Dynamic Interactions Between Interest Rate, Credit, and Liquidity Risks: Theory and Evidence from the Term Structure of Credit Default Swap Spreads

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ABSTRACT

Using a large data set on credit default swaps, we study how default risk interacts with interest-rate risk and liquidity risk to jointly determine the term structure of credit spreads. We classify the reference companies into two broad industry sectors, two broad credit rating classes, and two liquidity groups. We develop a class of dynamic term structure models that include (i) two benchmark interest-rate factors to capture the libor and swap rates term structure, (ii) two credit-risk factors to capture the credit swap spreads of high-liquidity group of each industry and rating class, and (iii) both an additional credit-risk factor and a liquidity-risk factor to capture the difference between the high- and low-liquidity groups. Estimation shows that companies in different industry and credit rating classes have different credit-risk dynamics. Nevertheless, in all cases, credit risks exhibit intricate dynamic interactions with the interest-rate factors. Interest-rate factors both affect credit spreads simultaneously, and impact subsequent moves in the credit-risk factors. Within each industry and credit rating class, we also find that the average credit default swap spreads for the high-liquidity group are significantly higher than for the low-liquidity group. Estimation shows that the difference is driven by both credit risk and liquidity differences. The low-liquidity group has a lower default arrival rate and also a much heavier discounting induced by the liquidity risk.

JEL Classification Codes: E43, G12, G13, C51.

Key Words: Credit default swap; credit risk; credit premium; term structure; interest rate risk; liquidity risk; liquidity premium; maximum likelihood estimation.

Dynamic Interactions Between Interest Rate, Credit, and Liquidity Risks: Theory and Evidence from the Term Structure of Credit Default Swap Spreads

It is important to understand how credit risk interacts with interest-rate risk and liquidity risk in determining the term structure of credit spreads on different reference entities. Nevertheless, limited data availability has severely hindered the understanding. Since defaults are rare events that often lead to termination or restructuring of the underlying reference entity, researchers need to rely heavily on cross-sectional averages of different entities over a long history to obtain any reasonable estimates of statistical default probabilities. Although corporate bond prices contain useful information on the default probability and the price of credit risk, the information is often mingled with the pricing of the underlying interest-rate risk and other factors such as liquidity and tax.[1]

The recent development in credit derivatives provides us with an excellent opportunity to better understand the pricing of credit risk, its interactions with interest-rate risk and liquidity, and the impacts on the term structure of credit spreads. The most widely traded credit derivative is in the form of credit default swap (CDS), written on a reference entity such as a sovereign country or a corporate company. According to surveys by the International Swaps and Derivatives Association, Inc., the outstanding notional amount of credit derivatives has reached $8.42 trillion by the end of 2004, more than doubling the size of the total equity derivatives market at $4.15 trillion for the same time period.

In this paper, using a large data set on CDS spread quotes, we perform a joint analysis of the term structure of interest rates, credit spreads, and liquidity premia, with a focus on the dynamic interactions between the three sources of risks. The data set includes daily CDS spread quotes on hundreds of corporate companies and across seven fixed maturities from one to ten years for each company. We classify the reference companies along three dimensions: (i) industry sectors (financial and non-financial), (ii) credit

[1] Many researchers strive to identify and distinguish the different components of corporate bond yields. Prominent examples include Fisher (1959), Jones, Mason, and Rosenfeld (1984), Longstaff and Schwartz (1995), Duffie and Singleton (1997), Duffee (1999), Elton, Gruber, Agrawal, and Mann (2001), Collin-Dufresne, Goldstein, and Martin (2001), Delianedis and Geske (2001), Liu, Longstaff, and Mandell (2000), Eom, Helwege, and Huang (2004), Huang and Huang (2003), Collin-Dufresne, Goldstein, and Helwege (2003), Ericsson and Renault (2005), and Longstaff, Mithal, and Neis (2005).

ratings (A and BBB), and (iii) quote updating frequency (high and low liquidity).[2] We also download from Bloomberg the eurodollar libor and swap rates of matching maturities and sample periods. Through model development and estimation, we address the following fundamental questions regarding credit risk and its dynamic interactions with interest rate and liquidity:

- How many factors govern the term structure of credit spreads?
- How do the credit-risk factors interact with interest-rate factors?
- How do the credit-risk dynamics and pricing differ across industry sectors and credit rating classes?
- What causes the liquidity difference in CDS trading across different reference entities and how does the different liquidity impact the pricing of CDS contracts?

To address these questions, we develop a class of dynamic term structure models of interest-rate risk, credit risk, and liquidity risk. First, we model the term structure of the benchmark libor and swap rates using two interest-rate factors. Second, we assume that the default arrival intensities of the high-liquidity companies at each industry sector and credit rating class are governed by either one or two dynamic factors. We allow changes in the interest-rate factors to affect both contemporaneous and subsequent changes in the credit-risk factors. We link these factors to the instantaneous benchmark interest rate and credit spread via both an affine and a quadratic specification, and compare their relative performance via estimation. Finally, we use an additional default-risk factor and a liquidity risk factor to capture the difference between the credit spreads of the high- and low-liquidity groups within each industry sector and credit rating class.

We estimate the models using a three-step procedure. In the first step, we estimate the interest-rate factor dynamics using the benchmark libor and swap rates. In the second step, we take the interest-rate factors extracted from the first step as given, and estimate the credit-risk dynamics for each industry sector and credit rating class using the average CDS spreads of the high-liquidity group for that sector and rating class. In the third step, we identify the additional credit-risk factor and the liquidity-risk factor using the average CDS spreads in the low-liquidity group. At each step, we cast the models into a state-space form, obtain forecasts on the conditional mean and variance of observed interest rates and CDS spreads using an efficient

[2] There are also data on reference companies with ratings above A or below BBB, but they do not have enough critical mass to be classified along the industry and liquidity dimensions.

nonlinear filtering technique, and build the likelihood function on the forecasting errors of the observed series, assuming that the forecasting errors are normally distributed. We estimate the model parameters by maximizing the likelihood functions.

Comparing the affine and quadratic specifications, we find that the quadratic specification generates better and more uniform performance across the term structure of interest rates and credit spreads. The interest-rate and credit-risk dynamics are also estimated with more precision under the quadratic specification, an indication of less model mis-specification.

Our estimation shows that one affine credit-risk factor can price the moderate-maturity CDS spread well, but the performance deteriorates toward both ends of the credit spread curve. Two affine credit-risk factors can price the whole term structure of credit spreads well. In contrast, under the quadratic specification, one default-risk factor is sufficient to explain over 90 percent of the variation on each of the seven CDS spread series for each industry sector and credit rating class. Adding an additional quadratic credit risk factor does not dramatically improve the performance. Hence, with a nonlinear, richer dynamic specification, one default-risk factor can explain the majority of the credit spread variation in the high-liquidity group.

Our estimation also shows that firms in different industry sectors and credit rating classes exhibit different credit-risk dynamics. In all cases, credit risk shows intricate dynamic interactions with the interest-rate factors. Interest-rate factors both have a contemporaneous impact on the credit spread, and affect subsequent changes in the credit-risk factors.

Within each industry sector and credit rating class, we find that the average CDS spreads for the high-liquidity group are significantly higher than for the low-liquidity group. The mean term structure of credit spreads is also more upward sloping for the high-liquidity group. Estimation shows that the different spreads between the two groups are driven by both credit-risk differences and liquidity differences. On average, the low-liquidity group has lower default arrival rates, and hence a lower instantaneous credit spread. We identify an additional credit-risk factor for the low-liquidity group that is strongly significant. This credit-risk factor shows strong risk-neutral persistence, indicating that it affects the term structure of credit spreads across both short and long maturities. We also identify a highly volatile but less persistent liquidity-risk factor for the credit spreads on the low-liquidity group. This liquidity-risk factor induces a strongly positive instantaneous spread on the discount factor. Thus, low liquidity induces a heavy discounting as a compensation for liquidity premium. Taken together, the lower credit risk and heavier liquidity discounting jointly determine the lower spread on the CDS contracts for the low-liquidity groups.

The remainder of this paper is organized as follows. The next section provides some background information on the CDS contract and the related literature. Section 2 describes the data sets and documents several interesting pieces of stylized evidence on the CDS spreads that motivate our theoretical efforts in Section 3, which develops the dynamic term structure models that allow intricate dynamic interactions between interest-rate risk, credit risk, and liquidity premia. Section 4 describes our model estimation strategy. Section 5 discusses the estimation results. Section 6 concludes.

1. Background Information on Credit Default Swap Spreads

A credit default swap is an over-the-counter contract that provides protection against credit risk. The protection buyer pays a fixed fee or premium, often termed as the "spread," to the seller for a period of time. If a certain pre-specified credit event occurs, the protection seller pays compensation to the protection buyer. A credit event can be a bankruptcy of the reference entity, or a default of a bond or other debt issued by the reference entity. If no credit event occurs during the term of the swap, the protection buyer continues to pay the premium until maturity.

The premium paid by the protection buyer to the seller is quoted in basis points per annum of the contract's notional value and is usually paid quarterly. There are no limits on the size or maturity of CDS contracts. However, most contracts are $10 million in notional. Maturity usually ranges from one to ten years, with the five-year maturity being the most common maturity.

Although the risk profile of a CDS is similar to that of a corporate bond of the reference entity, there are several important differences. A CDS does not require an initial funding, which allows leveraged positions. A CDS transaction can be entered where a cash bond of the reference entity at a particular maturity is not available. Furthermore, by entering a CDS contract as a protection seller, an investor can easily create a short position in the reference credit. With all these attractive attributes, trading activities on CDS contracts have proliferated during the past few years.

This explosive development can be attributed to four sets of players. The largest players in the CDS market are commercial banks. Traditionally, a bank's business involves credit risk since the bank originates loans to corporations. The CDS market offers a bank an attractive way to transfer the credit risk without removing assets from its balance sheet and without involving borrowers. Furthermore, a bank may use CDS contracts to diversify its portfolios, which often are concentrated in certain industries or geographic areas. Banks are the net buyers of credit derivatives. According to Fitch's 2003 survey, global banks hold net bought positions of $229 billion in credit derivatives, with gross sold positions of $1,324 billion.

On the other hand, insurance companies are increasingly becoming dominant participants in the CDS market, primarily as protection sellers, to enhance investment yields. Globally, insurance companies have net sold positions of $137 billion in 2003. Other players include financial guarantors, who are also big proection sellers, have net sold positions of $166 billion. Global hedge funds are also rumored to be active players in the CDS market, although their activities are opaque and not detected on any survey's radar screen.

Sovereign names were prevalent as reference entities in the early days of the CDS market, but the shares of sovereigns as reference entities have declined from over 50 percent in 1997 to less than 10 percent by 2003. In contrast, corporate reference entities have become more common, accounting for over 70 percent of all reference entities in 2003. This shift in reference entities reflects the rapid growth of the corporate bond market after the mid-1990s.

Given the nascent nature of the CDS contracts, academic studies using CDS data are relatively few. Our work constitutes the first comprehensive analysis of the joint term structure of interest rates, credit spreads, and liquidity premia using the CDS data. In related studies, Skinner and Diaz (2003) look at early CDS prices from September 1997 to February 1999 for 31 CDS contracts. They compare the pricing results of the Duffie and Singleton (1999) and Jarrow and Turnbull (1995) models. Blanco, Brennan, and Marsh (2004) compare the CDS spreads with credit spreads derived from corporate bond yields and find that overall the two sources of spreads match each other well. When the two sources of spreads deviate from each other, they find that CDS spreads have a clear lead in price discovery. Longstaff, Mithal, and Neis (2005) regard the spread from the CDS prices as purely due to credit risk and use it as a benchmark to identify the liquidity component of corporate yield spreads. They find that the majority of the corporate spread is due to credit spread. In addition to comparing bond spreads and CDS spreads, Hull, Predescu, and White (2004) examine the relation between the CDS spreads and announcements by rating agencies. Zhang (2005) uses sovereign CDS to study the case of Argentine default. Cremers, Driessen, Maenhout, and Weinbaum (2004) analyze the link between CDS spreads and stock option prices.

2. Data and Evidence

The CDS data are from JP Morgan Chase. They are daily CDS spread quotes on seven fixed maturities at one, two, three, four, five, seven, and ten years from May 21, 2003 to May 12, 2004 on each reference company. We obtain the credit rating information on each reference company from Standard & Poors, and its sector information from Reuters, publicly available on Yahoo.

The data set includes 592 reference companies, 409 of which have the relevant information for credit rating and industry sector available. We classify these companies into two broad industry sectors: financial and corporate. Within each sector, we further classify the companies into five credit rating classes: (1) AA and above, (2) A, including A+ and A-, (3) BBB, including BBB+ and BBB-, (4) BB, including BB+ and BB-, and (5) B and below. Furthermore, the CDS data show substantial differences in updating frequency. Within each industry sector and credit rating class, active quote updates are concentrated on only a few reference companies. To compare the quoting activity across different firms and during different time periods, we first expand each series into daily frequency by filling missing data points with previously available quotes. Then, we take daily differences. If the quotes are not updated between two consecutive days, the daily differences would be zero. Thus, we use the number of days that have non-zero daily quote differences to capture the quote updating frequency for a certain CDS series during a specific time period. As in Collin-Dufresne, Goldstein, and Martin (2001), we use this measure as a proxy for liquidity.

To obtain a general idea on how the CDS spreads vary across different industry sectors, credit rating classes, CDS maturities, and quoting frequencies, we estimate a series of panel regressions:

$$\begin{aligned}\text{Average CDS Spreads}(i,t,t+n) &= a_0 + a_1\ \text{Rating}_A(i,t,t+n) + a_2\ \text{Rating}_{BBB}(i,t,t+n) \\ &\quad + a_3\ \text{Rating}_{BB}(i,t,t+n) + a_4\ \text{Rating}_B(i,t,t+n) + a_5\ \text{Industry}(i) \\ &\quad + a_6\ \text{Maturity}(i) + a_7\ \text{Updates}(i,t,t+n) + e(i,t,t+n), \qquad (1)\end{aligned}$$

where i refers to a specific CDS series, $[t, t+n]$ denotes the sample averaging period, $Rating_j$, with $j = A, BBB, BB, B$ are dummy variables that are equal to one when the reference company has a j-credit rating during the specified sample period and zero otherwise,[3] the *Industry* dummy variable is one for financial firms and zero for non-financial firms, *Maturity* is in number of years, and *Updates* denotes the number of quote updates for the series under the specified time period. We estimate the panel regression with different averaging periods of $n = 30, 60, 90, 120, 150, 255$ days. In the case of $n = 255$, we average across the whole sample and hence the regression becomes purely cross-sectional. To make full use of the data, we generate the average spreads with overlapping sample periods. We estimate equation (1) using the generalized method of moments, with the weighting matrix computed according to Newey and West (1987) and the lags chosen optimally according to Andrews (1991) based on an VAR(1) specification. Table 1 reports the estimates and the absolute magnitudes of the t-statistics (in parentheses) of the panel regressions. The regression is based on 409 reference companies and across seven fixed maturities. Nevertheless, not all companies have CDS quotes available across all seven maturities and over the whole sample periods. The last column in Table 1 reports the actual sample size (N) for each regression.

