Determinants of Short-Term Corporate Yield Spreads: Evidence from the Chinese Commercial Paper Market*

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Abstract

What drives short-term credit spreads is a very important question in credit markets, yet the empirical literature on the determinants of such spreads is rather thin perhaps due to data limitations. Using a unique data set of *secondary* market transaction prices of Chinese commercial papers, this paper provides a comprehensive study on the determinants of short-term credit spreads within the structural framework of credit risk modeling. Specifically, we propose a model of risky debt pricing with rollover risk, jumps, and endogenous liquidity. Among other things, this model allows us to decompose commercial paper yield spreads into a credit component and a liquidity component in a unified manner. We find that both credit and liquidity factors are important determinants of short-term credit spreads and that on average, the proposed structural model can largely match levels of commercial paper spreads in our sample.

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1 Introduction

What drives short-term credit spreads is a very important question in credit markets, especially given the role played by short-term corporate debt in the recent financial crisis. However, in spite of a large literature on the determinants of credit spreads in general, the empirical literature on short-term spreads is thin perhaps due to data limitations. One exception is the study by Covitz and Downing (2007), who examine a sample of commercial paper (CP) issued by domestic U.S. nonfinancial firms and, based on regression analysis, conclude that surprisingly, credit risk is the more important determinant of CP spreads than liquidity. Although it is insightful, their study is not focused on no-arbitrage pricing of CP and, in particular, not on rollover risk, however.[1] Specifically, given that the data set used in Covitz and Downing (2007) consists of mainly new issues in the primary market, an important and interesting question not addressed in their study and the literature is how much of short-term yield spreads is due to credit risk or liquidity risk.

In this paper we shed light on the determinants of short-term corporate credit spreads from at least two new perspectives. First, we employ a unique data set of *secondary* market transactions in the Chinese commercial paper, the fastest growing CP market in the world. Second, we quantify liquidity and default risk components in short-term spreads using the well-known structural approach to credit risk modeling (Merton 1974). Specifically, we propose a jump-diffusion structural model with rollover risk and endogenous liquidity that is particularly suitable for modeling CP spreads. Among other things, this model allows us to decompose yield spreads into diffusive and jump credit risk components as well as liquidity component in a unified manner.

There are several reasons why we study the Chinese CP market. First, secondary market transactions account for 78% of total daily transaction volumes in this market, whereas it is

[1] This is not surprising, given that their empirical analysis is done using a (pre-crisis) sample period January 1998–October 2003.

less than 10% in the US market. This feature makes it possible to implement transaction-based liquidity measures for the CP market. On the other hand, Covitz and Downing (2007) only see the offer side of secondary market transactions and liquidity proxies they use are limited to trade volume, dollar volume, and CP maturity. Second, the Chinese CP issuers are heterogeneous in terms of creditworthiness, whereas almost all CP issuers in the US are large, well-capitalized firms. Third, longer-term corporate debts, e.g. medium-term notes (MTNs) and enterprise bonds (EBs), are traded in the same (interbank) market in China. This provides an ideal setting to investigate how the relative importance of credit/liquidity changes with the maturity.

To that end, we first conduct a regression analysis of CP yield spreads using credit risk-related variables suggested by structural models, credit ratings, and seven liquidity measures as examined in Schestag, Schuster, and Uhrig-Homburg (2016). We find that credit risk-related determinants explain about 4-6% of CP spread variations. On the other hand, we find that the liquidity measures have an unconditional R^2 of 26.1% and an incremental R^2 of 24.8%. That is, our results indicate that illiquidity is much more important than credit risk in explaining variations in the CP spread in the Chinese market. This finding on the relative importance of credit and liquidity proxies is different from the main finding of Covitz and Downing (2007). One possible reason for this difference is that the samples of CP used are very different. Another possible reason may have something to do with liquidity proxies used in their study, e.g., CP maturity.

We then conduct a similar regression analysis using spreads on MTNs and EBs, which have longer maturities than CP. We find that the credit-related variables indeed becomes more important than liquidity in the determination of spreads on MTNs and EBs. Furthermore, we observe the same pattern between shorter (1–3 years) and longer (3–5 years) MTNs and EBs.

Interestingly, our regression analysis results also provide evidence on potential role of structural credit risk models in the determination of short-term credit spreads. Specifically, we find that the distance-to-default (Kealhofer 2003) subsumes equity volatility as well as has incremental explanatory power for spreads over credit ratings. In addition, the regression results indicate that jump risk matters.

As a result, we next examine the predictive power of structural models for short-term credit spreads. We begin with the Black and Cox (1976) model, a simple, pure-diffusion model of risky zero-coupon bonds that allows for default prior to bond maturity. As such, it serves as the benchmark model in our empirical analysis. The consensus is that pure diffusion-based structural models are unable to generate sufficiently high short-term spreads consistent with levels of observed spreads. Indeed we find that the Black-Cox model implied CP spreads have a mean of 0.32% and median of 0.0%, way below their empirical counterparts of 1.53% and 1.34%, respectively. Furthermore, the model has substantial pricing errors: the mean pricing error is -1.09% and the mean percentage pricing error is -66.87%. Nonetheless, the model predicts lower-rating CP spreads better than higher-rating ones. For instance, the mean percentage pricing error is -72.31% for AAA issues and -56.0% for AA issues.

We then consider the double-exponential jump diffusion (DEJD) model of risky debt, which is used in Huang and Huang (2002, 2012) among others. This model can be considered to be an extension of the Black-Cox model to include jumps in its underlying asset return process. As expected, the DEJD model significantly improves the pricing performance. For instance, incorporating jumps raises the average and median model-implied spreads from 0.32% and 0.0% for the Black-Cox model to 1.07% and 0.48% for the DEJD model, respectively. In terms of pricing errors under the DEJD model, the mean pricing error is -0.70% and the mean percentage pricing error is -20.63% for the full sample. Nonetheless, the ability of the DEJD model to predict short-term spreads is still poor, especially for those CP issues with low observed spreads, as illustrated by the fact that the model-implied spreads have a right-skewed distribution. One implication of this finding is that part of CP spreads may be related to liquidity.

