark* strategy. For the longer holding horizons, post-transaction cost returns of the *Decomposition* strategy are positive and significant of 14.5%, while those of the *Benchmark* strategy are negative of −2.8%.

The returns discussed above are the total returns for each trade. To assess the trading performance of the strategies over time, we amortize the total return into the daily equivalents,[20] and for each trading day we accumulate the prior daily returns across all trades which are still active on that day. We compute the cumulative returns with and without transaction costs. Fig. 4 depicts the results.

[20] We divide total return by 5×365 since all CDS contracts in our analysis have maturities of 5 years.

Table 12
Trading performance on CDS-DOOMP convergence: DOOMP maturity effect.

	Ret^B	Ret^D	Ret^E	$Ret^D - Ret^B$	$Ret^D - Ret^E$
Panel A: Raw Returns (Maturity < 6M)					
Mean	0.355***	0.425***	0.216***	0.069**	0.209***
STD	0.526	0.512	0.516		
t-stat	17.783	18.214	6.069	2.263	4.915
FF5 Alpha	0.359***	0.433***	0.208***	0.049***	0.219***
t-stat	17.712	18.351	5.707	3.242	3.918
N Trades	693	482	211		
Panel B: Raw Returns (Maturity ≥ 6M)					
Mean	0.129***	0.192***	0.108***	0.062***	0.084***
STD	0.403	0.367	0.412		
t-stat	15.161	12.302	10.753	3.519	4.507
FF5 Alpha	0.127***	0.191***	0.105***	0.049***	0.085***
t-stat	14.771	12.034	10.414	2.587	3.019
N Trades	2237	555	1682		
Panel C: Transaction Cost Adjusted Returns (Maturity < 6M)					
Mean	−0.045*	0.069***	−0.287***	0.113***	0.356***
STD	0.603	0.564	0.622		
t-stat	−1.949	2.677	−6.702	3.295	7.124
FF5 Alpha	−0.043*	0.075***	−0.301***	0.066***	0.327***
t-stat	−1.857	2.847	−6.788	3.715	4.898
N Trades	693	482	211		
Panel D: Transaction Cost Adjusted Returns (Maturity ≥ 6M)					
Mean	−0.091***	0.011	−0.125***	0.102***	0.137***
STD	0.465	0.403	0.478		
t-stat	−9.276	0.664	−10.763	5.197	6.608
FF5 Alpha	−0.093***	0.010	−0.128***	0.075***	0.129***
t-stat	−9.450	0.569	−10.920	3.587	4.172
N Trades	2237	555	1682		

This table reports the strategy performance over the sample period from July 2012 to April 2016. Ret^B is the return for the *Benchmark* strategy, based on a total difference in hazard rates signal, Ret^D is the return for our *Decomposition* strategy, based on the both systematic and idiosyncratic differences, and Ret^E is the return for the trades that are excluded from the *Decomposition* strategy. Panels A and B use raw returns and trades involving DOOMPs with maturities below or above 6 months, respectively. Panels C and D report the corresponding transaction cost adjusted returns. ***, **, and * represent the significance of one sample or two sample t-test at the 1%, 5%, and 10% levels, respectively.

The *Decomposition* strategy delivers a more appealing profile over time, resulting in the cumulative total return of 27% before transaction costs and 8% after transaction costs, while the corresponding returns for the *Benchmark* strategy are 20% and 3% over the same period.

These results above provide evidence that decomposition of hazard rates into their rating-based and residual components captures the price dynamics of these two markets more accurately. Using the refined signal, it is possible to develop a trading strategy with a positive expected return even after transaction costs.

7. Information content of the aggregate CDS-DOOMP deviations

In the previous sections we have investigated whether individual deviations of hazard rates from their rating curves contain information about their future dynamics within the CDS and DOOMP markets, and if and how such predictions of cross-market movements can be exploited to construct profitable investments strategies. The intensity of the within-market deviations from the rating curves is related to market inefficiencies, while the cross-market differences of the curves are driven by market segmentation. Hence, while the factors capturing market efficiency and segmentation affect the within-market and cross-market differences in hazard rates, these differences themselves can serve as a gauge of the level of such inefficiencies. In a similar spirit, Hu et al. (2013) show that noise in the Treasury bond yields relative to the fitted yield curve contains important information about the aggregate market liquidity and availability of the arbitrage capital, and it can be used as a priced factor for, for example, hedge fund returns.