The estimates are relatively stable across different averaging periods (n). The estimates on the credit rating dummy variables (a_1 to a_4) become increasingly positive as the rating declines. Hence, as expected, the average CDS spreads are higher for lower-credit rating groups. The estimates for the industry dummy variable (a_5) are significantly positive except for the purely cross-sectional regression, the coefficient of which becomes negative but insignificant. The positive estimates suggest that on average financial firms have higher CDS spreads than non-financial firms. The slope estimates on the maturity variable (a_6) are all significantly positive, indicating that the mean term structure of the CDS spreads is upward sloping. Finally, the slope estimates on the updating frequency (a_7) are positive and highly significant, indicating that firms with more frequently updated CDS quotes also have higher CDS spreads. This last piece of evidence is interesting as it points to a liquidity effect on credit spreads that is different from what is observed from corporate bonds, if we regard the updating frequency as a liquidity measure. It has been documented that low-liquidity corporate and Treasury bonds are priced with a discount and hence with a higher yield (Amihud and Mendelson (1991) and Collin-Dufresne, Goldstein, and Martin (2001)). The estimates on a_7 indicate an

[3] If a company experiences rating migrations during $(t, t+n)$, we exclude the company from the regression for this period.

opposite liquidity effect on the CDS spreads: The spreads are higher for more frequently updated and hence more liquid contracts.

To further control the difference in credit default probabilities not captured by the discrete rating classification, we compute a "distance to default" (DD) measure according to the Moody's KMV default model. For this calculation, we use COMPUSTAT quarterly data for the matching sample period to obtain each company's book values of various liabilities, from which we compute a one-year equivalent debt (D) as half of the short-term liabilities and total liabilities. We use weekly equity price and number of shares outstanding data from CRSP daily files from January 2001 to May 12, 2004 to obtain the market value of equity (V_E) and its volatility (σ_E). Then, we solve for the firm value (V_A) and its standard deviation (σ_A) through the following two equations:

$$V_E = V_A N(d_1) - De^{-rT} N(d_2), \quad \sigma_E = \sigma_A \frac{V_A}{V_E} N(d_1), \tag{2}$$

where

$$d_1 = \frac{\ln V_A/D + (r + \sigma_A^2/2)T}{\sigma_A \sqrt{T}}, \quad d_2 = d_1 - \sigma_A \sqrt{T}.$$

The distance to default is computed as

$$\text{DD} = \frac{V_A - D}{V_A \sigma_A \sqrt{T}}. \tag{3}$$

With the computed distance to default, we re-estimate the cross-sectional regression with DD as an additional explanatory variable:

$$\begin{aligned} \text{Average CDS Spreads}(i) &= a_0 + a_1 \text{ Rating}_A(i) + a_2 \text{ Rating}_{BBB}(i) + a_3 \text{ Rating}_{BB}(i) \\ &\quad + a_5 \text{ Industry}(i) + a_6 \text{ Maturity}(i) + a_7 \text{ Updates}(i) + a_8 \text{ DD}(i) + e(i). \end{aligned} \tag{4}$$

We find the relevant information to compute the distance to default on 207 companies, none of which belong to the last credit rating class (B and below). Hence, we no longer have the dummy variable for the B rating class. The results for this regression are reported in the last two rows of Table 1. The DD variable generates a significantly negative coefficient, suggesting that the CDS spread declines with increasing distance to default. Nevertheless, the addition of the distance to default variable does not change the sign of other coefficients. The coefficient on the industry sector becomes positive but remains insignificant, indicating that the industry sector effect is not as strong as other effects. Importantly, the positive effect of updating frequency on the CDS spreads remains strong after controlling for variations in distance to default.

Based on the regression results, we classify the reference companies according the following three dimensions: (i) two broad industry classifications: financial and corporate, (ii) two broad credit rating groups: A (including A+ and A-) and BBB (including BBB+ and BBB-), and (iii) two liquidity groups: high and low. We classify a firm into the high-liquidity group if the quotes on the firm have no fewer than 364 total updates, corresponding to an average of one update per series per week. The low liquidity groups contains firms with less than 364 total updates, but no fewer than 182 quote updates, corresponding to an average updating frequency of at least once per series every two weeks. Then, at each date and maturity, we average the spread quotes across all the firms with each industry sector, credit rating class, and liquidity group. We estimate the credit risk dynamics using the time series of these average CDS spreads on the seven maturities. For this classification and averaging, we discard firms with quotes less than 182 total updates because we regard these quotes as too illiquid to be informative. We also discard firms with credit ratings higher than A and lower than BB because we do not have enough companies within these credit rating classes to make classifications along the industry and liquidity dimensions.

Figure 1 plots the time series of the average credit default swap spreads at each industry sector and credit rating class, with left panels for high-liquidity firms and right panels for low-liquidity firms. The seven lines in each panel correspond to the seven fixed maturities from one to ten years. The spreads were high during the start of our sample following the high default year of 2002. The spreads have declined since then, but have experienced significant variations during our sample period.

[Figure 1 about here.]

From Figure 1, we observe stronger co-movements between the spreads from the two rating groups within each industry sector than across the two industry sectors, evidence of common shocks within each industry sector. Within each industry sector, spreads on the BBB rating class are higher than the corresponding A group, corresponding to the higher default probabilities for the lower rating class. For each industry sector and credit rating class, high-liquidity firms have markedly higher spreads on low-liquidity firms. The last two observations are consistent with our regression analysis results. Overall, the time-series plots show that the behaviors of CDS spreads vary significantly across the three dimensions: industry sector, credit rating, and liquidity.

Figure 2 plots the term structure of the CDS spreads at different dates. During our sample period, the CDS spreads mostly show upward sloping term structures, generating the positive coefficient (a_6) on maturity in the regression analysis. Within each industry sector and rating class, we find that high-liquidity firms not only have wider CDS spreads, but also steeper term structures.

[Figure 2 about here.]

Table 2 reports the summary statistics of the average CDS spreads at the seven fixed maturities under each industry sector, credit rating class, and liquidity group. The mean spreads are higher at longer maturities and hence show upward-sloping mean term structures in all groups. Within each sector and rating class, the high-liquidity group generates much higher mean spreads than the low-liquidity group. The differences are especially large in the financial sector, where the mean spreads on the high-liquidity groups approximately double the mean spreads on the corresponding low-liquidity groups. Across the two credit rating classes, the mean spreads are larger for the BBB class than for the A class. The differences are again larger for the financial sector than for the corporate sector.

The standard deviations of the spreads at various maturities is upward sloping for financial sector and A rating class, but either downward sloping or hump-shaped for other groups. The skewness and excess kurtosis estimates are mostly small. The daily autocorrelation estimates are between 0.96 to 0.99, showing that the spreads are highly persistent.

To obtain the benchmark libor interest rate dynamics, we also download from Bloomberg the eurodollar libor and swap rates that match the maturity and sample period of the credit default swap spreads data. Table 3 reports the summary statistics of the 12-month libor and swap rates at maturities of two, three, four, five, seven, and ten years. The libor and swap rates are relatively low during our sample period, averaging at 1.39 percent for the 12-month libor and from 2.02 to 4.5 percent for the swap rates, generating an upward-sloping mean term structure. The standard deviations of the swap rates at different maturities are close to one another at around 0.4, but the standard deviation of the 12-month libor is about half as much. The skewness estimates are small, positive for the libor and negative for the six swap rates. The excess kurtosis estimates for the swap rates are small, but the estimate for the libor is relatively large at 1.95. The daily autocorrelation is about 0.96 for all the six swap rates, slightly lower at 0.95 for the libor.

3. A Dynamic Term Structure Model of Interest Rate, Default, and Liquidity

We value the credit default swap contract using the framework of Duffie and Singleton (1999), and Duffie, Pedersen, and Singleton (2003). First, we use r_t to denote the instantaneous benchmark interest rate. Historically, researchers often use Treasury yields to define the instantaneous interest rate and the benchmark yield curve. Houweling and Vorst (2003) perform daily calibration of reduced-form models using credit default swap spreads and find that eurodollar swap rates are better suited than the Treasury yields in defining the benchmark yield curve. Here, we define the benchmark instantaneous interest rate based on the eurodollar libor and swap rates. Libor and swap rates contain a credit-risk component. Using them as benchmarks, the estimated credit risk can be regarded as relative credit risk.

Second, we use $\{\lambda_t^i\}_{i=1}^n$ to denote the intensity of a Poisson process that governs the default of a reference entity i. By modeling the dynamics of the Poisson intensities λ_i and their interactions with the benchmark interest rates, we determine the term structure of credit default swap spreads for the high-liquidity group for each industry sector and credit rating class i.

Third, we use $\{q_t^i\}_{i=1}^n$ to denote an instantaneous liquidity spread that captures the liquidity difference between the low-liquidity group and the high-liquidity group within each credit rating and industry class i. To study whether the two liquidity groups also differ in credit risk, we also incorporate an additional credit risk component m_t^i for the low-liquidity group.

Formally, let $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t\geq 0}, \mathbb{Q})$ be a complete stochastic basis and $\mathbb{Q}$ be a risk-neutral probability measure. Under this measure $\mathbb{Q}$, the fair value of a benchmark zero-coupon bond with maturity τ relates to the instantaneous benchmark interest rate dynamics by,

$$P(\tau) = \mathbb{E}\left[\exp\left(-\int_0^\tau r_u du\right)\right], \tag{5}$$

where $\mathbb{E}[\cdot]$ denotes the expectation operator under the risk-neutral measure $\mathbb{Q}$. Our notation implicitly states our focus on time-homogeneous specifications.

We can represent the value of a defaultable coupon-bond in terms of the benchmark instantaneous interest rate r and the Poisson intensity λ of the default arrival by,

$$\begin{aligned} CB(c,w,\tau) &= \mathbb{E}\left[c\int_0^\tau \exp\left(-\int_0^t (r_u+\lambda_u)du\right)dt\right] \\ &+\mathbb{E}\left[\exp\left(-\int_0^\tau (r_u+\lambda_u)du\right)\right] \\ &+\mathbb{E}\left[(1-w)\int_0^\tau \lambda_t \exp\left(-\int_0^t (r_u+\lambda_u)du\right)dt\right], \end{aligned} \tag{6}$$

where c denotes the coupon rate and w denotes the loss rate, which is one minus the recovery rate. For expositional clarity, we assume continuous coupon payments.

For a credit default swap contract, we use S to denote the premium paid by the buyer of default protection. Assuming continuous payment, we can write the present value of the premium leg of the contract as,

$$\text{Premium}(\tau) = \mathbb{E}\left[S\int_0^\tau \exp\left(-\int_0^t (r_u+\lambda_u)du\right)dt\right]. \tag{7}$$

Similarly, the present value of the protection leg of the contract is

$$\text{Protection}(\tau) = \mathbb{E}\left[w\int_0^\tau \lambda_t \exp\left(-\int_0^t (r_u+\lambda_u)du\right)dt\right]. \tag{8}$$

Hence, by setting the present values of the two legs equal, we can solve for the credit default swap spread as

$$S = \frac{\mathbb{E}\left[w\int_0^\tau \lambda_t \exp\left(-\int_0^t (r_u+\lambda_u)du\right)dt\right]}{\mathbb{E}\left[\int_0^\tau \exp\left(-\int_0^t (r_u+\lambda_u)du\right)dt\right]}, \tag{9}$$

which can be thought of as the weighted average of the expected default loss. In model estimation, we discretize the above equation according to quarterly premium payment intervals. Following industry standard, we fix the recovery rate $(1-w)$ at 40 percent.

For an inactively traded credit default swap contract, the premium could potentially include a liquidity component. This liquidity component can also be modeled via an instantaneous liquidity premium spread, q, which enters the credit default swap spread as follows,

$$S = \frac{\mathbb{E}\left[w \int_0^\tau \lambda_t \exp\left(-\int_0^t (r_u + \lambda_u + q_u) du\right) dt\right]}{\mathbb{E}\left[\int_0^\tau \exp\left(-\int_0^t (r_u + \lambda_u + q_u) du\right) dt\right]}. \tag{10}$$

Under this framework, the benchmark libor and swap rate curve is determined by the dynamics of the instantaneous benchmark interest rate r. The CDS spreads of a certain reference entity are determined by the joint dynamics of instantaneous benchmark interest rate r and the default arrival rate λ. Furthermore, when the CDS contract is illiquid, the spreads may also include a liquidity premium that is controlled by the dynamics of the instantaneous liquidity premium spread q. We specify the three sets of dynamics in the following subsections.

3.1. Benchmark interest rate dynamics and the term structure

We use $X \in \mathbb{R}^2$ to denote a two-dimensional vector Markov process that represents the systematic state of the benchmark yield curve. We assume that under the risk-neutral measure $\mathbb{Q}$, the state vector is governed by an Ornstein-Uhlenbeck (OU) process,

$$dX_t = (\theta_x - \kappa_x X_t)\, dt + dW_{xt}, \tag{11}$$

where $\kappa \in \mathbb{R}^{2\times 2}$ controls the mean reversion of the vector process and $\kappa_x^{-1}\theta_x \in \mathbb{R}^2$ controls the long-run mean. For the OU process to be stationary, the real part of the eigenvalues of κ must be positive. For identification reasons, we normalize the state vector to have identity diffusion matrix. We also constrain κ to be a lower triangular matrix. Then, the diagonal values of the κ matrix correspond to its eigenvalues. To maintain stationarity, we constrain the diagonal values of κ_x to be positive in our estimation.