To accurately quantify the incremental role of liquidity, we incorporate endogenous liquidity into the DEJD model in the spirit of He and Xiong (2012). The resulting model can be considered to be the He and Xiong (2012) model augmented with jumps. One important feature of this model is that it takes into account rollover risk. Our empirical results show that on average, this extended He-Xiong model largely explains CP spreads in our sample. In fact, the average of predicted spreads in this model is 1.62%, higher than the average observed spread of 1.53%. Moreover, the mean percentage pricing error is positive, around 10.31%, although the mean pricing error is still negative (-0.30%). However, the model still underestimates the median CP spread. The model-implied CP spreads still have a right-skewed distribution. Furthermore, the model over-estimates spreads in the right tail and under-estimates spreads in the left tail, resulting in the positive mean percentage pricing error of 10.31% for the full sample. That is, while incorporating endogenous liquidity improves the pricing performance significantly, the resulting model suffers from the problem of inaccuracy as described by Eom, Helwege, and Huang (2004).

To summarize, this paper contributes to the literature in three main aspects. First, we provide a comprehensive study on the determinants of short-term credit spreads using a unique data set of commercial paper *secondary* market transaction prices. Second, we propose a structural model of credit risk with rollover risk, jumps, and endogenous liquidity. Importantly, this model allows us to decompose CP spreads into a credit component—further divided into the diffusion and jump components—and a liquidity component in a unified manner. Third, we find that both credit and liquidity factors are important determinants of short-term credit spreads and that on average, the proposed structural model can match levels of CP spreads in our sample.

The remainder of the paper is organized as follows. Section 2 discusses related literature, followed by Section 3, which describes the data we use. Section 4 introduces structural models of credit risk to be examined in study, including the proposed model with rollover risk, jumps, and endogenous liquidity. Section 5 presents results from our empirical analysis. Section 6 concludes.

2 Related Literature

This paper is most directly related to the literature on structural models of credit risk, originated from Black and Scholes (1973) and Merton (1974). However, the paper departs from this literature in two main aspects.

First, this paper contributes to the theoretical literature by proposing a new structural model that incorporates rollover risk, endogenous liquidity, and jumps in the underlying asset return process. There is a large theoretical literature on structural credit risk modeling (see, e.g., Huang and Huang, 2012; Sundaresan, 2013; and references therein). For tractability and comparison, we focus on three models with a flat default boundary—namely, the Black-Cox model for zero-coupon risky debt, the DEJD model, and the proposed model that extends the He-Xiong model to include jumps in the underlying asset return process.

The Black-Cox model is used in many studies, such as Bao (2009); Feldhütter and Schaefer (2018); Huang, Nozawa, and Shi (2018); Bai, Goldstein, and Yang (2019); Huang, Shi, and Zhou (2019). In addition to Huang and Huang (2002, 2012), other examples using the DEJD-based structural model include Cremers, Driessen, and Maenhout (2008); Bao (2009); Chen and Kou (2009); Bai, Goldstein, and Yang (2019); Huang, Shi, and Zhou (2019).[2] Studies using alternative structural models with jumps include Mason and Bhattacharya (1981); Duffie and Lando (2001); Zhou (2001). We focus on the DEJD model in our study for analytical tractability reasons. He and Xiong (2012); He and Milbradt (2014) consider both rollover risk and bond illiquidity. Our proposed model builds on the former, a diffusion-based

[2]Kou (2002) develops the first DEJD-based equity option pricing model. Ramezani and Zeng (2007) use the DEJD to model individual stock returns.

model.

Second, while the empirical literature on structural models has mainly investigated medium- or long-term corporate bonds and single-name credit default swap (CDS) contracts, this paper focuses on short-term debt claims, commercial papers. Importantly, we empirically examine the performance of the proposed structural model in predicting CP spreads. The only other empirical study of individual CP issues that we are aware of is the one by Covitz and Downing (2007). However, they do not include any structural models in their analysis; they use equity volatility, credit ratings, and EDFs from Moody's KMV as credit proxies in their regressions.

The empirical literature on structural models can be divided into two streams. One stream, going back to Jones, Mason, and Rosenfeld (1984), focuses on implications of structural models under the risk-neutral measure using alternative empirical methodologies. See, e.g., Jones, Mason, and Rosenfeld (1984); Eom, Helwege, and Huang (2004); Ericsson and Reneby (2005); Schaefer and Strebulaev (2008); Bao and Pan (2013); Bao and Hou (2017); Culp, Nozawa, and Veronesi (2018); Huang, Shi, and Zhou (2019).

Another stream of research explores model implications under both the risk-neutral and physical measures, such as studying the pricing performance of structural models by calibrating them to historical default losses. To resolve the credit spread puzzle documented in Huang and Huang (2012), many studies propose various economic channels to account for the credit component of yield spreads by incorporating additional sources of default premium. Examples include Bao (2009); Chen, Collin-Dufresne, and Goldstein (2009); Chen (2010); Bhamra, Kuehn, and Strebulaev (2010); Christoffersen, Du, and Elkamhi (2017); Du, Elkamhi, and Ericsson (2019); McQuade (2018); Shi (2019)

One of our main findings is that liquidity plays an important role in CP spreads. Krishnamurthy (2002) argues that CP spreads are essentially entirely due to liquidity, whereas Covitz and Downing (2007) find that credit risk is more important than liquidity in the determination of CP spreads. There is a large empirical literature on corporate bond illiquidity, however; see, e.g., Bao, Pan, and Wang (2011); Chen, Lesmond, and Wei (2007); Das and Hanouna (2009); Han and Zhou (2016); Helwege, Huang, and Wang (2014); Longstaff, Mithal, and Neis (2005); Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik (2008); Schestag, Schuster, and Uhrig-Homburg (2016); Bongaerts, De Jong, and Driessen (2017), among others.