In this section, we propose two aggregate measures of CDS and DOOMP market inefficiencies ($Noise^C$ and $Noise^P$), based on the residuals relative to the NS hazard rates curves fitted for each market separately, and a measure of market segmentation based on the cross-curve differences ($Segment^{CP}$).

To construct the monthly values of $Noise^C$ and $Noise^P$, we follow a similar procedure as in Hu et al. (2013) for the Treasury bond noise measure. We compute the square root of the average squared deviations of the individual hazard rates from their corresponding rating curve, scaled by the corresponding fitted value of the hazard rate. For example, for the CDS market each month we compute:

Table 13
Trading performance on CDS-DOOMP convergence: Holding period effect.

	Ret^B	Ret^D	Ret^E	$Ret^D - Ret^B$	$Ret^D - Ret^E$
Panel A: Raw Return (Holding ≤ 14 Days)					
Mean	0.101***	0.178***	0.057***	0.077***	0.120***
STD	0.271	0.318	0.229		
t-stat	14.104	12.865	7.542	4.938	7.646
FF5 Alpha	0.098***	0.183***	0.053***	0.069***	0.139***
t-stat	13.405	12.854	6.911	5.991	6.908
N Trades	1440	529	911		
Panel B: Raw Return (Holding > 14 Days)					
Mean	0.262***	0.427***	0.178***	0.166***	0.249***
STD	0.553	0.535	0.543		
t-stat	18.239	17.993	10.297	5.971	8.466
FF5 Alpha	0.260***	0.429***	0.176***	0.120***	0.249***
t-stat	18.111	17.945	10.173	5.437	6.223
N Trades	1490	508	982		
Panel C: Return with Transaction Cost (Holding ≤ 14 Days)					
Mean	−0.134***	−0.064***	−0.173***	0.070***	0.109***
STD	0.342	0.373	0.326		
t-stat	−14.843	−3.961	−16.057	3.748	5.604
FF5 Alpha	−0.136***	−0.060***	−0.176***	0.055***	0.121***
t-stat	−14.813	−3.568	−16.072	4.024	4.767
N Trades	1440	529	911		
Panel D: Return with Transaction Cost (Holding > 14 Days)					
Mean	−0.028*	0.145***	−0.115***	0.173***	0.260***
STD	0.612	0.560	0.615		
t-stat	−1.783	5.817	−5.881	5.862	8.210
FF5 Alpha	−0.029*	0.145***	−0.117***	0.120***	0.259***
t-stat	−1.853	5.806	−5.966	4.822	5.618
N Trades	1490	508	982		

This table reports the strategy performance over the sample period from July 2012 to April 2016. Ret^B is the return for the *Benchmark* strategy, based on a total difference in hazard rates signal, Ret^D is the return for our *Decomposition* strategy, based on the both systematic and idiosyncratic differences, and Ret^E is the return for the trades that are excluded from the *Decomposition* strategy. Panels A and B use raw returns and trades involving DOOMPs with holding periods below or above 14 days, respectively. Panels C and D report the corresponding transaction cost adjusted returns. ***, **, and * represents the significance of one sample or two sample t-test at the 1%, 5%, and 10% levels, respectively.

$$Noise^C = \sqrt{\frac{1}{N_C} \sum_i \frac{[H_i^C(t,\tau_C) - F_i^C(t,\tau_C)]^2}{F_i^C(t,\tau_C)}}, \tag{17}$$

where N_C is the total number of CDS contracts traded during the month of interest, $H_i^C(t,\tau_C)$ is individual CDS-implied hazard rate for CDS i traded during day t of the month and having the maturity τ_C. $F_i^C(t,\tau_C)$ is the fitted value of the NS-curve as of day t for maturity τ_C and the same rating as that of CDS i. $Noise^P$ is computed analogically using DOOMP-implied hazard rates and NS-curves.