We further assume that the instantaneous benchmark interest rate r is affine in the state vector X,

$$r_t = a_r + b_r^\top X_t, \tag{12}$$

where the parameter $a_r \in \mathbb{R}$ is a scalar and $b_r \in \mathbb{R}^{2+}$ is a vector. Our specifications in (11) and (12) belong to the affine class of term structure models of Duffie and Kan (1996). The model-implied fair value of the zero-coupon bond with maturity τ is exponential affine in the current level of the state vector, X_0,

$$P(X_0,\tau) = \exp\left(-a(\tau) - b(\tau)^\top X_0\right), \tag{13}$$

where the coefficients $a(\tau)$ and $b(\tau)$ are determined by the following ordinary differential equations:

$$\begin{aligned} a'(\tau) &= a_r + b(\tau)^\top \theta_x - b(\tau)^\top b(\tau)/2, \\ b'(\tau) &= b_r - \kappa_x^\top b(\tau), \end{aligned} \tag{14}$$

subject to the boundary conditions $a(0) = 0$ and $b(0) = 0$. The ordinary different equations can be solved via standard numerical procedures. Given the solutions to the zero-coupon bonds, the model-implied values for the libor and swap rates can be computed as

$$LIBOR(X_t,\tau) = \frac{100}{\tau}\left(\frac{1}{P(X_t,\tau)} - 1\right), \quad SWAP(X_t,\tau) = 100h \times \frac{1 - P(X_t,\tau)}{\sum_{i=1}^{h\tau} P(X_t, i/h)}, \tag{15}$$

where τ denotes the time-to-maturity and h denotes the number of payments in each year for the swap contract. The day counting convention for libor is actual over 360, starting two business days forward. For the U.S. dollar swap rates that we use, the number of payments is twice per year, $h = 2$, and the day counting convention is 30/360.

3.2. Default risk dynamics and the term structure of CDS spreads

We assume that the Poisson arrival rate of default underlying each industry sector and credit rating class i, λ_t^i, is governed by a vector of interest-rate factors X and credit-risk factors $Y \in \mathbb{R}^k$:

$$\lambda_t^i = a_i + b_i^\top X_t + c_i^\top Y_t, \tag{16}$$

where $b_i \in \mathbb{R}^2$ denotes the instantaneous response to the two benchmark interest-rate factors X, and $c_i \in \mathbb{R}^{k+}$ denotes the instantaneous response to the credit-risk factors Y. By allowing the default arrival intensity to be an explicit function of the benchmark interest-rate factors, our model specification captures the empirical evidence that credit spreads are related to interest rate levels. For model estimation, we consider both a one-factor and a two factor structure of the credit-risk factors $k = 1,2$ and compare their relative performance.

We assume the following dynamics for the credit-risk factors under the risk-neutral measure $\mathbb{Q}$,

$$dY_t = (\theta_y - \kappa_{xy} X_t - \kappa_y Y_t)\, dt + dW_{yt}, \tag{17}$$

where the benchmark interest-rate factors X_t are also allowed to impact subsequent changes in the credit-risk factors through $\kappa_{xy} \in \mathbb{R}^{2\times k}$. Thus, interest rate factors both have a contemporaneous effect on default arrival rate and affect subsequent changes in the credit-risk factors. For identification, we normalize the instantaneous covariance of Y_t to an identity matrix. In the two-factor specification, we further constrain κ_y to be a lower-triangular matrix with positive diagonal values.

The joint $\mathbb{Q}$-dynamics of $Z = [X^\top, Y^\top] \in \mathbb{R}^{2+k}$ is, in matrix form,

$$dZ_t = (\theta - \kappa Z_t)\, dt + dW_t, \quad \text{with} \quad \theta = \begin{bmatrix} \theta_x \\ \theta_y \end{bmatrix}, \quad \kappa = \begin{bmatrix} \kappa_x & 0 \\ \kappa_{xy} & \kappa_y \end{bmatrix}. \tag{18}$$

Given this compact specification, the present value of the premium leg of the CDS contract becomes,

$$\text{Premium}(Z_0,\tau) = \mathbb{E}\left[S\int_0^\tau \exp\left(-\int_0^t (r_u + \lambda_u) du\right) dt\right] = \mathbb{E}\left[S\int_0^\tau \exp\left(-\int_0^t (a_Z + b_Z^\top Z_u) du\right) dt\right] \tag{19}$$

with $a_Z = a_r + a_i$ and $b_Z = [(b_r + b_i)^\top, c_i^\top]^\top$. The solution is exponential affine in the state vector Z_0,

$$\text{Premium}(Z_0,\tau) = S\int_0^\tau \exp\left(-a(t) - b(t)^\top Z_0\right) dt, \tag{20}$$

where the coefficients $a(t)$ and $b(t)$ are determined by the following ordinary differential equations:

$$\begin{aligned} a'(t) &= a_Z + b(t)^\top \theta - b(t)^\top b(t)/2, \\ b'(t) &= b_Z - \kappa^\top b(t), \end{aligned} \tag{21}$$

subject to the boundary conditions $a(0) = 0$ and $b(0) = 0$.

The present value of the protection leg becomes,

$$\begin{aligned}\text{Protection}(Z_0,\tau) &= \mathbb{E}\left[w\int_0^\tau \lambda_t \exp\left(-\int_0^t (r_u+\lambda_u)du\right)dt\right]\\ &= \mathbb{E}\left[w\int_0^\tau \left(c_Z+d_Z^\top Z_t\right)\exp\left(-\int_0^t (a_Z+b_Z^\top Z_u)du\right)dt\right], \end{aligned} \tag{22}$$

with $c_Z = a_i$ and $d_Z = [b_i^\top, c_i^\top]^\top$. The solution is (e.g., Duffie, Pan, and Singleton (2000)),

$$\text{Protection}(Z_0,\tau) = w\int_0^\tau \left(c(t)+d(t)^\top Z_0\right)\exp\left(-a(t)-b(t)^\top Z_0\right)dt, \tag{23}$$

where the coefficients $[a(t), b(t)]$ are determined by the ordinary differential equations in (21) and the coefficients $[c(t), d(t)]$ are determined by the following ordinary differential equations:

$$c'(t) = d(t)^\top\theta - b(t)^\top d(t), \quad d'(t) = -\kappa^\top d(t), \tag{24}$$

with $c(0) = c_Z$ and $d(0) = d_Z$. The credit default swap spread can then be solved as,

$$S(Z_0,\tau) = \frac{w\int_0^\tau \left(c(t)+d(t)^\top Z_0\right)\exp\left(-a(t)-b(t)^\top Z_0\right)dt}{\int_0^\tau \exp\left(-a(t)-b(t)^\top Z_0\right)dt}. \tag{25}$$

3.3. Liquidity risk and the term structure of liquidity risk premium

For each industry sector and credit rating class, we further classify the companies into high- and low-liquidity groups based on the quote updating frequency. We first estimate the above credit-risk factors using the credit spreads of the high-liquidity group, and then ask whether the difference in credit spreads for the low-liquidity group is due to different credit risk, liquidity risk, or both.

To answer this question, we introduce both an additional credit-risk spread (m_t^i) and a liquidity risk premium (q_t^i) for the low-liquidity group, with the following risk-neutral dynamics,

$$m_t^i = a_m + c_m\xi_t^i, \quad d\xi_t^i = \left(\theta_m - \kappa_m\xi_t^i\right)dt + dW_{mt}, \tag{26}$$

$$q_t^i = a_q + b_q\zeta_t^i, \quad d\zeta_t^i = \left(\theta_q - \kappa_q\zeta_t^i\right)dt + dW_{qt}. \tag{27}$$

Then, the time-0 value of the swap spread at maturity τ can be written as

$$S(Z_0,\tau) = \frac{\mathbb{E}\left[w\int_0^\tau(\lambda_t+m_t)\exp\left(-\int_0^t(r_u+\lambda_u+m_u+q_u)du\right)dt\right]}{\mathbb{E}\left[\int_0^\tau\exp\left(-\int_0^t(r_u+\lambda_u+m_u+q_u)du\right)dt\right]}, \tag{28}$$

where λ_t here refers to the high-liquidity group default arrival rate, q_t denotes an instantaneous liquidity spread induced by the liquidity difference between the high- and low-liquidity group, and m_t captures the difference in default arrival between the high- and low-liquidity group. Thus, $\lambda_t + m_t$ represents the default arrival intensity of the low-liquidity group.

We further expand the definition of the state vector $Z = [X^\top, Y^\top, \xi, \zeta] \in \mathbb{R}^{4+k}$, with

$$\theta = \begin{bmatrix} \theta_x \\ \theta_y \\ \theta_m \\ \theta_q \end{bmatrix}, \quad \kappa = \begin{bmatrix} \kappa_x & 0 & 0 & 0 \\ \kappa_{xy} & \kappa_y & 0 & 0 \\ 0 & 0 & \kappa_m & 0 \\ 0 & 0 & 0 & \kappa_q \end{bmatrix},$$

so that we can write the present values of the premium and protection legs of the swap contract in analogous forms to equations (19) and (23):

$$S(Z_0,\tau) = \frac{\mathbb{E}\left[w\int_0^\tau\left(c_Z+d_Z^\top Z_t\right)\exp\left(-\int_0^t(a_Z+b_Z^\top Z_u)du\right)dt\right]}{\mathbb{E}\left[\int_0^\tau\exp\left(-\int_0^t(a_Z+b_Z^\top Z_u)du\right)dt\right]}. \tag{29}$$

Thus, the solution also takes the same form as in equation (25), with the following redefinitions induced by the state vector expansions:

$$\begin{aligned} a_Z &= a_r + a_i + a_m + a_q, \quad & b_Z &= [(b_r+b_i)^\top, c_i^\top, c_m, b_q]^\top, \\ c_Z &= a_i + a_m, & d_Z &= [b_i^\top, c_i^\top, c_m, 0]^\top. \end{aligned}$$

3.4. Market prices of risks

Our estimation identifies both the risk-neutral and the statistical dynamics of the interest-rate, credit-risk, and liquidity-risk factors. To derive the statistical dynamics, we assume an affine market price of risk on all the risk factors,

$$\gamma(Z_t) = \gamma_0 + \langle \gamma_1 \rangle Z_t \tag{30}$$

with γ_0 and γ_1 are both vectors of the relevant dimension and $\langle \cdot \rangle$ denotes a diagonal matrix, with the diagonal elements given by the vector inside. The affine market price of risk specification dictates that the state vector Z_t remains Ornstein-Uhlenbeck under the statistical measure $\mathbb{P}$, but with an adjustment to the drift term,

$$dZ_t = \left(\theta + \gamma_0 - \kappa^{\mathbb{P}} Z_t\right) dt + dW_t, \quad \kappa^{\mathbb{P}} = \kappa - \gamma_1. \tag{31}$$

For stationarity, we also constrain the diagonal elements of $\kappa^{\mathbb{P}}$ to be positive. For identification, we normalize the long-run mean of the state vector Z to zero under the statistical measure $\mathbb{P}$ so that $\theta = -\gamma_0$.

3.5. Nonlinear interest-rate and default arrival dynamics: A quadratic specification

The affine framework employed in the above specifications enjoys great analytical tractability and popularity. Nevertheless, several studies identify nonlinearity in interest rate dynamics, e.g., Aït-Sahalia (1996a,b), Hong and Li (2005), and Stanton (1997). In this subsection, we propose an alternative class of models that are equally tractable but can generate richer nonlinear interest-rate and default arrival dynamics. While maintaining the same factor dynamics, we now let the instantaneous interest rate and credit spread be a quadratic function of the factors:

$$r_t = a_r + X_t^\top \langle b_r \rangle X_t, \quad \lambda_t^i = a_i + X_t^\top \langle b_i \rangle X_t + Y_t^\top \langle c_i \rangle Y_t. \tag{32}$$

The quadratic specification in (32) has the same number of model parameters as the previous affine specification. According to Leippold and Wu (2002), the benchmark zero-coupon bond price becomes exponential quadratic in the state vector,

$$P(X_0,\tau) = \exp(-a(\tau) - b(\tau)^\top X_0 - X_0^\top B(\tau) X_0), \tag{33}$$

with the coefficients solving the following ordinary differential equations,

$$\begin{aligned} a'(\tau) &= a_r + b(\tau)^\top \theta_x + \mathtt{tr} B(\tau) - b(\tau)^\top b(\tau)/2, \\ b'(\tau) &= 2B(\tau)\theta_x - \kappa_x^\top b(\tau) - 2B(\tau) b(\tau), \\ B'(\tau) &= \langle b_r \rangle - B(\tau)\kappa_x - \kappa_x^\top B(\tau) - 2B(\tau)^2, \end{aligned} \tag{34}$$

starting at $B(0) = 0$, $b(0) = 0$ and $a(0) = 0$.

Analogously, we can derive the credit default swap premium as

$$S(Z_0,\tau) = \frac{w \int_0^\tau \left(c(t) + d(t)^\top Z_0 + Z_0^\top D(t) Z_0\right) \exp\left(-a(t) - Z_0^\top b(t) Z_0\right)}{\int_0^\tau \exp\left(-a(t) - b(t)^\top Z_0 - Z_0^\top B(t) Z_0\right)}, \tag{35}$$

with the coefficients solving the following ordinary differential equations:

$$\begin{aligned} a'(\tau) &= a_Z + b(\tau)^\top \theta + \mathtt{tr} B(\tau) - b(\tau)^\top b(\tau)/2, \\ b'(\tau) &= l_Z + 2B(\tau)\theta - \kappa^\top b(\tau) - 2B(\tau) b(\tau), \\ B'(\tau) &= \langle b_Z \rangle - B(\tau)\kappa - \kappa^\top B(\tau) - 2B(\tau)^2, \\ c'(t) &= d(\tau)^\top \theta + \mathtt{tr} D(\tau) - d(\tau)^\top b(\tau), \\ d'(t) &= 2D(t)\theta - \kappa^\top d(t) - 2D(t) b(t) - 2B(t) d(t), \\ D'(t) &= -D(t)\kappa - \kappa^\top D(t) - 4B(t) D(t), \end{aligned} \tag{36}$$

starting at $a(0) = 0$, $b(0) = 0$, $B(0) = 0$, $c(0) = c_Z$, $d(0) = 0$, and $D(0) = \langle d_Z \rangle$. In equation (36), l_Z is a vector of zeros, which will become nonzero in the presence of linear liquidity or credit risk factors. The details of the derivation are available upon request.