Our paper is also related to the new literature on the Chinese credit market. Amstad and He (2019); Mo and Subrahmanyam (2018) provide a comprehensive overview of this market. Chen, Chen, He, Liu, and Xie (2019) study a unique feature of the Chinese corporate bond markets—where bonds with identical fundamentals are simultaneously traded on two segmented markets that feature different rules for repo transactions—and document causal evidence for the value of asset pledgeability. Geng and Pan (2019) focus on the segmentation of the Chinese corporate bond market. Our paper differs from these studies in that we focus on the Chinese CP market.

3 Data

3.1 Commercial Paper Data

In this study, we focus on the commercial paper data obtained from the China Foreign Exchange Trade System (CFETS, also known as the National Interbank Funding Center) over the period May 2014–December 2018.[3] As a sub-institution directly affiliated to the

[3]According to CFETS, the transaction data before 2014 is relatively sparse and unreliable. Mo and Subrahmanyam (2018) also find that in the early years of the CFETS data set, which goes back to 2006, many data points have missing information on transaction prices for all types of bonds. Our sample period starts after the first default of publicly issued bonds, the default of Shanghai Chaori Solar on its one billion RMB bond. As such, we avoid the issue uncovered by Geng and Pan (2019) that, during the pre-default era, corporate debt pricing in China is de-coupled from the issuer's fundamental default risk (with wide spread belief that bond investors will always be paid in full).

People's Bank of China, CFETS plays a similar role to FINRA in terms of serving and monitoring the over-the-counter bond market. Our data set consists of end-of-day transaction summaries of all corporate debts traded in the interbank market. Compared to standard data sets on exchange-traded markets, i.g. CRSP Daily Stock File, it contains additional information on daily volume-weight average price, which is the key variable in our calculation of yield spreads and liquidity measures. This pricing data is matched to WIND IBQ database to obtain the characteristics of each issue, including the name of the issuer, seniority, face value, issuance date, maturity date, credit rating, and redemption features etc.

Table 1 provides summary statistics on trading activities in the Chinese commercial paper market. We partition the data into six maturity categories: 1 to 30 days; 31 to 60 days; 61 to 90 days; 91 to 180 days; 181 to 270 days; and greater than 270 days. Within each of these maturity categories, we compute the average daily shares of the total par amount traded accounted for by primary and secondary transactions.[4] We find that, over average, secondary market transactions account for more than 78% of total daily transaction volumes. This finding stands in stark contrast to the US CP market, in which primary market transactions completely dominates. Indeed, this ratio for the US market is about 8.34% according to Covitz and Downing (2007). The intense transaction activity on the Chinese CP market is largely attributable to the regulatory constraint imposed on money market funds, i.e., the overall duration of their portfolio cannot exceed 120 days. In response, fund managers actively adjust their portfolios to make full use of upper limit on the duration. Consequently, while the average initial maturity is days, the trading volume of CPs with even less than 30 days to maturity is substantial and makes up about 9% of all secondary transactions.

Another notable difference from the U.S. CP market arises from the primary market. Rather than concentrating on the shortest maturities—1 to 4 days as reported in Covitz and Downing (2007)—primary issues in China has maturities evenly spread across ranges. If the

[4]Note that the shares do not sum to 100% in each panel because they are averages of daily shares.

decision of initial maturity is partially driven by the clientele effect, this evidence suggests that institutional investors in China are not excessively concerned about the secondary market liquidity so that they do not aggressively demand extremely short maturities to create de facto liquid.

3.2 Corporate Yield Spreads

For corporate bond i at month t, we calculate its end-of-month yield using the volume-weighted average price of all trades within 7 days of the month-end (Bao and Pan, 2013). As is the case of US market, CPs in China do not carry a coupon, though the interest is calculated on an actual/365 basis. Therefore, credit spread can be simply measured as the difference between the annualized CP yield and the default-free zero yield of the same maturity. Following Covitz and Downing (2007), we use the yield curve derived from repurchase agreements and relevant derivatives as the reference curve to calculate credit spreads. Specifically, we collect from WIND the data of 7-day interbank fixing repo rate (FR007) as well as swaps with a fixed rate versus it;[5] the swap rates are means of the bid and ask rates from major swap dealers' quoted rates and cover the maturities from one month to ten years. The term structure of risk-free zero rates is then constructed via standard bootstrapping techniques. Finally, we remove upper 1% and lower 1% tails of the credit spreads in order to avoid the influence of outliers (Campbell and Taksler, 2003).

Figure 1 presents the face-value-weighted average CP yield spreads for different rating/maturity categories. Since there are five rating agencies dominating the Chinese interbank bond market, we extract rating information from them in order of market share. That is, for each CP issue we first search for its issuer's rating in Chengxin International Rating.

[5] Interbank fixing repo rates (including FR001, FR007 and FR014) are based on repo trading rate for interbank market between 9:00-11:30 a.m. and released to the public at 11:30 a.m. on each trading day. Among them, FR007 serves as the most important benchmark rate in the Chinese money market. Accordingly, FR007-based swaps accounts for more than 70% of the trading volumes of all interest rate swaps, and swaps based on 3-month SHIBOR constitute the second largest market.