The monthly market segmentation measure $Segment^{CP}$ is computed as the square root of the average squared difference between the NS-fitted values for CDS and DOOMP curves computed at maturity of 5 years ($\tau = 5$), scaled by the average value of the fitted values:

$$Segment^{CP} = \sqrt{\frac{1}{N_F} \sum_t \sum_r \frac{[F_t^P(\tau=5,r) - F_t^C(\tau=5,r)]^2}{0.5 \times [F_t^P(\tau=5,r) + F_t^C(\tau=5,r)]}}, \tag{18}$$

where N_F is the total number of fitted curves across all ratings r and all days of the month t, and $F_t^P(\tau=5,r)$ and $F_t^C(\tau=5,r)$ are NS-fitted curve value for DOOMP and CDS markets, respectively, fitted at day t, for maturity 5 years, and rating r.

Table 14 reports the descriptive statistics of the resulting noise and market segmentation measure, as well as their correlation with several factors, capturing market performance and risk. In particular, we use the excess market return over the risk-free rate ($Mkt - Rf$) from K. French website, the volatility index VIX from CBOE, Pastor and Stambaugh (2003) traded liquidity measure (PS_LIQ), and the illiquidity measure based on noise in Treasury bonds ($ILLIQ^{TB}$) of Hu et al. (2013).[21] The original bond

[21] The corresponding data are obtained at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, https://www.cboe.com/tradable_products/vix/vix_historical_data/, https://finance.wharton.upenn.edu/~stambaug/, and https://en.saif.sjtu.edu.cn/junpan/.