Since the signs of the idiosyncratic credit risk premium (m_t) and the idiosyncratic liquidity premium (q_t) can be either negative or positive, it is appropriate to maintain the original Gaussian affine assumption on both. In the presence of these two risk factors, the pricing formula for the credit default swap retains the same form as in (35), only with a corresponding expansion on the state vector $Z = [X^\top, Y^\top, \xi, \zeta]^\top$ and the following redefinitions on the coefficients: $a_Z = a_r + a_i + a_m + a_q$, $l_Z = [0, 0, c_m, b_q]^\top$, $b_Z = [(b_r + b_i)^\top, c_i^\top, 0, 0]^\top$, $c_Z = a_i + a_m$, and $d_Z = [b_i^\top, c_i^\top, 0, 0]^\top$. Furthermore, the initial condition on $d(0)$ adjusts from zero to $d(0) = [0, 0, c_m, 0]^\top$.

4. Estimation Strategy

We estimate the dynamics of benchmark interest-rate risk, credit risk, and liquidity risk in three consecutive steps, all using a quasi-maximum likelihood method. At each step, we cast the models into a state-space form, obtain efficient forecasts on the conditional mean and variance of observed interest rates and credit default swap spreads using an efficient nonlinear filtering technique, and build the likelihood function on the forecasting errors of the observed series, assuming that the forecasting errors are normally distributed. The model parameters are estimated by maximizing the likelihood function.

In the first step, we estimate the interest-rate factor dynamics using libor and swap rates. In the state-space form, we regard the two interest-rate factors (X) as the unobservable states and specify the state-propagation equation using an Euler approximation of statistical dynamics of the interest-rate factors embedded in equation (31):

$$X_t = \Phi_x X_{t-1} + \sqrt{\mathcal{Q}_x}\varepsilon_{xt}, \tag{37}$$

where $\Phi_x = \exp(-\kappa_x^{\mathbb{P}} \Delta t)$ denotes the autocorrelation matrix of X, $\mathcal{Q}_x = I\Delta t$ denotes the instantaneous covariance matrix of X, with I denoting an identity matrix of the relevant dimension and $\Delta t = 1/252$ denoting the daily frequency, and ε_{xt} denotes a two-dimensional i.i.d. standard normal innovation vector. The measurement equations are constructed based on the observed libor and swap rates, assuming additive, normally-distributed measurement errors,

$$y_t = \begin{bmatrix} LIBOR(X_t, i) \\ SWAP(X_t, j) \end{bmatrix} + e_t, \quad cov(e_t) = \mathcal{R}, \qquad \begin{array}{l} i = 12 \text{ months}, \\ j = 2, 3, 4, 5, 7, 10 \text{ years}. \end{array} \tag{38}$$

In the second step, we take the estimated interest-rate factor dynamics in the first step as given, and estimate the credit-risk factor dynamics (Y) at each industry sector and credit rating class using the seven average credit default swap spread series for the high-liquidity groups. The state-propagation equation is an Euler approximation of statistical dynamics of the credit-risk factors embedded in equation (31):

$$Y_t = \Phi_y Y_{t-1} + \sqrt{\mathcal{Q}_y}\varepsilon_{yt}, \tag{39}$$

with $\Phi_y = \exp(-\kappa_y^{\mathbb{P}}\Delta t)$, $\mathcal{Q}_y = I\Delta t$, and ε_{yt} being a k-dimensional i.i.d. standard normal innovation vector. We estimate models with both $k = 1$ and $k = 2$. The measurement equations are defined on the CDS spreads at the seven maturities,

$$y_t = S(X_t, Y_t, \tau, i) + e_t, \quad cov(e_t) = \mathcal{R}, \tau = 1, 2, 3, 4, 5, 7, 10 \text{ years}, \tag{40}$$

where $i = 1, 2, 3, 4$ denotes the ith industry sector and credit rating class. We repeat this step eight times, for both one and two credit risk factors and for each of two industry sectors and two credit rating classes.

In the third step, we estimate the additional credit-risk factor (m_t) and liquidity-risk factor (q_t) dynamics for each industry sector and credit rating class using the CDS spreads on the low-liquidity firms. The state-propagation equation is an Euler approximation of the factor dynamics in (26) and (27):

$$\begin{bmatrix} \xi_t \\ \zeta_t \end{bmatrix} = \Phi_q \begin{bmatrix} \xi_{t-1} \\ \zeta_{t-1} \end{bmatrix} + \sqrt{\mathcal{Q}_q}\varepsilon_{qt}, \tag{41}$$

with $\Phi_q = \langle \exp(-\kappa_m^{\mathbb{P}}\Delta t), \exp(-\kappa_q^{\mathbb{P}}\Delta t)\rangle$, $\mathcal{Q}_q = I\Delta t$, and ε_{qt} being a two-dimensional i.i.d. standard normal innovation vector. The measurement equations are on the seven average CDS spreads for the low-liquidity firms at each industry and credit rating class i,

$$y_t = S(X_t, Y_t, \xi_t, \zeta_t, \tau, i) + e_t, \quad cov(e_t) = \mathcal{R}, \quad \tau = 1, 2, 3, 4, 5, 7, 10 \text{ years}. \tag{42}$$

We repeat this step on each of two industry sectors and two credit rating classes.

Given the definition of the state-propagation equation and measurement equations at each step, we use an extended version of the Kalman filter to filter out the mean and covariance matrix of the state variables conditional on the observed series, and construct the predictive mean and covariance matrix of the observed series based on the filtered state variables. Then, we define the daily log likelihood function assuming normal forecasting errors on the observed series:

$$l_{t+1}(\Theta) = -\frac{1}{2}\log\left|\overline{V}_{t+1}\right| - \frac{1}{2}\left(\left(y_{t+1}-\bar{y}_{t+1}\right)^{\top}\left(\overline{V}_{t+1}\right)^{-1}\left(y_{t+1}-\bar{y}_{t+1}\right)\right), \tag{43}$$

where $\bar{y}$ and $\overline{V}$ denote the conditional mean and variance forecasts on the observed series, respectively. The model parameters, Θ, are estimated by maximizing the sum of the daily log likelihood values,

$$\Theta \equiv \arg\max_{\Theta} \mathcal{L}(\Theta, \{y_t\}_{t=1}^{N}), \quad \texttt{with} \quad \mathcal{L}(\Theta, \{y_t\}_{t=1}^{N}) = \sum_{t=0}^{N-1} l_{t+1}(\Theta), \tag{44}$$

where $N = 256$ denotes the number of observations for each series. For each step, we assume that the measurement errors on each series are independent but with distinct variance.

5. Term Structure of Interest Rates, Credit Spreads, and Liquidity Premia

First, we summarize the performance of the different dynamic term structure models in pricing interest rates and credit default swap spreads. Then, from the estimated model parameters we analyze the dynamics and pricing of benchmark interest-rate risk, credit risk, and liquidity risk, and their impacts on the term structure of interest rates, credit spreads, and liquidity premia.

5.1. Model performance

Table 4 reports the summary statistics on the pricing errors of libor and swap rates under the two-factor affine and quadratic model specifications. The affine model explains the swap rates well, but fails miserably in explaining the 12-month libor. The discrepancy between libor and swap rates is well known in the industry. Nevertheless, the very poor performance reveals some deficiency of the two-factor affine specification. In contrast, the quadratic model performs much better on the libor series. Its performance across the six swap rates is also more uniform. Thus, the richer, nonlinear dynamic specification of the quadratic model captures the joint term structure of the libor and swap rates better.

The maximized log likelihood values ($\mathcal{L}$) are 5067.1 for the affine model and 5229.7 for the quadratic model, also indicating superior performance from the quadratic model. Since these two models are not nested, we cannot employ the standard likelihood ratio tests to gauge the significance of the likelihood difference. Nevertheless, we follow Vuong (1989) in constructing a statistic based on the difference between the daily log likelihood values from the two non-nested models:

$$lr_t = l_t^Q - l_t^A \tag{45}$$

where l_t^Q and l_t^A denote the time-t log likelihood value of the quadratic and affine models, respectively. Vuong constructs a statistic based on the likelihood ratio:

$$\mathcal{M} = \sqrt{T}\mu_{lr}/\sigma_{lr}, \tag{46}$$

where μ_{lr} and σ_{lr} denote the sample mean and standard deviation of the log likelihood ratio. Under the null hypothesis that the two models are equivalent, Vuong proves that $\mathcal{M}$ has an asymptotic normal distribution with zero mean and unit variance. We construct the log likelihood ratio, and estimate the sample mean at 0.6352, and sample standard deviation at 3.0054. The standard deviation calculation adjusts for serial dependence according to Newey and West (1987), with the number of lags chosen optimally according to Andrews (1991) based on an AR(1) specification. The $\mathcal{M}$-statistic is estimated at 3.38, indicating that the quadratic model performs significantly better than the affine model in explaining the benchmark libor term structure.

Table 5 reports the summary statistics of the pricing errors of the credit default swap spreads on the high-liquidity firms using one credit risk factor for both the affine and the quadratic specifications. The affine model provides an almost perfect fit for the four-year CDS spread, but the performance deteriorates toward both short (one year) and long (ten year) maturities. In contrast, the performance of the quadratic specification is more uniform across different maturities. Under the quadratic specification, one credit risk factor, together with the previously identified two benchmark interest-rate factors, can explain all CDS spread series by over 90 percent. The one-factor quadratic model also generates higher likelihood values than the corresponding affine model for each of the four industry sector and credit rating classes, but the differences are not statistically significant in terms of the Vuong (1989) statistic.

For comparison, we also estimate models with two credit-risk factors. Table 6 reports the summary statistics of the pricing errors. Adding one additional credit risk factor significantly improves the performance of the affine model at the two ends of the CDS term structure. Two affine factors explain over 98 percent of the credit spread variations except for one series. With the quadratic specification, since one credit risk factor performs reasonably well, adding another credit-risk factor does not generate as much improvement. With two credit-risk factors, the maximized likelihood values from the affine and quadratic specifications are close to one another. The quadratic specification no longer dominates the affine specification.

To account for the different movements of CDS spreads for the low-liquidity firms, we introduce an additional credit-risk factor and a liquidity factor in addition to the two benchmark interest-rate factors and the two credit-risk factors identified from the CDS spreads on high-liquidity firms. Table 7 reports the summary statistics of the pricing errors on the CDS spreads for the low-liquidity firms. These two additional factors can explain most of the different variations in the low-liquidity groups. Most series can be explained over 95 percent.

Overall, two interest-rate factors, especially in the quadratic forms, can explain the term structure of the benchmark interest rates well. Two additional credit-risk factors are more than enough to explain the term structure of credit spreads for high-liquidity firms under each industry sector and rating class. Finally, by incorporating an additional credit risk factor and a liquidity risk factor, the model also performs well in explaining the term structure of credit spreads on low-liquidity firms

5.2. Dynamics and term structure of benchmark interest rates

Table 8 reports the parameter estimates and the absolute magnitudes of the t-statistics (in parentheses) that govern the dynamics and term structure of benchmark libor and swap rates. Under both affine and the quadratic specifications, κ_x determines the mean-reversion of the interest-rate factor X under the risk-neutral measure $\mathbb{Q}$. The small estimates on the diagonal elements of κ_x capture the persistence of interest rates. The significantly negative estimates on the off-diagonal element suggest that positive shocks to the first factor impact positively on subsequent moves in the second factor.

The estimates for the constant part of the market price of risk γ_{x0} are negative for both factors under the affine model. Under the quadratic model, the market price is positive on the first factor and negative on the second factor. The proportional coefficients estimates, γ_{x1}, are small and not statistically different from zero for both factors under the affine specification, indicating that the market price of risk does not vary significantly with the factor level. The estimates under the quadratic model are also small and only statistically significant for the first factor.

The estimates on b_r capture the contemporaneous impact of the two interest-rate factors on the instantaneous interest rate. Under both models, the estimates suggest that the second factor has a stronger contemporaneous impact on the instantaneous interest rate. The coefficients interact with the risk-neutral factor dynamics (κ_x) to determine the response of the whole yield curve to unit shocks from the interest-rate factors. Under the affine model, the contemporaneous responses of the continuously compounded spot rate to the two dynamic factors are linear, with $a(\tau)/\tau$ measuring the mean term structure and $b(\tau)/\tau$ measuring the response coefficients. Equation (14) shows how a_r, γ_{x0}, b_r, and κ interact to determine $a(\tau)$ and $b(\tau)$. Figure 3 plots $a(\tau)/\tau$ (left panel) and $b(\tau)/\tau$ (right panel) as a function of maturity τ under the affine model. The solid line in the left panel shows an upward sloping mean term structure. In the right panel, the solid line represents the first element of $b(\tau)/\tau$, which captures the contemporaneous response of the spot rate curve to the first interest-rate factor. This factor's impact is stronger at longer maturities than at shorter maturities. The dashed line plots the impact of the second factor, which is stronger at the short end of the yield curve. The different impulse-response patterns relate not only to the different magnitudes of the two elements of the b_r estimates, but also to the difference in risk-neutral persistence between the two factors. Under the affine model, the first factor is estimated to be more persistent than the second factor. Hence, the impact of the first factor extends to longer maturities.

[Figure 3 about here.]

5.3. Default arrival dynamics and the term structure of credit spreads

Tables 9 and 10 report the parameter estimates and t-statistics on the dynamics and pricing of the default arrival rate for high-liquidity firms under each industry sector and credit rating class. Tables 9 reports estimates on the one-factor credit-risk specification. Tables 10 reports estimates on the two-factor credit-risk specification. The two tables reveal several common features about the default arrival rate dynamics.

First, the default arrival intensity shows intricate dynamic interactions with the interest-rate factors. The κ_{xy} matrix captures the predictive power of interest-rate factors on the default risk factors, whereas the b_i vector captures the contemporaneous impact of the interest-rate factors on the default arrival λ^i. Estimates on both sets of parameters are significant in most cases, indicating that the interest-rate factors both predict default arrivals via the drift dynamics κ_{xy} and impact the default arrivals contemporaneously via the coefficients b_i.