If it is missing, we use the rating from China Lianhe Rating and if this is missing as well, we look up the rating from Dagong Global Credit Rating, and so on. This practice is adopted by, i.g., (Dick-Nielsen et al., 2012) and switching to the lowest-rating principal (Collin-Dufresne et al., 2001) makes little difference. The reason is that the rating industry in China is rather homogenous and rating decisions across agencies offer little variation (Amstad and He, 2019).

As credit ratings in China are substantially inflated,[6] it is not surprising to find that for a given nominal rating, the average CP spread in China tends to be several times as high as that in US, i.g., for AAA issuers it ranges from 82 basis points (1 to 60 days) to 122 basis points (301 to 365 days).Despite that the upward bias in rating assignment, the CP yield spread does monotonically decrease with the credit rating in each maturity category. As shown in Geng and Pan (2019), China's domestic ratings contain information above and beyond the issuer's financial healthiness, such as implicit government guarantee. For this reason, in the regression analysis we include credit rating as a default proxy, along with credit measures based on structural models. Another important takeaway from Figure 1 is that the term structure of yield spreads is generally upward sloping for all rating classes. If money market funds engage in reaching-for-yield behavior, they are supposed to exhaust the 120-day upper limit on portfolio duration.

3.3 Liquidity Measures

There is no consensus on how to measure the liquidity of commercial paper markets. Due to the sparseness of secondary market transactions, Covitz and Downing (2007) use issuance size and time to maturity as liquidity proxies. On the other hand, studies on the corporate bond market tend to employ liquidity measures based on intra-day and daily transaction data. In this paper, we consider both types of liquidity variables to examine if market-based

[6] Amstad and He (2019) argue that AA is generally viewed by Chinese institutional investors "as the lowest investment-grade level while this is BBB in global ratings."

liquidity measures contain additional information not captured by static or deterministic proxies.

For the list of liquidity measures we refer to Schestag et al. (2016), who conduct a comprehensive analysis of dozens of liquidity measures using data from the US corporate bond market. As our data set is not organized in a transaction-by-transaction manner, we are only able to implement what they term "low-frequency" measures based on daily data. Table 2 shows that, based on the six transaction cost measures considered in this paper, we obtain average bid-ask spread estimates between 46 and 168 basis points. Compared to summary statistics for the same measures as reported by Schestag et al. (2016), the overall trading cost in the Chinese CP market is generally comparable to that in the US corporate bond market.

On the other hand, these transaction cost measures are closely correlated, with the pairwise correlation coefficient ranging from 13% to 80%. To examine if most of their relevant information can be summarized by a low-dimensional vector, we perform a principal component(PC) analysis in Panel B. We find that the first component loads somewhat evenly on the six measures and explains 44% of their variations. Therefore, we follow Dick-Nielsen et al. (2012) by defining a trading cost factor, TC, as the average of different measures. This factor does not only serve as our primary liquidity variable in regression analysis, but also provide a comprehensive and robust estimate of effective bid-ask spreads, which is a key model input when we quantify the liquidity component in yield spread.

Regarding another important dimension of market liquidity, we consider two price impact measures which are proposed by Amihud (2002) and Pástor and Stambaugh (2003). Compared to transaction cost measures, these two measures incorporates the volume information in a more direct way and thus may offer additional explanatory power for CP yield spreads (Dick-Nielsen et al., 2012; Rossi, 2014; He et al., 2019).

4 Structural Models of Credit Risk

In this section we introduce credit risk models to be used in our empirical analysis. We first review the general framework that underlies these models. We then begin with the Black and Cox (1976) model, the benchmark model in our empirical analysis (Section 4.1.1). We next consider the double-exponential jump diffusion model, an extension of the Black-Cox model to include jumps in the asset return process (Section 4.1.2). We then add liquidity and obtain a jump-diffusion model with endogenous liquidity, which can be considered to be the He and Xiong (2012) model augmented with jumps (Section 4.1.3). Lastly, we discuss the implementation of these models (Section 4.2).

4.1 Modeling Framework

To place corporate default risk and debt market illiquidity into a unified framework, we consider a firm maintaining a stationary debt structure. Specifically, the firm continuously issues a constant amount of new zero-coupon debt with a initial maturity of T years; new bond principal is issued at a rate $f = F/T$ per year, where F is the total principal value of all outstanding bonds. As long as the firm remains solvent, at any time t, the total outstanding debt principal will be F and has a uniform distribution over maturities in the interval $(t, t+T)$. It follows that the average maturity of the firm's outstanding bonds is $T/2$. Overall, this structure of zero-coupon debt rollover is particularly relevant to the CP pricing.

Following the standard assumption for zero-coupon debts (Bao, 2009), we define the recovery rate R as an exogenously specified fraction of the price of an otherwise identical Treasury (non-defaultable) bond. The time-t price of a debt with τ years to maturity is thus given by

$$d_t(\tau) = e^{-r\tau} f \left[1 - \pi(\tau)(1-R)\right], \tag{1}$$

where π denotes the risk-neutral default probability as derived from the model. We follow Leland and Toft (1996) by postulating that the firm's liability cannot be financed through the sale of assets. In other words, if the firm's cash flow is insufficient to cover the rollover cost $f - d_t(\tau)$, new equity will be issued.

4.1.1 The Black-Cox Model

The Black-Cox (1976) model provides a framework to price a corporate bond that can default before maturity due to covenant violation. The idea is, if the firm value falls enough relative to the face value of debt, firms may default even before the maturity of the debt. The firm value threshold K at which firms choose to or are forced to default is called default boundary.