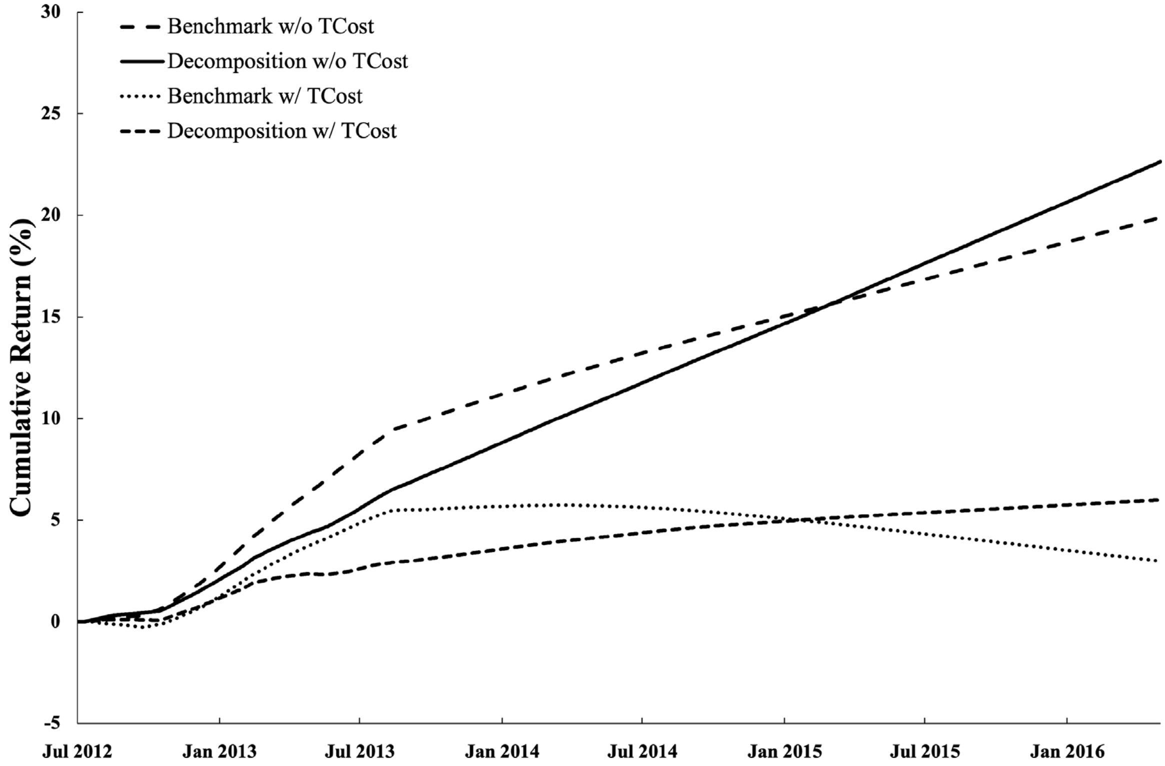


Fig. 4. Time series plot for cumulative trading returns.
This figure plots the cumulative returns of the *Benchmark* and *Decomposition* trading strategies from July 2012 to April 2016 before and after transaction costs.

Table 14
CDS and DOOMP segmentation and noise.

Panel A: Descriptive statistics

	Mean	Median	STD	N
$Segment^{CP}$	1.04	1.00	0.16	45
$Noise^{C}$	0.25	0.25	0.06	45
$Noise^{P}$	0.81	0.58	1.12	45

Panel B: Correlation matrix

	$Noise^{C}$	$Noise^{P}$	$ILLIQ^{TB}$	$Mkt-Rf$	VIX	PS_LIQ
$Segment^{CP}$	−0.37	0.08	0.43	−0.49	0.30	−0.01
$Noise^{C}$		−0.34	−0.06	0.15	−0.14	−0.09
$Noise^{P}$			−0.13	−0.11	0.26	0.14
$ILLIQ^{TB}$				−0.16	0.02	0.14
$Mkt-Rf$					−0.77	−0.20
VIX						0.28

This table reports the descriptive statistics of the CDS and DOOMP market segmentation measure ($Segment^{CP}$) and CDS and DOOMP noise measures ($Noise^{C}$ and $Noise^{P}$), as well as their correlation coefficients of the monthly values of the market segmentation measure with the Hu et al. (2013) noise measure of the Treasure bond market ($ILLIQ^{TB}$), the excess return of the market over the risk-free rate ($Mkt-Rf$), the VIX index, and the Pastor and Stambaugh (2003) traded liquidity measure. The sample period is from July 2012 to April 2016.

noise measure is computed on a daily frequency, and we take the average value within a month to create a monthly time series. Our market segmentation measure $Segment^{CP}$ is relatively highly correlated to $ILLIQ^{TB}$ (0.43) and VIX (0.30), and negatively correlated with the excess market return (−0.49). This suggests that during periods with low market return, high volatility and lack of arbitrage capital, CDS and DOOMP markets tend to become more segmented. As for the noise measures, $Noise^{P}$ is relatively highly correlated with VIX (0.26), while the correlations with other factors considered are much lower in absolute values. $Noise^{C}$ does not exhibit high correlations with the factors considered. These observations suggest that $Noise^{P}$ and $Noise^{C}$ capture inefficiencies in the DOOMP and CDS markets, which might be due to lack of arbitrage capital in these markets, and these inefficiencies are not captured by the existing measures – market return, VIX, $ILLIQ^{TB}$, or PS_LIQ.

Table 15
Hedge fund descriptive statistics and abnormal returns.

Panel A: Hedge fund portfolios monthly return descriptive statistics								
	All	CTA/MgtF	Event Dr	Fixed Inc	LS Equity	Macro	Multi Strat	Value
Mean	0.47	0.48	0.72	0.47	0.44	0.29	0.53	0.55
Median	0.80	0.89	0.87	0.69	0.61	0.30	0.60	0.97
STD	1.19	1.47	1.03	1.26	1.15	1.65	1.53	1.30

