

# The Components of the CDS Bid-Ask Spreads: A Reduced-form Approach

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Understanding and estimating various components of the bid-ask spreads have been one of the key topics in the market microstructure literature.

The bid-ask spread is not only important in the equity market, it is also key understanding the CDS market.

Unlike conventional securities such as stocks and corporate bonds, each CDS contract has two legs. Dealers in the CDS market have different considerations for two legs when quoting bid and ask CDS premiums.

This unique security design allows a natural identification scheme for modeling various components in the CDS bid and ask quote spreads.

# Contributions

We provide an empirical study of the CDS market structure through the lens of a structural model that quantifies the components in the CDS bid-ask spreads;

We find that the recovery-related liquidity component accounts for a big portion of the bid-ask spreads, around about 60% on average across different maturities. This component is highly correlated with the market-wide liquidity factor, NOISE (Huang, Pan, and Wang 2013 JF).

The next largest components (around 35%) are adverse selection related with the sell side adverse selection much larger than the buy side;

## Contributions (cont.)

The monopolist profits is a sizeable component in the bid-ask spread, accounting for around 5% on average and concentrating on 5-year maturity;

Consistent with classic market microstructure theories, the identified adverse selection components predict future changes in the CDS premiums and explain cross-sectional distribution of the CDS returns;

During the pandemic, the CDS market has become less competitive, reflecting the higher monopolist profits, and less efficient (more informational frictions), reflected in more concerns for the adverse selection and the counterparty risk from the sell side.

## Benchmark quote

## Constant risk-neutral default intensity

Exponentially distributed default time with survival probability  $S_{D_t}$  and density  $\lambda e^{-\lambda t}$ .

For time to maturity  $D_t$ , the premium leg  $Q_{D_t}$  and protection leg  $P_{D_t}$  are given as:

$$Q_{D_t} = S_{D_t} \int_0^{D_t} e^{-\lambda t} dt ;$$

$$P_{D_t} = w \int_0^{D_t} e^{-\lambda t} dt ;$$

## Benchmark quote (cont.)

The CDS spread is the one equalising  $Q_{Dt}$  and  $P_{Dt}$ , i.e.,

$$s_{Dt} = \frac{wl \int_0^{T_{Dt}} e^{-\lambda t} dt}{R_{Dt} \int_0^{T_{Dt}} e^{-\lambda t} dt} = wl :$$

where  $w$  is the LGD and  $\lambda$  is the default intensity.

# Adding liquidity premium to LGD

We capture this by using a liquidity convenience yield to discount recovery given default  $(1 - w)$ .

That is, the protection leg is now given as

$$P_{Dt} = \int_0^{Z_{Dt}} (1 - w) e^{-\int_t^h r_{ts} ds} e^{-\int_t^l r_{ts} ds} dt;$$

and CDS premium is:

$$s_{Dt} = \frac{\int_0^{R_{Dt}} [1 - (1 - w) e^{-\int_t^h r_{ts} ds}] e^{-\int_t^l r_{ts} ds} dt}{\int_0^{R_{Dt}} e^{-\int_t^l r_{ts} ds} dt} = \int_0^1 \frac{g(l + h; Dt)}{g(l; Dt)} (1 - w) dx;$$

where  $g(x; t) = \frac{1 - e^{-x}}{x}$ :



Selling dealer adjusts the default intensity upward for adverse selection of buyers

$$\lambda_A = \lambda + \lambda_A^*$$

Selling dealer's market power is reflected in further discount of buyer's premium payments at rate  $\theta_A$ :

$$Q_{A;Dt} = S_{A;Dt} \int_0^{Z_{Dt}} e^{-t(\lambda_A + g_A)} dt;$$

$$P_{A;Dt} = \lambda_A \int_0^{Z_{Dt}} (1 - w) e^{-t\lambda_A} dt;$$

## Ask quote (cont.)

and the CDS premium ask quote is

$$S_{A;Dt} = I_A \frac{g(I_A; Dt)}{g(I_A + g_A; Dt)} \left( 1 - \frac{g(I_A + h; Dt)}{g(I_A; Dt)} \right) (1 - w) :$$

Buying dealer adjusts the default intensity downward for adverse selection of sellers:

$$\lambda_B = \lambda - \lambda_B$$

The sellers' counterparty risk is priced in the bid quote through additional discounting of protection payment at rate  $w$ :

$$Q_{B;Dt} = S_{B;Dt} \int_0^T Z_{Dt} e^{-\int_t^s \lambda_B dt} ds;$$

$$P_{B;Dt} = I_B \int_0^T Z_{Dt} (1 - w) e^{-\int_t^s (\lambda_B + g_B) dt} ds;$$

## Bid quote (cont.)

and the CDS premium ask quote is

$$S_{B;Dt} = I_B \frac{g(I_B + g_B; Dt)}{g(I_B; Dt)} - 1 - \frac{g(I_B + g_B + h; Dt)}{g(I_B + g_B; Dt)} (1 - w) :$$

# Adverse selection induced inventory cost

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When dealers raise the ask quote to compensate for selling to informed clients, they also raise the bid quote to increase the likelihood of unloading the short position.