Second, the estimates on κ_y under the one-factor affine model are very small and not significantly different from zero. Under the two-factor affine specification, the estimates for one of the diagonal elements of κ_y are close to zero. The small estimates indicate a near unit root behavior for the credit risk dynamics. The estimates under the quadratic specification are larger and also with better precision (larger t-values). Thus, with a nonlinear structure under the quadratic model, we can more accurately identify a more stationary credit-risk dynamics, while delivering a better and more uniform pricing performance on CDS spreads across all maturities.

Nevertheless, we also observe that the credit-risk dynamics and the market prices vary significantly across different industry sectors and rating classes. These different dynamics and pricing generate distinct term structure behaviors for the CDS spreads. Based on the model parameter estimates for the two-factor affine credit-risk specification in Table 10, we compute $b^i(\tau)/\tau$ as a function of maturity τ. Figure 4 plots the third (solid lines) and fourth (dashed lines) elements of $b^i(\tau)/\tau$ under each industry sector and rating class. These two lines represent the contemporaneous response of the continuously compounded spot rate to unit shocks in the two credit-risk factors. Since the credit-risk factors do not enter the benchmark interest-rate curve, the lines also directly measure the impact on the credit spread between the corporate spot rate and the libor spot rate.

[Figure 4 about here.]

Under all four industry and credit rating classifications, the contemporaneous impacts of the two credit-risk factors are downward sloping along the term structure of credit spreads. Nevertheless, the impact patterns show noticeable differences between the financial and corporate sectors. The factor responses in the financial sector present an exponential decay with increasing maturities, but in the corporate sector the responses are approximately linear along the term structure. Furthermore, the loading differences between the two credit rating classes are much larger in the financial sector than in the corporate sector, suggesting that financial firms are more sensitive to rating changes between A and BBB classes. A lower rating generates much larger spreads for the financial firms.

5.4. Liquidity risk and liquidity premia

The liquidity of the CDS contracts as revealed by the quote updating frequency varies greatly across different reference companies. Within each industry sector and credit rating class, the liquidity is concentrated on a few firms. An important question is what makes investors concentrate the trading on one company versus another. Also important is to understand whether and how the liquidity difference impacts the pricing of CDS contracts.

Table 11 reports the parameter estimates and t-statistics (in parentheses) on the additional credit-risk factor and the liquidity-risk factor that account for the different movements of the CDS spreads underlying the low-liquidity firms. The loading parameter estimates on the additional credit-risk factor (c_m) are strongly significant, showing that the default arrival rates for firms in the low-liquidity groups have their own movements that are independent of the default arrival dynamics identified from the corresponding high-liquidity group within the same industry sector and credit rating class.

The estimates on the intercept a_m are negative under all four classifications and for both model specifications. The negative intercept estimates suggest that firms in the low-liquidity group on average have lower default risk and hence experience lower instantaneous credit spreads than firms in the corresponding high-liquidity group. This observation is intriguing. It implies that, within the same industry and credit rating class, firms with active CDS trading activities are associated with higher perceived credit risk than firms with less active CDS trading activities. Either investors choose to trade CDS contracts on firms that they perceive to have higher chances of downward rating migrations, or that high-profile firms generate more awareness of its potential risk of default.

The instantaneous loading estimates on the liquidity-risk factor (b_q) are large in magnitudes and also highly significant, showing that liquidity plays a key role in the credit spread differences between the two liquidity groups. The intercept estimates on a_q are all positive, suggesting a higher discounting for the low-liquidity contracts. Therefore, the lower average CDS spreads on low-liquidity firms can be attributed to a combination of low credit risk and high liquidity discounting.

The estimates on κ_m, which measures the risk-neutral mean-reversion behavior of the credit-risk factor, are very small, suggesting that this credit-risk factor has highly persistent risk-neutral dynamics, similar to the credit-risk factors identified from the high-liquidity groups. Hence, this credit-risk factor impacts the term structure of credit spreads across all maturities.

In contrast, the estimates on the risk-neutral mean-reversion parameter κ_q for the liquidity-risk factor are much larger and are highly significant, suggesting that the liquidity-risk factor has a more transient impact on the term structure of discounting. Based on the parameter estimates, Figure 5 plots the contemporaneous response of the continuously compounded spot rates to unit shocks from the additional credit-risk factor (solid lines, in basis points) and the liquidity-risk factor (dashed lines, in percentage points) under the affine specification. Consistent with the difference in dynamics, the response patterns on the two factors are quite different. The impacts of the persistent credit-risk factor are relatively uniform across the whole term structure, whereas the impacts of the more transient liquidity-risk factor decline steadily as the maturity increases.

[Figure 5 about here.]

The market also prices the credit-risk factor and liquidity-risk factor differently. The estimates for γ_{m0} are negative and statistically significant in most cases, indicating that this additional credit-risk factor has a negative market price of risk. The negative market price of risk implies a positive risk-neutral drift (θ) for the credit-risk factor. As suggested by the ordinary differential equations in (21), a positive θ for the credit-risk factor helps generate an upward sloping mean term structure of credit spreads. On the other hand, the estimates on the pricing of the liquidity risk (γ_{q0}) are significantly positive in five cases, and negative but statistically insignificant in the other three cases. The positive market prices on the liquidity-risk factor generate a downward-sloping effect on the term structure of credit spreads. As a result, the CDS spreads on the low-liquidity firms have a flatter mean term structure than the CDS spreads on the high-liquidity firms.

Overall, our estimation suggests that within the same industry sector and credit rating class, firms with active CDS trading activities tend to have higher credit risks than firms with low CDS trading activities. Furthermore, low-liquidity firms induce heavier discounting on the yield curve and generate lower CDS spreads. Finally, positive market pricing on the liquidity-risk renders the mean term structure of CDS spreads flatter on low-liquidity firms.

6. Conclusion

Using a large data set on CDS spread quotes, we perform a comprehensive analysis of the term structure of interest rates, credit spreads, and liquidity premia. Through model construction and estimation, we find that credit-risk dynamics differ across different industry sectors and credit rating groups, but in all cases they show intricate interactions with the interest-rate dynamics and liquidity.

Interest-rate factors both affect credit spreads simultaneously, and impact subsequent moves in the credit-risk factors. Within each industry and credit rating class, we also find that the average credit default swap spreads for the high-liquidity group are significantly higher than for the low-liquidity group. Estimation shows that the difference is driven by both credit risk and liquidity differences. The low-liquidity group has a lower default arrival rate and also a much heavier discounting induced by the liquidity risk.

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Table 1

Regression analysis of the CDS spreads

Entries report the estimates and the absolute magnitudes of the t-statistics (in parentheses) of various versions of the following panel regressions:

$$\begin{aligned}\text{Average CDS Spreads}(i,t,t+n) &= a_0 + a_1 \text{ Rating}_A(i,t,t+n) + a_2 \text{ Rating}_{BBB}(i,t,t+n) \\ &+ a_3 \text{ Rating}_{BB}(i,t,t+n) + a_4 \text{ Rating}_B(i,t,t+n) + a_5 \text{ Industry}(i) \\ &+ a_6 \text{ Maturity}(i) + a_7 \text{ Updates}(i,t,t+n) + a_8 \text{DD} + e(i,t,t+n),\end{aligned}$$

where i refers to a specific CDS series, $(t,t+n)$ denotes the sample averaging period, $Rating_j$, $j = A, BBB, BB, B$ are dummy variables that are equal to one when the reference company has a j-credit rating during the specified sample period and zero otherwise, the *Industry* dummy variable is one for financial firms and zero for non-financial firms, *Maturity* is in number of years, *Updates* denotes the number of quote updates for the series under the specified time period, and *DD* denotes the distance to default computed using Moody's default model. We estimate the panel regression with different averaging periods of $n = 30, 60, 90, 120, 150, 255$ days. In the case of $n = 255$, we average across the whole sample and hence the regression becomes purely cross-sectional. We estimate the equations using the generalized method of moments, with the weighting matrix constructed according to Newey and West (1987). The last column reports the sample size (N) for each regression.

n	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	N
30	-16.609	6.132	53.025	238.538	547.290	18.239	4.314	3.928	—	414,926
	(40.02)	(25.17)	(155.07)	(267.74)	(92.95)	(57.54)	(53.78)	(69.82)	—	
60	-17.588	4.173	47.843	231.050	677.572	17.496	4.216	2.306	—	349,254
	(42.21)	(17.07)	(131.72)	(234.59)	(66.96)	(55.12)	(54.69)	(77.23)	—	
90	-18.706	3.062	45.054	219.100	764.298	17.692	4.137	1.710	—	290,545
	(42.92)	(12.47)	(116.07)	(205.63)	(61.87)	(54.56)	(54.21)	(83.43)	—	
120	-19.321	2.476	43.388	213.024	790.661	17.741	4.086	1.372	—	234,482
	(41.24)	(9.49)	(101.18)	(186.98)	(58.45)	(51.85)	(51.05)	(82.25)	—	
150	-19.599	2.294	43.051	213.497	809.851	17.844	4.038	1.125	—	178,916
	(37.20)	(7.86)	(87.92)	(168.63)	(53.00)	(47.02)	(45.40)	(75.35)	—	
180	-20.022	2.237	43.299	216.469	832.460	18.110	3.996	0.953	—	123,356
	(31.54)	(6.43)	(73.45)	(142.23)	(45.38)	(40.02)	(37.74)	(64.73)	—	
255	-4.972	5.213	21.085	231.191	1499.524	-0.559	4.205	0.445	—	1,425
	(1.89)	(4.44)	(9.15)	(19.89)	(21.63)	(-0.37)	(7.97)	(9.50)	—	
255	2.631	11.505	50.218	223.584	—	5.416	2.805	0.498	-1.391	620
	(0.36)	(1.94)	(7.88)	(25.80)	—	(1.02)	(3.12)	(10.69)	(4.00)	

Table 2

Summary statistics of credit default swap spreads

Entries report the summary statistics of the credit default swap spreads (in basis points) at the seven fixed maturities under each credit rating class, industry sector, and liquidity groups. Mean, Std, Skew, Kurtosis, and Auto denote the sample estimates of the mean, standard deviation, skewness, excess kurtosis, and the first-order autocorrelation, respectively. Data are daily from May 21, 2003 to May 12, 2004.

Maturity	High Liquidity					Low Liquidity				
Years	Mean	Std	Skew	Kurtosis	Auto	Mean	Std	Skew	Kurtosis	Auto
(i) Sector: Financial; Rating: A										
1	30.16	8.72	1.00	-0.33	0.98	14.53	4.70	1.59	2.46	0.97
2	39.41	10.34	0.95	-0.38	0.98	20.13	6.27	1.51	2.20	0.97
3	43.03	11.04	0.96	-0.36	0.98	22.08	6.85	1.47	2.13	0.97
4	49.69	12.41	0.91	-0.43	0.98	25.75	7.31	1.54	2.57	0.97
5	54.42	13.36	0.89	-0.49	0.98	28.35	7.67	1.58	2.75	0.97
7	61.29	13.43	0.84	-0.39	0.98	31.92	7.85	1.55	2.96	0.97
10	68.68	13.67	0.71	-0.57	0.98	35.30	8.16	1.47	2.95	0.97
(ii) Sector: Financial; Rating: BBB										
1	92.68	25.42	0.27	-1.16	0.98	51.64	12.62	0.76	-0.62	0.98
2	100.30	25.51	0.39	-1.13	0.98	55.65	14.09	0.74	-0.77	0.98
3	103.69	25.87	0.39	-1.13	0.98	56.89	14.73	0.73	-0.81	0.98
4	108.55	25.00	0.46	-1.08	0.98	58.50	12.94	0.82	-0.54	0.98
5	111.83	24.61	0.48	-1.04	0.98	60.01	11.76	0.88	-0.32	0.98
7	117.29	22.51	0.32	-1.17	0.98	60.96	9.23	0.85	0.04	0.97
10	123.18	20.52	0.16	-1.28	0.98	63.56	7.04	0.28	-0.22	0.96
(iii) Sector: Corporate; Rating: A										
1	28.85	8.17	0.78	-0.43	0.98	26.93	5.07	0.97	0.92	0.98
2	39.67	9.55	0.64	-0.77	0.98	31.37	5.39	0.54	0.23	0.98
3	43.77	10.01	0.64	-0.79	0.98	32.93	5.54	0.44	0.09	0.98
4	48.88	10.38	0.72	-0.56	0.98	36.52	5.78	0.32	-0.04	0.98
5	52.34	10.62	0.76	-0.42	0.98	39.06	5.92	0.23	-0.15	0.98
7	58.29	10.31	0.67	-0.42	0.98	41.78	5.62	-0.07	-1.02	0.99
10	64.46	9.57	0.46	-0.50	0.98	45.25	6.11	0.34	-1.06	0.99
(iv) Sector: Corporate; Rating: BBB										
1	63.35	17.89	1.30	0.88	0.98	39.55	6.49	0.51	0.05	0.98
2	75.09	19.31	1.22	0.64	0.98	46.26	7.04	0.37	0.12	0.98
3	79.17	19.76	1.20	0.58	0.98	48.61	7.16	0.31	0.12	0.98
4	83.66	19.28	1.15	0.38	0.98	52.21	6.92	0.00	-0.11	0.98
5	86.71	19.00	1.11	0.28	0.98	54.79	6.82	-0.16	-0.31	0.98
7	91.97	17.14	1.08	0.28	0.98	58.41	6.51	-0.31	-0.94	0.98
10	97.23	15.31	0.97	0.19	0.98	62.89	7.13	-0.00	-1.19	0.98

Table 3
Summary statistics of libor and swap rates
Entries report the summary statistics of the U.S. dollar libor at one-year maturity and swap rates at two, three, four, five, seven, and ten years. Mean, Std, Skew, Kurtosis, and Auto denote the sample estimates of the mean, standard deviation, skewness, excess kurtosis, and the first-order autocorrelation, respectively. Data are daily from May 21, 2003 to May 12, 2004.