Panel B: Hedge fund performance related to Fung and Hsieh 7 factors								
	All	CTA/MgtF	Event Dr	Fixed Inc	LS Equity	Macro	Multi Strat	Value
Constant	0.106	0.040	0.522***	0.084	0.079	−0.190	0.137	0.140
	[1.30]	[0.39]	[4.13]	[0.85]	[1.00]	[−1.39]	[1.12]	[1.31]
Mkt-Rf	0.312***	0.395***	0.182***	0.325***	0.296***	0.384***	0.321***	0.349***
	[10.83]	[12.30]	[4.85]	[11.57]	[10.24]	[10.74]	[6.68]	[9.31]
SMB	−0.002	0.028	−0.066	0.004	−0.012	0.067	0.073	−0.004
	[−0.06]	[0.55]	[−0.81]	[0.09]	[−0.29]	[1.31]	[1.50]	[−0.09]
PTFSBD	−0.009	0.000	−0.006	−0.006	−0.011*	−0.015	−0.015	−0.006
	[−1.36]	[0.03]	[−0.48]	[−0.93]	[−1.79]	[−1.10]	[−1.25]	[−0.68]
PTFSFX	0.015***	0.011**	0.025**	0.012**	0.016***	0.010	0.019**	0.007
	[3.41]	[2.18]	[2.46]	[2.56]	[3.40]	[1.37]	[2.25]	[1.27]
PTFSCOM	−0.007	−0.008	−0.005	−0.007	−0.007	−0.007	−0.008	−0.006
	[−1.40]	[−1.36]	[−0.58]	[−1.40]	[−1.40]	[−0.78]	[−0.97]	[−0.91]
Bond Mkt	−0.009*	−0.009*	−0.001	−0.010**	−0.009*	−0.028***	−0.001	−0.011**
	[−1.94]	[−1.81]	[−0.11]	[−2.16]	[−1.92]	[−3.60]	[−0.10]	[−2.42]
Credit Spr	−0.016**	−0.018**	−0.011	−0.019***	−0.015**	−0.032***	−0.027**	−0.006
	[−2.29]	[−2.16]	[−1.33]	[−2.73]	[−2.19]	[−4.34]	[−2.22]	[−0.56]
Adj. R-sqr	0.79	0.81	0.31	0.79	0.77	0.77	0.68	0.71
N	45	45	45	45	45	45	45	45

Panel A of this table reports the descriptive statistics of portfolios of hedge funds following different investment styles. The individual funds come from a union of the Eurekahedge and Barlayhedge databases. The sample period is from July 2012 to April 2016. Panel B reports the regression results of the hedge fund portfolio returns on the Fung and Hsieh (2001) seven factors. The standard errors are adjusted for heteroskedasticity and serial correlation using Newey–West correction and are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

CDS and DOOMP markets are often populated by skilled institutional investors, such as hedge funds. If our new factors capture the existence of unexploited arbitrage opportunities in those markets, we may see that they significantly affect performance of these arbitrageurs. In order to test this conjecture, we use the union of the Eurekahedge and Barclayhedge hedge fund databases and create portfolios of hedge funds as the simple average of their reported performance during our sample period (July 2012 to April 2016). We create portfolios of all hedge funds (All), as well as funds following particular investment strategies including CTA/Managed Futures, Event Driven, Fixed Income, Long-Short Equity, Macro, Multi-strategy, and Value. Panel A of Table 15 reports the descriptive statistics of the hedge fund portfolio returns. Over our sample period, Event Driven funds exhibit the highest mean return of 0.72% per month, while Macro funds have the weakest performance with the mean return of 0.29% per month. Panel B of Table 15 further reports the regression results of hedge fund portfolio returns on the Fung and Hsieh (2001) seven factors.[22] Event Driven funds are the only category exhibiting a positive and significant alpha in our sample of 0.52% per month. Important to note, however, that the Fung and Hsieh (2001) model has the weakest explanatory power for these funds, with adjusted R-square being 31%.

We further evaluate performance of hedge fund portfolios relative to our noise and market segmentation measures, as well as $ILLIQ^{TB}$ of Hu et al. (2013) and Fung and Hsieh (2001) seven factors. Panel A of Table 16 reports the results using the contemporaneous values of the noise and market segmentation factors.[23] $Noise^P$ seems to be capturing the existence of contemporaneous arbitrage opportunities that can be exploited by arbitrageurs almost instantly. This factor is significantly positively related to performance of almost all hedge fund strategies. On average, one standard deviation increase in $Noise^P$ corresponds to around 13 basis points increase in the average risk adjusted return of hedge funds. $Noise^C$ relates positively to the performance of Event Driven and Fixed Income funds, with the effect on performance of Event Driven funds being the strongest. One standard deviation increase in $Noise^C$ corresponds to about 24 basis points increase in monthly abnormal returns of Event Driven funds. In the presence of this factor, the abnormal return of Event Driven funds is no longer significant, similar to other funds in our sample.