The dynamics of firm's asset value A_t is specified as

$$\frac{dA_t}{A_t} = (r - \delta)dt + \sigma dW_t, \tag{2}$$

where r denotes the risk-free rate, δ the payout rate, and σ the asset volatility. It follows that the resultant risk-neutral default probability has the following expression (Bao, 2009):

$$\pi_{BC}(\tau) = N(h_1(\nu)) + (K/A_t)^{2\nu/\sigma^2} N(h_2(\nu)), \tag{3}$$

where

$$h_{1,2}(\nu) = \frac{\log(K/A_t) \mp \nu\tau}{\sigma\sqrt{\tau}},$$

$$\nu = r - \delta - \sigma^2/2,$$

and $N(\cdot)$ is the cumulative standard normal density function. Based on Eq. (1), we have the Black-Cox credit spread

$$cs_{BC} = -\frac{\log\left(1 - \pi_{BC}(\tau)(1 - R)\right)}{\tau}. \tag{4}$$

4.1.2 The Double-Exponential Jump Diffusion Model

It is well-known that purely diffusion models are unable to generate sizable credit spreads on short-maturity bonds (see, for example, Duffie and Lando 2001). In this paper, we focus on the double-exponential jump diffusion (DEJD) model which allows for analytically tractable solutions,

$$\frac{dA_t}{A_t} = (r-\delta)dt + \sigma dW_t + d\left[\sum_{i=1}^{N_t}(Z_i - 1)\right] - \lambda\xi dt$$

where N is a Poisson process with a constant intensity λ, and $Y \equiv \ln(Z_1)$ has a double-exponential distribution

$$f(y|p_u, p_d, \eta_u, \eta_d) = p_u\eta_u e^{-\eta_u y}\mathbf{1}_{\{y\geq 0\}} + p_d\eta_d e^{\eta_d y}\mathbf{1}_{\{y<0\}}$$

It follows that the mean percentage jump size ζ is given by

$$\zeta = \mathbf{E}\left[e^Y - 1\right] = \frac{p_u\eta_u}{\eta_u - 1} + \frac{p_d\eta_d}{\eta_d + 1} - 1.$$

The default-triggering mechanism and default recovery rule are assumed to be the same as those in the Black-Cox model. Therefore, the impact of discontinuous movements in the asset return is mainly reflected in the modified function of default probability, which is denoted by π_J. We can calculate π_{JD} numerically through an inverse Laplace transform (see, e.g., Huang and Huang 2012). Replacing π_{BC} with π_{JD} in Eq. (4) results in the DEJD model credit spread cs_{JD}.

4.1.3 The He-Xiong Model with Jumps

To quantify the liquidity component in CP yield spreads, we model endogenous liquidity through a market structure similar to Amihud and Mendelson (1986) and He and Xiong (2012). That is, we assume that each bond investor is hit by a liquidity shock with probability ξ. Liquidity shocks bring about liquidity needs, which has to be covered by selling the bond holding in the illiquid secondary market. As such, the (fractional) transaction cost k enters into bond pricing through its product with the liquidity shock intensity

$$d_t(\tau) = e^{-(r+\xi k)\tau} f\left(1 - \pi(\tau)\right) + e^{-r\tau} fRG(\xi k, \tau), \tag{5}$$

where $G(z,)$ denotes the Arrow-Debreu default claim with the discount rate equal to z. If the asset value process follows Eq. (2), we have $\pi = \pi_{BC}$ and $G = G_{BC}$, where

$$\begin{aligned} G_{BC}(\xi k, \tau) =& (K/A_t)^{(\nu - g(\xi k))/\sigma^2} N\left(h_1(g(\xi k))\right) + (K/A_t)^{(\nu + g(\xi k))/\sigma^2} N\left(h_2(g(\xi k))\right), \\ g(\xi k) =& \sqrt{\nu^2 + 2\xi k \sigma^2}. \end{aligned}$$

As illustrated in He and Xiong (2012), ξk represents the adjustment made to the discount rate and thus determines the liquidity premium in corporate yield spreads. If bond investors are not exposed to liquidity shocks ($\xi = 0$), $\widetilde{G}(\tau)$ degenerates to $\pi_{BC}(\tau)$ and Eq. (5) coincides with $d_{BC}(\tau)$.

Considering the crucial importance of jump risk to short-term credit spreads, we set $\pi(\tau) = \pi_{JD}(\tau)$ in our model-based spread decomposition to fully account for the credit component. Accordingly, $\widetilde{G}(\tau)$ needs to be computed numerically as shown in Huang, Shi, and Zhou (2019), and the corresponding model spread is denoted by cs_{HXJ}. It follows that the incremental contribution of liquidity risk to yield spreads is given by $cs_{HXJ} - cs_{JD}$.

4.2 Implementation

We start with the calculation of Black-Cox credit spreads, which requires estimates of (1) market value of the firm's asset and (2) asset volatility. Following Bao (2009), we extend the estimation method of Jones, Mason, and Rosenfeld (1984) to the Black-Cox model to identify the values of A_t and σ.[7] Specifically, by matching model-implied values of market

[7]Applications of this estimator to the original Merton model include Campbell et al. (2008), Hillegeist et al. (2004) and Bai and Wu (2016).

leverage and equity volatility to observed values, we obtain the following equation set:

$$L_t = \frac{F}{E_t(A_t,\sigma)+F}, \tag{6}$$

$$\sigma_E = \frac{\partial E}{\partial A}\frac{A_t}{E_t}\sigma. \tag{7}$$

where L is termed quasi-market leverage by Schaefer and Strebulaev (2008), and σ_E denotes the equity volatility. The modeled equity value $E(A_t,\sigma)$ is derived as

$$E_t(A_t,\sigma) = A_t - \left[KG_{BC} - \frac{FR}{rT}(G_{BC}(r,T) - e^{-rT}\pi_{BC}(T))\right] - D_t(A_t,\sigma), \tag{8}$$

where the three terms on the right-hand side capture the unlevered value of the firm, the deadweight loss of default and the total market value of outstanding debt, respectively. The solution for D_t follows Leland and Toft (1996),

$$\begin{aligned} D_t = &\int_0^T d_t(\tau)d\tau, \\ =&\frac{F}{rT}\left[1 - G_{BC}(r,T)(1-R) - e^{-rT}(1-\pi_{BC}(T)(1-R))\right]. \end{aligned}$$