Maturity (Years)	Mean	Std	Skew	Kurtosis	Auto
1	1.39	0.18	0.68	1.95	0.95
2	2.02	0.33	-0.01	0.45	0.96
3	2.60	0.39	-0.38	0.28	0.96
4	3.07	0.42	-0.55	0.23	0.96
5	3.45	0.43	-0.62	0.16	0.96
7	3.99	0.42	-0.68	0.11	0.96
10	4.50	0.40	-0.73	0.09	0.96

Table 4

Summary statistics of pricing errors on the libor and swap rates

Entries report the summary statistics of the pricing errors on the U.S. dollar libor and swap rates under the two-factor Gaussian affine model (left hand side under "Affine") and the two-factor Gaussian quadratic model (left hand side under "Quadratic"). We estimate both models by using quasi-maximum likelihood method joint with unscented Kalman filter. We define the pricing error as the difference between the observed interest rate quotes and the model-implied fair values, in basis points. The columns titled Mean, Std, Auto, Max, and VR denote, respectively, the sample mean, the standard deviation, the first-order autocorrelation, the maximum absolute error, and the explained percentage variance, defined as one minus the ratio of pricing error variance to interest rate variance, in percentages. The last row reports the maximized log likelihood for each model.

Maturity	Affine					Quadratic				
Years	Mean	Std	Auto	Max	VR	Mean	Std	Auto	Max	VR
1	7.56	17.35	0.91	46.89	5.08	-1.53	7.99	0.78	33.21	79.85
2	-0.23	4.09	0.88	10.38	98.46	-0.23	2.81	0.66	11.56	99.27
3	-0.05	0.22	0.16	1.11	99.99	0.30	1.59	0.57	7.33	99.84
4	0.08	0.95	0.41	5.05	99.95	-0.13	1.15	0.40	7.81	99.93
5	0.36	0.85	0.30	6.51	99.96	0.06	0.70	0.34	5.75	99.97
7	-0.72	1.03	0.74	3.87	99.94	-0.48	1.15	0.60	4.46	99.93
10	0.50	1.85	0.76	6.60	99.78	0.70	2.10	0.70	7.57	99.72
Average	1.07	3.76	0.59	11.49	86.17	-0.19	2.50	0.58	11.10	96.93
$\mathcal{L}$			5067.1					5229.7		

Table 5
Summary statistics of pricing errors on credit default swap spreads with one credit risk factor
Entries report the summary statistics of the pricing errors on the credit default swap spreads under both affine and quadratic specifications. Both specifications use one credit risk factor to price the high-liquidity credit-default swap spread at each industry and credit rating class. We estimate both models by using quasi-maximum likelihood method joint with unscented Kalman filter. We define the pricing error as the difference between the spread quotes and the model-implied fair values, in basis points. The columns titled Mean, Std, Auto, Max, and VR denote, respectively, the sample mean, the standard deviation, the first-order autocorrelation, the maximum absolute error, and the explained percentage variance, defined as one minus the ratio of pricing error variance to interest rate variance.

Maturity	Affine					Quadratic				
Years	Mean	Std	Auto	Max	VR	Mean	Std	Auto	Max	VR
(i) Sector: Financial; Rating: A										
1	-0.35	3.86	0.97	12.55	80.41	-1.31	2.69	0.83	18.98	90.49
2	1.33	2.07	0.97	5.48	96.01	1.58	1.74	0.57	17.96	97.15
3	-1.37	1.36	0.96	6.07	98.47	-1.16	1.50	0.35	22.59	98.14
4	-0.00	0.02	0.66	0.08	100.00	-0.06	1.14	0.09	18.07	99.16
5	0.25	1.00	0.96	2.48	99.44	-0.04	1.19	0.27	15.85	99.21
7	0.02	1.26	0.93	3.59	99.12	-0.35	1.21	0.43	13.07	99.19
10	-0.26	2.44	0.95	7.77	96.81	0.09	2.20	0.84	10.89	97.40
(iii) Sector: Corporate; Rating: A										
1	-4.66	1.88	0.96	8.89	94.72	-3.66	2.23	0.75	20.74	92.55
2	0.10	0.84	0.91	2.51	99.23	0.33	1.40	0.39	17.53	97.86
3	-0.85	0.66	0.93	2.93	99.56	-0.62	1.37	0.35	19.63	98.13
4	0.00	0.01	0.80	0.02	100.00	0.19	1.11	0.19	16.72	98.86
5	-0.13	0.35	0.90	1.40	99.89	-0.06	0.94	0.07	14.91	99.22
7	0.03	1.28	0.95	4.36	98.47	-0.03	1.04	0.39	13.14	98.98
10	-0.24	3.23	0.97	8.73	88.59	0.23	1.97	0.86	11.00	95.78
(ii) Sector: Financial; Rating: BBB										
1	-2.26	4.00	0.96	15.81	97.52	-1.19	6.37	0.79	47.22	93.73
2	0.33	2.32	0.95	7.69	99.17	0.37	3.62	0.41	45.79	97.99
3	-0.82	2.08	0.96	7.64	99.35	-1.01	3.30	0.38	44.58	98.37
4	0.01	0.01	0.84	0.04	100.00	-0.14	2.47	0.08	39.28	99.03
5	-0.26	1.25	0.96	3.86	99.74	-0.26	2.44	0.24	34.00	99.02
7	-0.57	2.97	0.97	6.92	98.26	-0.21	2.57	0.45	29.23	98.70
10	-0.40	5.52	0.97	12.38	92.75	0.05	3.78	0.79	23.08	96.61
(iv) Sector: Corporate; Rating: BBB										
1	-5.81	2.68	0.96	11.90	97.75	-2.98	5.54	0.58	63.04	90.40
2	0.19	1.29	0.95	3.91	99.56	0.55	3.72	0.23	54.39	96.29
3	-0.51	1.09	0.95	4.35	99.70	-0.57	3.23	0.16	49.68	97.33
4	0.00	0.00	0.65	0.01	100.00	-0.09	2.88	0.11	45.70	97.76
5	-0.27	0.68	0.96	2.18	99.87	-0.32	2.62	0.13	40.86	98.10
7	-0.17	2.88	0.98	6.62	97.18	-0.07	2.65	0.38	34.19	97.61
10	-0.16	5.38	0.98	12.13	87.64	0.32	3.35	0.73	26.09	95.22

Table 6

Summary statistics of pricing errors on credit default swap spreads with two credit risk factor

Entries report the summary statistics of the pricing errors on the credit default swap spreads under both affine and quadratic specifications. Both specifications use two credit risk factors to price the high-liquidity credit-default swap spread at each industry and credit rating class. We define the pricing error as the difference between the spread quotes and the model-implied fair values, in basis points. The columns titled Mean, Std, Auto, Max, and VR denote, respectively, the sample mean, the standard deviation, the first-order autocorrelation, the maximum absolute error, and the explained percentage variance, defined as one minus the ratio of pricing error variance to interest rate variance.

Maturity	Affine					Quadratic				
Years	Mean	Std	Auto	Max	VR	Mean	Std	Auto	Max	VR
(i) Sector: Financial; Rating: A										
1	0.01	0.08	0.43	0.38	99.99	-0.40	1.64	0.85	5.45	96.46
2	1.39	0.72	0.91	2.62	99.52	1.26	1.09	0.72	6.36	98.89
3	-1.38	0.80	0.94	4.11	99.48	-1.44	1.02	0.61	12.27	99.15
4	0.00	0.00	0.22	0.00	100.00	-0.05	0.57	0.08	8.96	99.79
5	0.27	0.76	0.93	2.09	99.68	0.21	0.93	0.65	8.02	99.52
7	0.05	0.75	0.89	2.02	99.68	-0.04	0.50	0.06	7.95	99.86
10	-0.20	1.72	0.95	3.88	98.42	-0.25	1.50	0.85	9.58	98.80
(iii) Sector: Corporate; Rating: A										
1	-0.44	1.88	0.98	3.98	94.72	-0.65	2.16	0.69	19.36	93.00
2	1.94	0.92	0.95	3.64	99.07	1.73	1.56	0.39	18.15	97.34
3	-0.28	0.53	0.93	2.01	99.72	-0.41	1.37	0.21	21.07	98.12
4	0.00	0.00	0.50	0.01	100.00	-0.02	1.15	0.08	18.24	98.77
5	-0.30	0.30	0.94	0.81	99.92	-0.25	1.04	0.09	16.18	99.03
7	0.01	0.09	0.43	0.38	99.99	0.08	0.96	0.17	13.89	99.13
10	-0.14	0.98	0.96	2.39	98.95	-0.02	1.10	0.51	12.05	98.69
(ii) Sector: Financial; Rating: BBB										
1	-0.64	1.59	0.93	3.85	99.61	-0.10	1.83	0.74	10.63	99.48
2	0.07	0.11	0.39	0.53	100.00	-0.00	0.44	0.02	6.74	99.97
3	-1.42	1.20	0.94	4.59	99.78	-1.18	1.32	0.90	6.41	99.74
4	-0.32	1.06	0.93	2.84	99.82	-0.00	0.25	0.01	3.68	99.99
5	-0.16	1.68	0.97	3.13	99.53	0.03	0.82	0.91	1.74	99.89
7	0.01	0.03	0.41	0.20	100.00	-0.05	1.53	0.91	4.21	99.54
10	-0.51	1.56	0.94	3.97	99.43	-0.27	3.05	0.94	7.00	97.79
(iv) Sector: Corporate; Rating: BBB										
1	-3.39	4.22	0.98	15.16	94.44	-0.60	3.14	0.52	37.52	96.92
2	1.18	1.75	0.98	3.46	99.18	1.92	2.11	0.36	26.61	98.81
3	-0.24	0.63	0.96	2.06	99.90	-0.19	1.38	0.13	21.21	99.51
4	0.00	0.00	0.04	0.00	100.00	-0.05	1.12	0.06	17.76	99.67
5	-0.30	0.56	0.98	1.04	99.91	-0.31	1.03	0.27	14.29	99.70
7	0.00	0.00	0.08	0.01	100.00	-0.03	0.72	0.07	11.42	99.82
10	-0.00	0.54	0.92	2.40	99.88	-0.05	0.95	0.66	9.01	99.62

Table 7

Summary statistics of pricing errors on the low-liquidity credit default swap spreads

Entries report the summary statistics of the pricing errors on the low-liquidity credit default swap spreads. In addition to two interest rate factors and two credit risk factors that have been identified using the benchmark interest rates and the high-liquidity credit default swap spreads, we add one additional idiosyncratic credit risk factor and a liquidity risk factor to account for the credit spread movements in the low-liquidity groups. We define the pricing error as the difference between the spread quotes and the model-implied fair values, in basis points. The columns titled Mean, Std, Auto, Max, and VR denote, respectively, the sample mean, the standard deviation, the first-order autocorrelation, the maximum absolute error, and the explained percentage variance, defined as one minus the ratio of pricing error variance to interest rate variance.

Maturity	Affine					Quadratic				
Years	Mean	Std	Auto	Max	VR	Mean	Std	Auto	Max	VR
(i) Sector: Financial; Rating: A										
1	2.82	1.29	0.96	5.93	97.82	0.10	1.59	0.97	3.77	96.69
2	2.13	0.78	0.95	3.62	99.43	0.80	0.87	0.95	2.53	99.29
3	-0.37	0.32	0.93	1.27	99.92	-0.78	0.35	0.94	1.76	99.90
4	-0.00	0.00	0.29	0.02	100.00	-0.00	0.00	0.01	0.04	100.00
5	0.07	0.28	0.94	0.66	99.96	0.17	0.31	0.95	0.82	99.95
7	0.02	0.17	0.88	0.45	99.98	0.02	0.20	0.89	0.46	99.98
10	-0.00	0.04	0.49	0.15	100.00	0.00	0.01	0.07	0.05	100.00
(iii) Sector: Corporate; Rating: A										
1	-0.08	3.47	0.99	7.27	81.96	0.62	2.82	0.98	5.91	88.14
2	-0.06	1.93	0.99	4.61	95.93	0.29	1.82	0.98	4.20	96.35
3	-1.33	0.78	0.98	3.48	99.39	-1.23	0.76	0.98	3.35	99.42
4	0.00	0.01	0.49	0.10	100.00	-0.00	0.02	0.55	0.16	100.00
5	0.60	0.69	0.98	2.27	99.57	0.58	0.69	0.98	2.28	99.58
7	0.02	0.10	0.53	0.88	99.99	0.03	0.09	0.56	0.77	99.99
10	-0.24	0.73	0.96	1.49	99.42	-0.35	0.65	0.95	1.41	99.55
(ii) Sector: Financial; Rating: BBB										
1	-1.45	2.54	0.99	5.92	99.00	-1.05	2.53	0.99	5.50	99.01
2	0.00	0.16	0.13	2.23	100.00	0.01	0.18	0.17	2.52	100.00
3	-0.29	1.39	0.97	2.70	99.71	-0.29	1.39	0.97	2.78	99.71
4	0.00	0.10	0.03	1.53	100.00	0.01	0.09	0.12	1.42	100.00
5	0.21	0.77	0.98	1.25	99.90	0.19	0.76	0.98	1.32	99.90
7	-1.63	2.81	0.99	6.00	98.45	-1.68	2.82	0.98	6.14	98.43
10	-3.52	4.85	0.98	11.41	94.41	-3.37	5.01	0.98	11.68	94.04
(iv) Sector: Corporate; Rating: BBB										
1	0.66	2.87	0.98	7.72	97.43	0.38	1.71	0.91	7.98	99.09
2	1.33	1.34	0.98	3.46	99.51	0.77	1.09	0.96	2.91	99.68
3	-0.50	0.40	0.95	1.45	99.96	-0.76	0.29	0.92	1.57	99.98
4	-0.00	0.00	0.27	0.03	100.00	0.00	0.00	0.23	0.04	100.00
5	0.15	0.36	0.97	0.88	99.96	0.26	0.35	0.96	1.19	99.97
7	0.00	0.05	0.57	0.20	100.00	0.02	0.07	0.35	0.53	100.00
10	0.01	0.28	0.91	0.95	99.97	-0.16	0.42	0.92	1.00	99.93

Table 8

Dynamic and term structure of the benchmark libor interest rates

Entries report the parameter estimates and the absolute magnitudes of the *t*-statistics (in parentheses) that determine the dynamics and term structure of the benchmark libor interest rates. The estimations are based on 12-month libor and swap rates of two, three, five, seven, and ten years, with quasi-maximum likelihood method.