In Panel B of Table 16 we use the lagged values of noise and segmentation factors to test for their time-series predictability for hedge fund returns. A remarkable feature emerges in the lagged results: while $Noise^P$ remains positively related to performance of all hedge funds on average and of some individual strategies, the measure of market segmentation $Segment^{CP}$ is negatively related to future performance of hedge funds. One standard deviation increase in market segmentation measure predicts a decline by 22 basis points of the average hedge fund abnormal return one month ahead.

Overall, our findings suggest that market-specific noise measures capture the likelihood of existence of exploitable arbitrage opportunities. During periods with high values of these factors, hedge funds as a group tend to perform better, potentially gaining

[22] https://people.duke.edu/~dah7/.

[23] We do not report the loadings on the Fung and Hsieh (2001) seven factors and the intercept in this table for the sake of space.

Table 16
CDS and DOOMP segmentation and noise: Hedge fund performance.

Panel A: Contemporaneous effects

	All	CTA/MgtF	Event Dr	Fixed Inc	LS Equity	Macro	Multi Strat	Value
$ILLIQ^{TB}$	−0.157	−0.094	0.272	−0.048	−0.232	−0.188	−0.358	−0.228
	[−0.98]	[−0.46]	[1.14]	[−0.27]	[−1.48]	[−0.67]	[−1.44]	[−1.22]
$Noise^{C}$	1.500	1.722	3.994***	2.038*	1.328	0.424	−2.585	1.615
	[1.58]	[1.62]	[2.95]	[1.88]	[1.30]	[0.28]	[−1.48]	[1.32]
$Noise^{P}$	0.114***	0.128***	−0.039	0.116***	0.130***	0.189***	0.166***	0.065
	[3.74]	[3.20]	[−0.92]	[3.78]	[4.09]	[4.83]	[2.74]	[1.28]
$Segment^{CP}$	−0.907	−0.636	−1.614*	−0.992	−0.986	−0.154	−0.949	−0.053
	[−1.31]	[−0.72]	[−1.86]	[−1.42]	[−1.41]	[−0.16]	[−0.90]	[−0.07]
Fung & Hsieh factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-sqr	0.81	0.81	0.39	0.80	0.81	0.76	0.71	0.69
N	45	45	45	45	45	45	45	45

Panel B: Lagged effects

	All	CTA/MgtF	Event Dr	Fixed Inc	LS Equity	Macro	Multi Strat	Value
$ILLIQ^{TB}$ (t−1)	0.009	0.012	0.528*	0.027	−0.024	−0.055	0.063	−0.275
	[0.04]	[0.05]	[1.88]	[0.14]	[−0.12]	[−0.15]	[0.20]	[−0.97]
$Noise^{C}$ (t−1)	0.443	0.215	3.446	1.970	−0.239	−0.315	−2.302	1.374
	[0.32]	[0.13]	[1.59]	[1.31]	[−0.17]	[−0.11]	[−1.28]	[0.72]
$Noise^{P}$ (t−1)	0.096**	0.021	0.095	0.091*	0.124**	0.076	0.249***	−0.042
	[2.04]	[0.38]	[1.45]	[1.87]	[2.51]	[1.01]	[3.76]	[−0.63]
$Segment^{CP}$ (t−1)	−1.348**	−1.144	−2.028**	−1.134*	−1.502**	−1.022	−1.924**	−0.135
	[−2.22]	[−1.52]	[−2.11]	[−1.81]	[−2.43]	[−1.06]	[−2.40]	[−0.18]
Fung & Hsieh factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-sqr	0.82	0.81	0.46	0.80	0.81	0.75	0.74	0.70
N	44	44	44	44	44	44	44	44