Following the standard established by Moodys KMV (Crosbie and Bohn, 2003), the default boundary K is measured as the firm's book measure of short-term debt, plus one half of its long-term debt, based on its quarterly accounting balance sheet. This specification of default boundary is especially suitable for the pricing of default risk at a short horizon, which explains why it was initially employed in KMV's Expected Default Frequency (EDF) measure.[8] Studies that have used the same specification include Eom, Helwege, and Huang (2004); Vassalou and Xing (2004); Duffie, Saita, and Wang (2007).

Estimation of jump parameters $\{\lambda, p_u, \eta_u, \eta_d\}$ involves estimating their counterparts under the physical measure $\{\lambda^{\mathbb{P}}, p_u^{\mathbb{P}}, \eta_u^{\mathbb{P}}, \eta_d^{\mathbb{P}}\}$ and converting them to the risk-neutral measure. We adopt the specification of Huang and Huang (2012) that the transformation from $\mathbb{P}$-

[8]The EDF measure initially focused on one-year default probabilities.

measure jump parameters to $\mathbb{Q}$-measure ones is controlled by a single parameter

$$\gamma = \frac{\lambda\zeta}{\lambda^{\mathbb{P}}\zeta^{\mathbb{P}}}.$$

Since a joint estimation of all these parameters is fairly complicated and might not be numerically robust, we identify them separately by carrying out the following scheme.

First, we use index option prices to identify the jump risk premium parameter γ. Until December 23, 2019, options on the SSE 50 Index ETF were the only option product traded in mainland China. To make the estimation of γ independent of other jump parameters, we assume that SSE 50 Index returns directly follow a DEJD process

$$\frac{dS_t}{S_t} = rdt + \sigma_s dW_t + d\left[\sum_{i=1}^{N_{s,t}} (Z_{s,i} - 1)\right] - \lambda_s \zeta_s dt \tag{9}$$

$$= \mu_s dt + \sigma_s dW_t^{\mathbb{P}} + d\left[\sum_{i=1}^{N_{s,t}^{\mathbb{P}}} (Z_{s,i}^{\mathbb{P}} - 1)\right] - \lambda_s^{\mathbb{P}} \zeta_s^{\mathbb{P}} dt. \tag{10}$$

In the spirit of Eraker (2004), we employ a Markov Chain Monte Carlo(MCMC) estimator for joint options and index returns data. To reduce the computational burden, we follow Pan (2002) by only selecting only near-the-money short-dated option contracts into our estimation. As such, we obtain an estimate of γ at 2.30, along with the estimates of other parameters in Eqs. (9) and (10).

Next, we use high-frequency equity returns to pin down the values of λ and p_u for each debt issuer. To be specific, we apply the jump detection method of Tauchen and Zhou (2011) to five-minute returns on individual stocks.The intra-day equity data is retrieved from CSMAR China Security Market Trade & Quote Research Database, and we eliminate days with less than 60 trades. Once the individual jump size is filtered out, we can easily estimate the jump intensity and the probability of upward jumps. We find that on average CP issuers have 3.95 jumps per year, and upward jumps are slightly more likely than downward jumps, with the mean of p_u equal to 0.53.

Finally, we adopt the assumption of Huang and Huang (2012), $\eta_u = \eta_d = \eta$, when estimating parameters on the jump size. In our estimation of eta, we follow Bao (2009)'s procedures in the sense that (1) we use the moment condition equalizes the empirical and model-implied fourth moments of equity returns; (2) we do not adjust the estimate of diffusion volatility σ for the inclusion of jumps, such that the differential $cs_{JD} - cs_{BC}$ purely reflects the incremental contribution of the additive jump component.[9]

The implementation of He-Xiong_Jump Model (HX_J Model hereinafter) requires estimates of the fractional trading cost k and liquidity shock intensity ξ. The former can be easily calibrated to our transaction cost measure TC, which varies across issues and over time. The latter is identified by targeting the average turnover rate in the Chinese CP market, as in the calibration analysis of He and Xiong (2012). Over our sample period, the turnover averages at 64.1%, which is close to the 70% estimated by He and Milbradt (2014) with the TRACE database for the US corporate bond market.

5 Empirical Results

5.1 Determinants of CP Spreads: Evidence from Regressions

Table 3 reports results from panel regressions of CP yield spreads on credit-risk related variables. Model M1 considers three key variables as suggested by the original Merton model: the risk-free rate, leverage, and equity volatility (Ericsson et al., 2009). M2 moves forward toward the Merton model by examining the distance-to-default (DD), a nonlinear function of these three variables which in theory directly determines the default probability. The results from these two regression models show that individual equity volatility is significantly positive and DD is significantly negative. M3 combines M2 with M1 and indicates that DD

[9] According to Cremers et al. (2008), the inclusion of double-exponential jumps has minimum impact on the estimation of diffusion volatility, merely decreasing its estimate from 19.95% to 19.88%.

subsumes equity volatility, which lends support for the functional form of model spread.