Model	κ_x		γ_{x0}	γ_{x1}	a_r	b_r
Affine	0.2365	0	−0.1987	0.0819		0.0000
	(5.22)	−−	(4.45)	(0.05)	0.0046	(0.04)
	−0.9338	0.3073	−0.9752	−0.0321	(1.04)	0.0116
	(12.87)	(5.35)	(3.77)	(0.00)		(20.2)
Quadratic	0.7597	0	1.1885	0.7581		0.0006
	(64.5)	−−	(15.7)	(3.79)	0.0081	(8.20)
	−0.6567	0.1196	−1.6100	0.0774	(79.7)	0.0025
	(38.17)	(26.6)	(25.8)	(0.06)		(22.9)

Table 9

One-factor default arrival dynamics and the term structure of credit spreads

Entries report the second-stage parameter estimates and the absolute magnitudes of the t-statistics (in parentheses) that determine the one-factor default arrival dynamics and the term structure of credit spreads. The estimations are based on high-liquidity credit default swap spreads at each of the four industry and credit rating classes with quasi-maximum likelihood method.

Θ		κ_{xy}		κ_y	γ_{y0}	γ_{y1}	a_i	$b_i^\top$		c_i
				(i) Affine Models						
Financial	A	-0.0363	0.1033	0.0001	-0.0230	0.0232	0.0143	-0.0014	0.0015	0.0038
		(1.00)	(5.57)	(0.03)	(0.07)	(0.04)	(1.62)	(5.39)	(41.5)	(19.5)
Corporate	A	0.1974	0.0618	0.0001	-0.0226	0.0227	0.0128	0.0002	0.0015	0.0035
		(7.72)	(6.49)	(0.03)	(0.05)	(0.04)	(1.69)	(0.67)	(15.0)	(23.1)
Financial	BBB	0.0486	-0.0421	0.0001	-0.0175	0.0176	0.0369	0.0017	0.0021	0.0137
		(2.13)	(5.28)	(0.02)	(0.01)	(0.01)	(1.71)	(1.53)	(16.3)	(18.1)
Corporate	BBB	-0.1196	0.0735	0.0001	-0.0224	0.0225	0.0308	-0.0029	0.0008	0.0056
		(2.90)	(3.55)	(0.01)	(0.08)	(0.04)	(6.36)	(7.08)	(10.0)	(14.4)
				(ii) Quadratic Models						
Financial	A	0.3922	-0.0211	0.0718	0.0181	0.0537	0.0061	0.0006	-0.0007	0.0032
		(28.7)	(11.3)	(9.24)	(0.00)	(0.02)	(28.1)	(23.00)	(12.6)	(20.7)
Corporate	A	0.1108	0.0079	0.1396	0.0875	0.0521	0.0050	-0.0008	-0.0010	0.0083
		(20.5)	(5.94)	(24.5)	(0.00)	(0.01)	(27.6)	(45.9)	(20.7)	(44.0)
Financial	BBB	0.2768	0.0947	0.2043	0.1493	0.0551	0.0186	0.0009	-0.0030	0.0112
		(24.2)	(32.1)	(28.9)	(0.02)	(0.02)	(47.0)	(5.32)	(45.7)	(16.4)
Corporate	BBB	0.1906	0.0646	0.2056	0.1536	0.0520	0.0125	-0.0014	-0.0020	0.0140
		(24.9)	(48.8)	(30.3)	(0.01)	(0.01)	(21.6)	(19.8)	(20.2)	(17.3)

Table 10

Two-factor default arrival dynamics and the term structure of credit spreads

Entries report the second-stage parameter estimates and the absolute magnitudes of the t-statistics (in parentheses) that determine the two-factor default arrival dynamics and the term structure of credit spreads. The estimations are based on high-liquidity credit default swap spreads at each of the four industry and credit rating classes with quasi-maximum likelihood method.

Θ		κ_{xy}		κ_y		γ_{y0}	γ_{y1}	a_i	b_i	c_i
				(i) Affine Models						
Financial	A	-0.1694	0.0686	0.0001	0	0.0287	-0.0060	0.0069	0.0005	0.0003
		(3.36)	(3.43)	(0.01)	—	(0.42)	(0.06)	(1.27)	(0.41)	(0.13)
		0.2931	-0.2120	0.4474	0.7912	-1.9590	0.7815	—	0.0004	0.0067
		(1.95)	(4.90)	(2.58)	(8.57)	(1.92)	(0.02)	—	(2.69)	(4.07)
Corporate	A	-0.1975	0.6094	0.0005	0	-1.8568	-0.0019	0.0103	0.0002	0.0012
		(0.61)	(5.27)	(0.01)	—	(7.00)	(0.00)	(1.79)	(0.32)	(0.30)
		0.4848	-0.1206	0.0965	0.0418	-0.1767	0.0325	—	0.0034	0.0055
		(3.32)	(0.28)	(3.15)	(0.60)	(0.13)	(0.01)	—	(19.5)	(5.74)
Financial	BBB	0.6387	0.1686	0.4582	0	-0.2490	0.4515	0.0342	0.0044	0.0089
		(7.80)	(5.37)	(10.29)	—	(0.15)	(0.02)	(0.25)	(2.33)	(3.99)
		0.2125	0.0112	0.1718	0.0947	0.0573	0.0873	—	0.0071	0.0172
		(2.13)	(0.39)	(3.60)	(11.6)	(0.19)	(0.03)	—	(12.5)	(10.1)
Corporate	BBB	-0.3278	0.2385	0.0006	0	-0.5814	-0.0041	0.0320	-0.0029	0.0011
		(4.37)	(5.70)	(0.01)	—	(4.64)	(0.00)	(0.45)	(6.34)	(0.52)
		0.0480	0.0277	0.1494	0.0147	-0.1889	0.0104	—	0.0016	0.0055
		(0.47)	(0.34)	(7.50)	(0.27)	(0.05)	(0.01)	—	(17.2)	(12.4)
				(ii) Quadratic Models						
Financial	A	-0.0407	-0.0320	0.5577	0	0.5019	0.5520	0.0041	0.0003	0.0067
		(1.74)	(2.03)	(9.85)	—	(4.93)	(0.02)	(12.2)	(6.48)	(9.05)
		-0.4381	0.0742	-0.1412	0.0120	-1.2139	0.0032	—	-0.0011	0.0021
		(21.3)	(21.1)	(2.57)	(1.31)	(21.6)	(0.00)	—	(68.4)	(20.5)
Corporate	A	0.6625	-0.0392	0.0004	0	1.1627	-0.0054	0.0039	-0.0010	0.0006
		(28.0)	(7.08)	(0.06)	—	(17.1)	(0.00)	(23.3)	(59.0)	(11.95)
		-0.2741	0.0274	-0.0621	0.1090	-0.7897	0.1001	—	-0.0008	0.0049
		(13.8)	(6.40)	(7.25)	(5.99)	(18.1)	(0.02)	—	(105.7)	(21.2)
Financial	BBB	0.0159	0.0628	0.1034	0	-0.2342	0.0980	0.0092	-0.0008	0.0002
		(0.37)	(13.8)	(14.5)	—	(2.30)	(0.13)	(7.3)	(4.68)	(1.01)
		-0.0261	-0.2045	0.4805	1.6345	-1.5258	1.6254	—	-0.0015	0.0325
		(0.96)	(7.89)	(9.31)	(14.2)	(8.9)	(0.07)	—	(49.6)	(12.1)
Corporate	BBB	-0.0569	0.0087	0.0846	0	-0.1380	0.0846	0.0098	0.0006	0.0001
		(1.60)	(1.36)	(6.44)	—	(1.83)	(0.07)	(15.0)	(9.46)	(0.74)
		-0.1874	-0.0738	0.1988	0.4640	-0.8735	0.4640	—	-0.0011	0.0120
		(9.76)	(8.12)	(12.3)	(17.6)	(11.0)	(0.02)	—	(79.9)	(11.4)

Table 11
Idiosyncratic credit and liquidity risk

Entries report the third-stage parameter estimates and t-statistics (in parentheses) that determine the idiosyncratic credit and liquidity risk dynamics in accounting for the idiosyncratic credit spreads embedded in the low-liquidity credit default swaps. The parameters are estimated using quasi-maximum likelihood method.

		Credit Risk					Liquidity Risk				
Θ		κ_m	γ_{m0}	γ_{m1}	a_m	c_m	κ_q	γ_{q0}	γ_{q1}	a_q	b_q
(i) Affine Models											
Financial	A	0.0010	-0.0275	-0.0500	-0.0062	0.0030	0.3312	-0.1299	0.2832	0.3423	0.2822
		(0.06)	(0.51)	(0.01)	(13.9)	(26.3)	(9.55)	(0.47)	(0.16)	(1.48)	(7.89)
Corporate	A	0.0012	-1.0741	-0.0577	-0.0011	0.0028	0.8452	4.9606	0.8448	6.0187	0.9083
		(0.01)	(1.58)	(0.01)	(2.00)	(9.92)	(36.34)	(4.14)	(1.38)	(6.08)	(17.1)
Financial	BBB	0.0001	-0.0732	-0.0381	-0.0150	0.0093	0.9375	-0.4433	0.9374	2.9285	2.7536
		(0.00)	(2.53)	(0.01)	(1.24)	(30.7)	(10.6)	(0.75)	(0.11)	(2.44)	(9.07)
Corporate	BBB	0.0009	-0.0991	-0.0434	-0.0176	0.0042	0.3376	0.6776	0.2911	1.0670	0.3245
		(0.10)	(5.08)	(0.19)	(9.67)	(27.9)	(15.6)	(3.48)	(0.44)	(7.73)	(11.8)
(ii) Quadratic Models											
Financial	A	0.0008	-0.5700	-0.0502	-0.0067	0.0038	0.9494	1.8194	0.9003	2.3761	0.8999
		(0.02)	(6.08)	(0.01)	(1.08)	(45.2)	(28.0)	(2.72)	(0.45)	(5.82)	(8.67)
Corporate	A	0.0102	-0.2178	-0.0399	-0.0043	0.0052	0.6745	2.9258	0.6735	4.2633	0.8047
		(0.11)	(1.40)	(0.01)	(1.49)	(17.6)	(28.3)	(3.46)	(1.60)	(5.38)	(14.0)
Financial	BBB	0.0001	-0.0902	-0.0381	-0.0166	0.0105	0.9070	-0.4327	0.9070	2.9863	2.6709
		(0.00)	(2.52)	(0.01)	(4.01)	(26.5)	(17.0)	(0.91)	(0.12)	(3.50)	(11.6)
Corporate	BBB	0.0068	-0.2343	-0.0087	-0.0229	0.0082	0.5273	3.3088	0.5204	2.7831	0.3963
		(0.22)	(6.28)	(0.00)	(0.56)	(17.8)	(39.4)	(8.57)	(1.61)	(19.1)	(19.1)

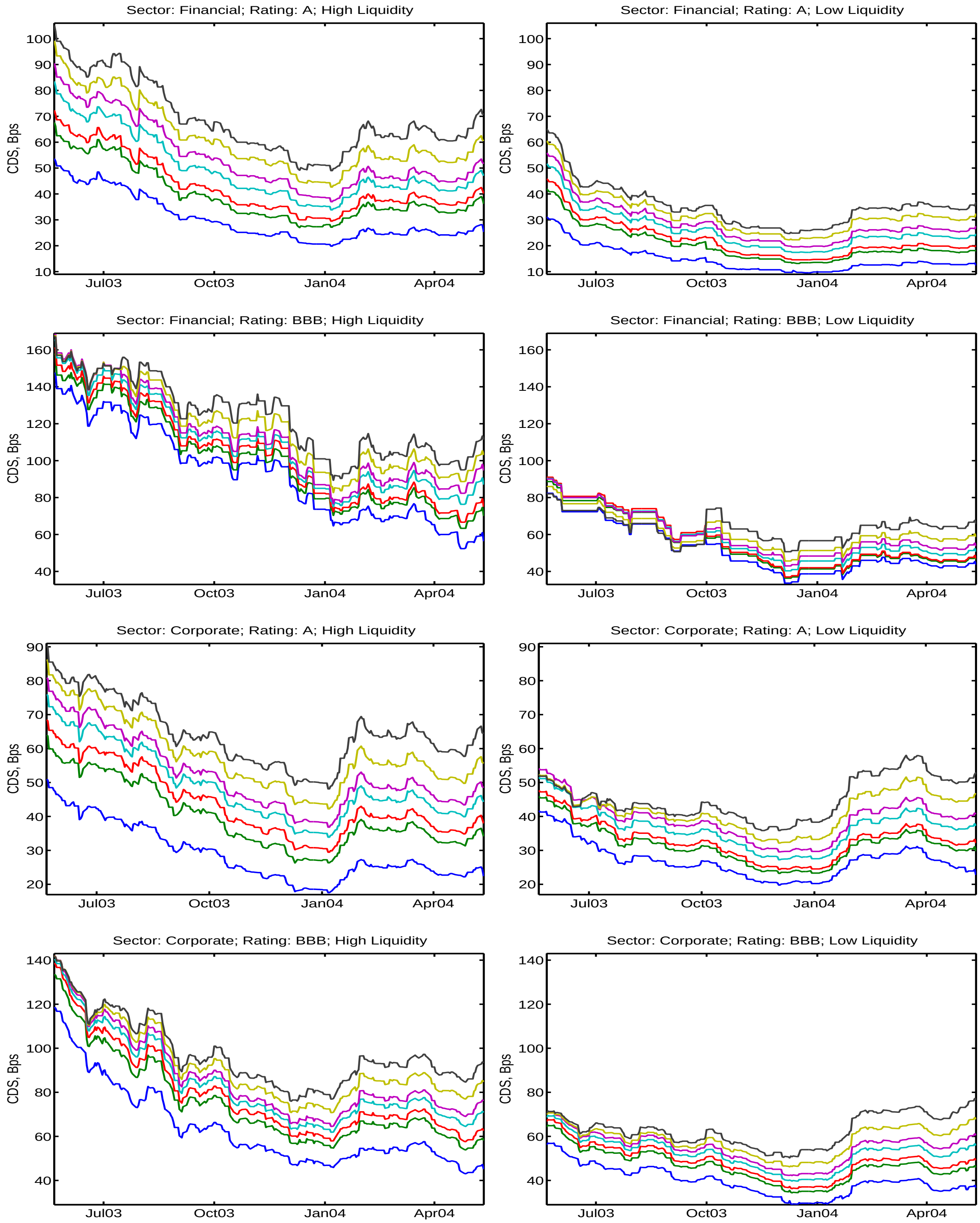

Figure 1

Time series of credit default swap spreads.