When dealers reduce the bid quote to compensate for buying from informed clients, they also reduce the ask quote to increase the likelihood of unloading the long position.

$$l_A = l_A^0 + b l_B^0;$$

$$l_B = l_B^0 + a l_A^0;$$

$a l_A^0$  and  $b l_B^0$  represent adverse selection induced inventory costs.

## General properties

## Proposition

Given positive  $\delta$ ,  $l_A$ ,  $h$ ,  $g_A$ ,  $g_B$ , and  $0 < w < 1$  and  $0 < l_B < l$ , for any  $\Delta t > 0$  the following are true:

- ①  $\frac{\partial S_{\Delta t}}{\partial l} > w$ ;  $\frac{\partial S_{A;\Delta t}}{\partial l_A} > w$ ; and  $\frac{\partial S_{B;\Delta t}}{\partial l_B} > 0$ ;
- ②  $BA_{\Delta t} = S_{A;\Delta t} - S_{B;\Delta t}$  is positive;
- ③  $\frac{\partial BA_{\Delta t}}{\partial g_A} > 0$ ;  $\frac{\partial BA_{\Delta t}}{\partial g_B} > 0$ ;  $\frac{\partial BA_{\Delta t}}{\partial l_A} > 0$ ; and  $\frac{\partial BA_{\Delta t}}{\partial l_B} > 0$ ;
- ④  $\frac{\partial BA_{\Delta t}}{\partial w} > 0$  if  $g_A > h$ , and  $\frac{\partial BA_{\Delta t}}{\partial h} > 0$  if  $l_A + l_B > g_B$ .

# Market size and activities

# CDS premiums and bid-ask spreads



## Fitting model to data

8 tenors are observed each day, with 8 bid and ask quotes.

$l$ ,  $w$ ,  $h$  do not depend on CDS tenor.

In this version we assume  $\rho = 1$ .  $e^l$  reduce dimensionality by 1 while allowing LGD and PD to be positively correlated.

More empirically driven parametrization can be easily accommodated.

$l_A$ ,  $l_B$ ,  $g_A$ , and  $g_B$  are tenor-specific.

Each is interpolated using splines with exact values at 6 months, 5 years, and 10 years.

Thus, 14 parameters are fitted to 16 observed values each day by minimizing RMSE.

We will use this model like how we use Black-Scholes: constant volatility parameter is backed out and used to forecast future realized volatility.

# Fitting T-Mobile's time-series averages

a) CDS premium

b) Bid-Ask Spreads

CDS Bid-Ask  
Spreads

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# T-Mobile's bid-ask spread components across maturities

# T-Mobile's bid-ask spread components over time

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# Distribution of bid-ask spread components across maturities

# Cross-sectional distribution of bid-ask spread components over time

## Relation with market-wide liquidity

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Table: Regressing the components to the market-wide liquidity

RHS \ LHS	DBAS(5yr)	$\overline{DI}_A$	$\overline{DI}_B$	Dh	$\overline{Dg}_A$	$\overline{Dg}_B$	DI
D NOISE	0.670***	-0.020	0.042	11.412**	-0.009	-0.003	0.569
laggedD NOISE	0.706***	-0.027**	0.039	10.646**	-0.001	0.000	1.526**
lagged LHS	0.057***	-0.214***	-0.205***	-0.185***	-0.269***	-0.196***	-0.128***

# Predicting future CDS premiums



# Predicting future CDS premiums (cont.)

CDS Bid-Ask  
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## High minus low portfolio returns

Table: Double sorting average high-minus-low portfolio returns

Variables	Full sample	Low premium sample	Mid premium sample	High premium sample
$\overline{BAS}$	-0.52	-0.15	-0.68	-0.05
$\overline{I}_A$	0.57*	0.66	0.71	0.41
$\overline{I}_B$	-0.96*	-0.95**	-0.44	-0.64
$\overline{I}_A \quad \overline{I}_B$	1.16**	0.90**	0.61	0.67
$h$	0.42	0.37	0.02	0.29
$\overline{g}_A$	-1.22***	-1.01**	-0.58	-0.94
$\overline{g}_B$	0.00	0.21	-0.42	-0.70

# Misspecification analysis