Interestingly, augmenting M3 with the credit rating variable ($Rating_{i,t}$) slightly strengthens the impact of DD (model M4). This result implies that DD contains incremental information about spreads over credit ratings, consistent with Campbell and Taksler (2003) to some extent. M5 and M6 consider other explanatory variables included into the benchmark regression of Collin-Dufresne et al. (2001). Including the slope of yield curves and the equity market return ($CSI300_t$) does not drive out DD and $Rating_{i,t}$ (model M5). Finally, the option-implied volatility ($CIVIX_t$) and the slope of its "smirk" ($Jump_t$) are used as proxies for variations in volatility and jump magnitude/probabilitie. Augmenting M5 with these two variables raises the adjusted R^2 substantially from 4.8% to 6.4%. Especially, $Jump_t$ is highly significant with the expected sign, consistent with the notion that jumps are essential for structural models to generate plausible spreads for short-maturity debts (Zhou, 2001).

Given the moderate $\bar{R}^2$ of 6.4% in M6, we now examine potential explanatory power of bond market illiquidity for spreads. Univariate regression results reported in Table 4 indicate that all six transaction cost measures are significantly positive. In particular, they coincide with the finding of Schestag et al. (2016) that Roll (1984)'s measure and Hasbrouck (2009)'s Gibbs measure deliver the best performance among low-frequency measures, as each of them captures more than 15% of variations in CP spreads. On the other hand, the Pastor-Stambaugh measure for price impact is associated with an insignificant coefficient with a counter-intuitive sign.

To assess the relative importance of liquidity- and credit-related variables in explaining the CP spreads, we estimate nine regression models and report the results in Table 5. M1 starts with four traditional liquidity proxies considered in Covitz and Downing (2007). We find that, while $OfferAmt_i$ and $InitMat_i$ are significant with expected signs, the four proxies explain little variation in the spread with an $\bar{R}^2$ of merely 0.7%. In contrast, our proposed measure for trading cost, TC_i, is significantly positive with an R^2 of 21.4% (M2), which is greater than any individual measure. Augmenting M2 with $Amihud_i$ raises the $\bar{R}^2$ to 26.1% (M3). Augmenting M3 with the four traditional liquidity proxies has only marginal impact on $\bar{R}^2$ and renders $OfferAmt_i$ and $InitMat_i$ insignificant. This evidence suggests that conclusion of Covitz and Downing (2007) on the role of liquidity is likely driven by their focus on static/deterministic measures.

Given the results in Table 3, we use DD_i and $Rating_i$ as our baseline credit variables and consider the incremental contribution of $Jump_t$ as well. M5 shows that both DD_i and $Rating_i$ are significant with expected signs albeit with a low $\bar{R}^2$ of 3.4%. Augmenting M5 with TC_i and $Amihud_i$ weakens the impact of DD_i and $Rating_i$ although the two credit-related variables are still significant (M6). Interestingly, M6 has an $\bar{R}^2$ of 26.1%, much higher than that of M5 and the same as that of M3. In other words, the results from M2 through M6 indicate that the liquidity proxies are much more important than the credit-related variables in explaining the variation in the CP spread. The results from M7 and M8—M5 and M6 augmented with $Jump_t$ respectively—confirm this conclusion. Still, including $Jump_t$ raises the $\bar{R}^2$ significantly percentage-wise, increasing $\bar{R}^2 = 3.4\%$ for M5 to 4.1% for M7 (a 20% increase in the relative term). Lastly, we augment M8 with more market-wide variables, including $Slope_t$, $CSI300_t$, $CIVIX_t$, TED_t, along with $YearEng$ and SCP. Among these variables, only $CSI300_t$, $CIVIX_t$ are significant (M9). Moreover, M9 has an $\bar{R}^2$ of 27.5%, almost the same as that of M8 (27.2%).

5.2 Determinants of Spreads on MTNs and EBs

Intuitively, credit-related variables become more important in determining the spreads of longer-maturity corporate debts. In this subsection we repeat the analysis of Section 5.1 using MTNs and EBs to examine if the relative importance of firm's fundamentals increases with the debt maturity.

Consider short-term MTNs and EBs with maturities of 1–3 years first. We make several observations from the results reported in Table 6. First, while both TC_i and $Amihud_i$ are highly significant, the former alone has an R^2 of 24.0% (M1) and the latter has an incremental R^2 of 0.8% only (M2). Namely, $Amihud_i$ becomes less important than it is for the CP spreads (see M2 and M3 in Table 5). Second, the credit variables, DD_i and $Rating_i$, are both significant with expected signs and together have an $\bar{R}^2$ of 9.3% (M3), much higher than their counterpart for CP spreads (3.4% of M5 in Table 5). Furthermore, DD_i and $Rating_i$ together have a marginal R^2 of 0.03 (more than 10% increase) over TC_i and $Amihud_i$ (M4 and M2). Third, $Jump_t$ is highly significant with correct sign but its incremental explanatory power over DD_i and $Rating_i$ becomes weaker than it does for CP spreads. For instance, including $Jump_t$ raises the $\bar{R}^2$ of 9.3% for M3 to 9.8% for M5, a 5% increase in the relative term (as opposed to a 20% increase in the case of CP spreads). Fourth, the results from M6 and M7 show that $Slope_t$, $CSI300_t$, $CIVIX_t$, TED_t, $YearEng$ and SCP together add little incremental explanatory power over (TC_i, DD_i, $Rating_i$, $Jump_t$).

To summarize, the main takeaway from Table 6 is that when we move from CP to longer maturity, short-term MTNs and EBs, the credit variables become relatively more important than the liquidity proxies but the jump risk becomes less important relative to the other credit variables.