The seven lines in each panel plot the time-series of the average quotes on credit default swap spreads at seven fixed maturities for each industry sector, credit rating class, and liquidity group. Data are from JP Morgan Chase, daily from May 21, 2003 to May 12, 2004.

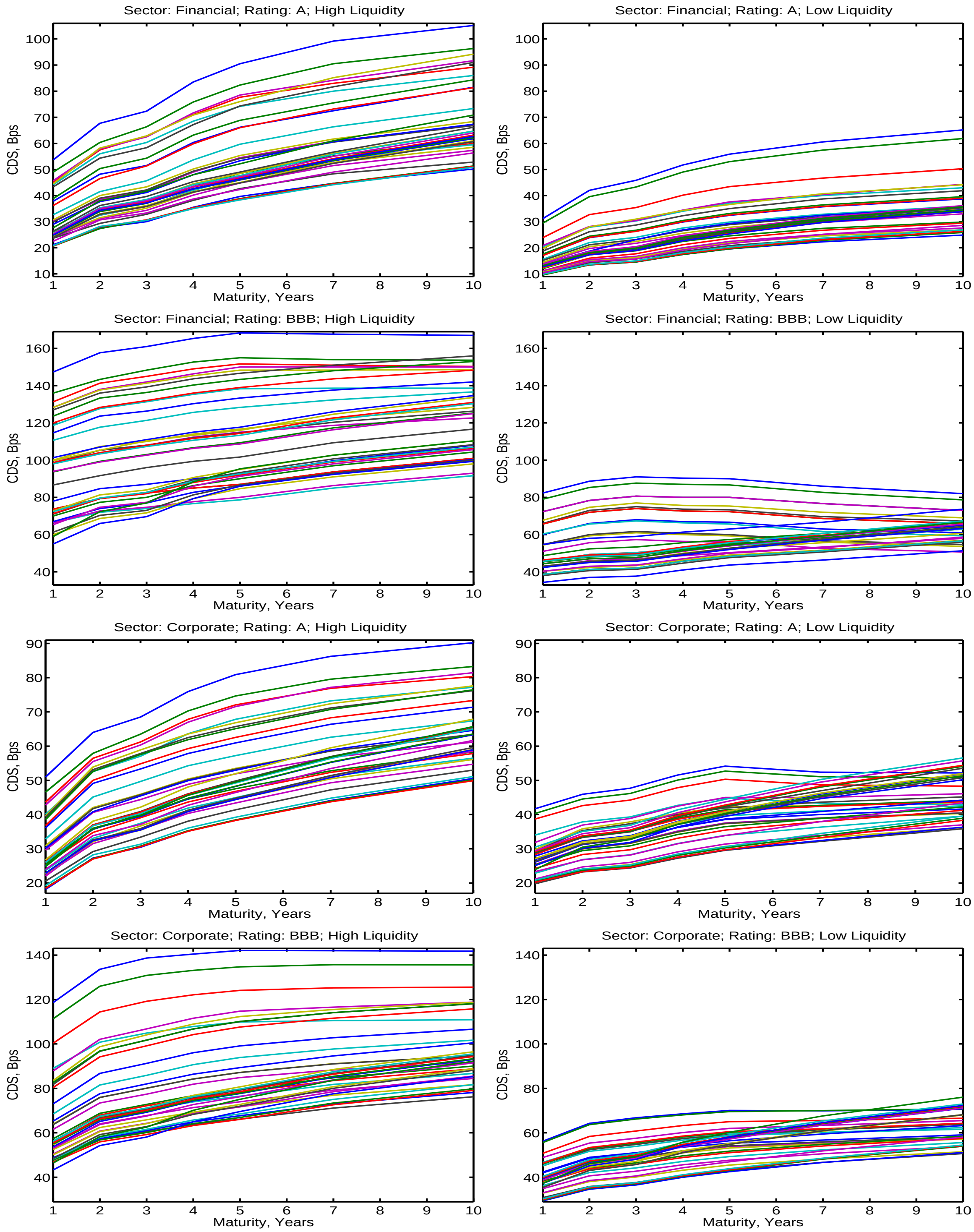

Figure 2
Term structure of credit default swap spreads.
Lines in each panel plot the term structure of the average quotes on credit default swap spreads at different days for each credit rating class, industry sector, and liquidity group. Data are are from JP Morgan Chase, daily from May 21, 2003 to May 12, 2004.

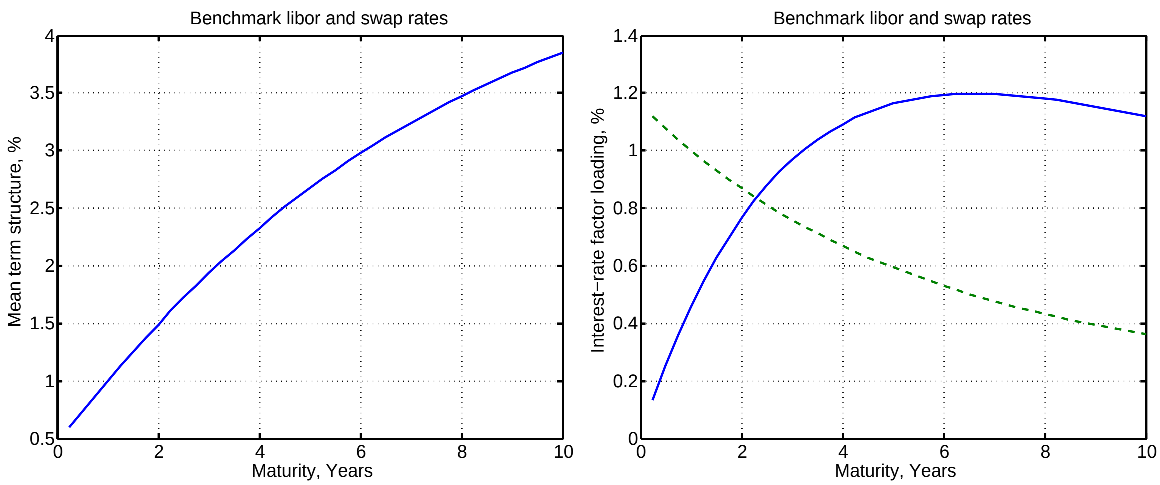

Figure 3

Mean term structure and impulse-response of benchmark interest rates.

Solid line in the left panel plots the mean term structure of continuously compounded spot rate. The two lines in the right panel depict the contemporaneous response of the continuously compounded benchmark spot rate to unit shocks from the first (solid line) and second (dashed line) interest-rate factors. The lines are computed based on the estimated two-factor affine model.

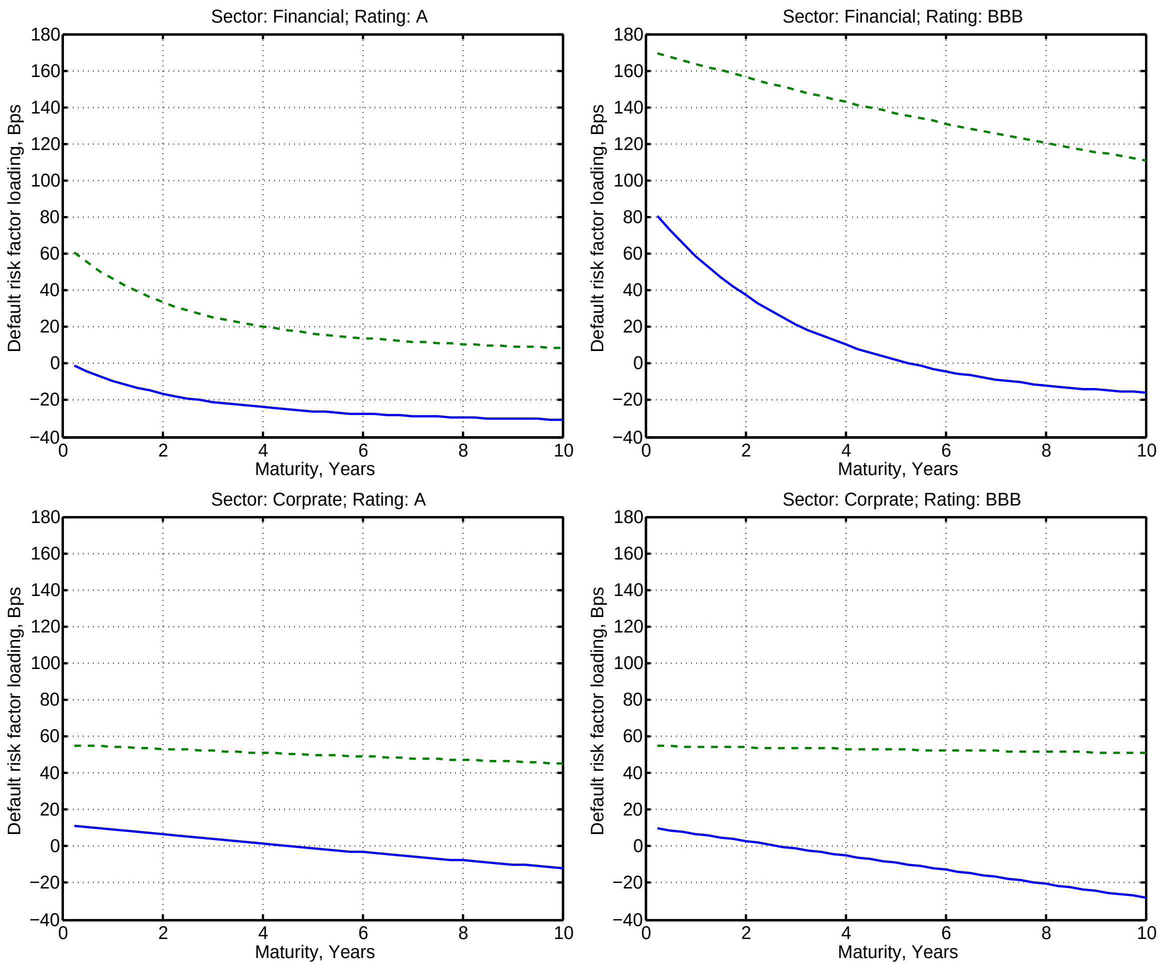

Figure 4

Credit-risk factor loading on the term structure of credit spreads under affine specifications.
Solid lines denote the contemporaneous response of the continuously compounded corporate spot rate to unit shocks from the first credit-risk factor. Dashed lines plot the response to unit shocks from the second credit-risk factor. The loadings are computed based on the parameter estimates of the two-factor affine credit-risk specification.

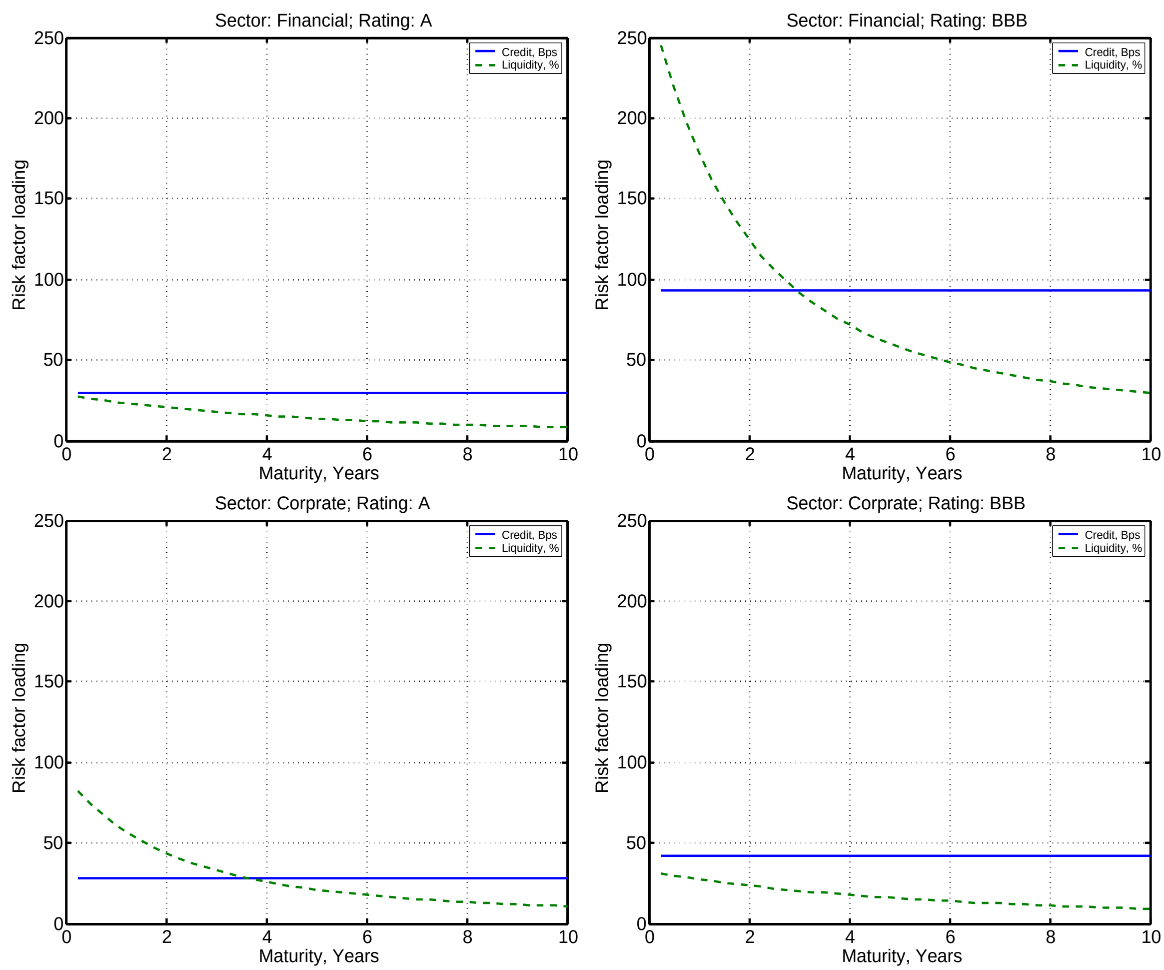

Figure 5

Idiosyncratic default risk and liquidity risk factor loading.

Lines plot the contemporaneous response of the spot rate on the low-liquidity group to unit shocks from the additional credit-risk factor (solid lines, in basis points) and the liquidity-risk factor (dashed lines, in percentages), respectively.