This table reports the estimation results of hedge fund portfolio return on the contemporaneous (Panel A) and lagged (Panel B) CDS and DOOMP market segmentation measure ($Segment^{CP}$) and CDS and DOOMP noise measures ($Noise^{C}$ and $Noise^{P}$), as well as Hu et al. (2013) noise measure of the Treasure bond market ($ILLIQ^{TB}$). The sample period is from July 2012 to April 2016. We control for Fung and Hsieh (2001) seven factors in all the regressions. The standard errors are adjusted for heteroskedasticity and serial correlation using Newey–West correction and are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

from trading on convergence of individual contracts to rating curves, and further contributing to faster convergence by their trades. Exploiting market segmentation seems to be harder and potentially more costly since it may require moving capital across different markets. These opportunities do not seem to be exploited by hedge funds. Instead, current market segmentation tends to preclude the efficient exploitation of future trading opportunities, leading to reduction in hedge fund abnormal returns one month ahead. Professional arbitrageurs seem to benefit from within-market inefficiencies and, by trading on these inefficiencies, they help to reduce them. However, such arbitrageurs do not seem to contribute sufficiently to reduction of cross-market mispricing and market segmentation.

8. Conclusion

Both credit default swap (CDS) and deep out-of-the-money put (DOOMP) options provide protection against firm's default. If the law of one price holds, the hazard rates implied by these two types of contracts written on the same underlying firm should be identical or very close, except when there are significant market frictions (Carr and Wu, 2011).

In this paper, we argue that the law of one price partially fails as these two markets are very different. They attract different types of investors with different levels of risk aversion, information sets, and optimization horizons. The dynamics of prices in these two markets are characterized by a within-market convergence to their respective rating-based consensus pricing curves, and a cross-market convergence of those rating-based curves. Often, these two movements do not go in the same direction, making the individual CDS and DOOMP prices harder to predict.

The rating-based curves are estimated from the implied hazard rates using the Nelson–Siegel term structure, and represent the "rating-consensus" components of the hazard rates. The differences in these components for CDS and DOOMP markets decrease for lower rating classes, where firms have very high hazard rates. The individual deviations from the fitted curves by the implied hazard rates are related to market frictions.

Time-series convergence in hazard rates is driven by two forces: a within-market convergence of individual hazard rates to their respective rating curves, and a cross-market convergence of the curves. The overall convergence in hazard rates is observed only if both cross-market differences reduce, that is, when the two markets become closer substitutes for each other and the market frictions are lower.

We test if the differences in hazard rates and their components can be exploited as trading signals for a cross-market trading strategy in CDSs and DOOMP options, written on the same underlying. The *Benchmark* strategy trades on total difference between the two implied hazard rates, which is expected to deliver a positive average return according to Carr and Wu (2011). Our *Decomposition* strategy requires that both rating-based and residual differences have the same sign. Ignoring transaction costs, both strategies produce statistically significant positive returns, with the return of the *Decomposition* strategy being much higher than that of the *Benchmark* strategy. When transaction costs are included, our results show a negative expected return for the *Benchmark* strategy, whereas the *Decomposition* strategy still produces a positive return.

Finally, we assess the aggregate information content of within-market deviations of individual hazard rates from the rating-based curves (noise) and cross-market differences of the curves (market segmentation), and their effect on performance of sophisticated arbitrageurs, such as hedge funds. The noise measures seem to capture the likelihood of the existence of exploitable arbitrage opportunities, and they are positively related to the aggregate performance of portfolios of hedge funds. The curve difference, however, captures market segmentation. It seems to be costly for capital to quickly flow between the markets; hence, even hedge funds do not seem to be able to exploit such cross-market differences for their benefit. Such market segmentation, on the contrary, negatively impacts their future performance.

Overall, our results highlight the benefits and importance of a separate analysis of the dynamics of the rating-based and residual components of implied hazard rates. This decomposition approach allows us to more comprehensively assess price informativeness, potential convergence between the CDS and DOOMP option markets, the existence of arbitrage opportunities and the overall market efficiency.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jempfin.2023.03.008.

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