Next we repeat the above analysis using intermediate MTNs and EBs with maturities of 3–5 years and report the results in Table 7. We make the following observations. First, a comparison of M1 and M2 with their counterparts for short-term MTNs and EBs (Table 6) indicates that while TC_i is equally important for intermediate-term MTNs and EBs as for the short-term ones, $Amihud_i$ is no longer significant conditional on TC_i (M2). Second, DD_i and $Rating_i$ are both highly significant with expected signs and together have an $\bar{R}^2$ of 37.8%, higher than that of TC_i (M1) and especially, much higher than their counterpart for either CP spreads (3.4% of M5 in Table 5) or short-term MTNs and EBs (9.3% of M3 in Table 6). Third, $Jump_t$ is only marginally significant now and has very little incremental explanatory power over either DD_i and $Rating_i$ (M5) or them along with TC_i (M6). Fourth, TC_i, DD_i, and $Rating_i$ together have an $\bar{R}^2$ of 42.7% (M4); adding those market-wide variables raises the $\bar{R}^2$ marginally. In summary, Table 7 provides more evidence supporting the main takeaway from Table 6.

To better illustrate the relative importance of credit- or liquidity-related proxies in explaining yield spreads, Figure 2 plots their $\bar{R}^2$'s for CPs, short-maturity MTNs and EBs, and intermediate-maturity MTNs and EBs, respectively. Credit-related variables considered include DD_i and $Rating_i$ with (in blue) and without $Jump_t$ (in navy blue). Liquidity-related variables considered include TC with (in yellow) and without $Amihud_i$. The main takeaway from the figure is that while the liquidity proxies together have a relatively stable $\bar{R}^2$ of around 25%, the credit-risk proxies have an increasing $\bar{R}^2$ as maturities of issues become longer.

5.3 Pricing Performance of Structural Models

The regression-based evidence in Sections 5.1 & 5.2 sheds light on the role of credit and liquidity in capturing spread variations. However, since there is a nontrivial overlap in the information covered by those credit and liquidity variables, we are unable to perform a yield spread accounting without a structural framework. In this subsection, we aim to quantify the contributions of default and liquidity risks to the level of CP yield spreads. To this end, we examine the pricing performance of the three structural models as reviewed in Section 4.

We implement each of the three structural models as described in Section 4.2 and calculate the model-implied spread of every CP issue in our final sample. Before analyzing the pricing performance of these models, we examine the empirical distributions of observed CP spreads as well as the model-implied spreads, which are illustrated for both the full sample and the subsamples by credit ratings in Table 8.

Consider the full sample first. The consensus is that pure diffusion-based structural models are unable to generate sufficiently high short-term spreads consistent with levels of observed spreads. Clearly, the Black-Cox (pure-diffusion) model substantially underestimates the CP spread, although this problem is relatively less severe for CPs with super high spreads on the right tail. For instance, the Black-Cox model implied CP spreads have a mean of 0.32% and median of 0.0%, way below their empirical counterparts of 1.53% and 1.34%, respectively. Note that the model-implied spreads are severely right-skewed. This fact indicates that judging the performance of the model by the mean predicted spread alone may lead to a misleading conclusion.

As expected, the DEJD model significantly improves the pricing performance, especially at the right tail. For instance, the Black-Cox, DEJD-implied, and observed spreads at the 90th percentile are 0.96%, 2.62% and 2.88%, respectively. Also, incorporating jumps raises the average and median model-implied spreads from 0.32% and 0.0% for the Black-Cox model to 1.07% and 0.48% for the DEJD model, respectively. However, the DEJD model-implied spread at the left tail are still substantially below their empirical counterparts. For example, the DEJD-implied and observed spreads at the 10th percentile are 0.06% and 0.45%, respectively. Moreover, the DEJD model-implied spreads are still right skewed. One implication of these findings is that part of CP spreads may be related to liquidity.

Consider next the extended He and Xiong (2012) model with jumps, which is proposed in this paper. Recall that this model can also be considered to be an extension of the DEJD model to include endogenous liquidity. Note first from the top panel of Table 8 that the average model-implied spread is 1.62%, higher than the average observed spread of 1.53%. The model-implied spreads at the right tail exceed their observed counterparts even more: the model-implied and observed spreads at the 90th percentile are 3.43% and 2.88%, respectively. However, the model-implied median spread and especially, those at the right tail are substantially below their empirical counterparts. Moreover, the extended He-Xiong model-implied spreads are still right skewed. That is, while incorporating endogenous liquidity improves the overall pricing performance significantly, the resulting model may still under-estimates those "safer" CP spreads but over-estimates spreads of those "more risky" CP issues. To some extent, this problem is analogous to what is noted in Eom, Helwege, and Huang (2004) about some other structural models that they use to predict corporate bond yield spreads. One caveat to keep in mind, however: the model-implied and observed spreads at a given percentile may come from different CP issues.

The results for four different subsamples by credit ratings, reported in Table 8, provide similar patterns as those for the full sample.

We now proceed to examine the pricing errors of these three structural models, which are reported for both the full sample and the subsamples by credit ratings in Table 9. We make three observations from the mean pricing errors reported in panel A. First, the three models all have negative pricing errors, regardless of the credit ratings considered. The mean pricing error ranges from -2.11% for the "Other" group from the Black-Cox model to -0.17% for the AAA group from the extended He-Xiong model (the HX-Jumps model). Second, adding jumps and then endogenous liquidity to the benchmark Black-Cox model each separately reduces the magnitudes of the mean pricing errors, controlling for credit ratings. Third, under a given model, the higher the credit rating, the lower the magnitude of the mean pricing error. Fourth, the average pricing error of the HX-Jumps model is statistically insignificantly different from zero for the full sample as well as the AAA and AA+ subsamples; namely, on average the model can match the levels of CP spreads for the full sample, the AAA group, or the AA+ subsample.

The mean percentage pricing errors, reported in panel B of Table 9, show different patterns from the mean pricing errors in panel A. First, the mean percentage pricing error is negative except for the full sample, and the AAA and the AA+ subsamples, all under the HX-Jumps model. The mean percentage pricing error ranges from -72.31% for the AAA group under the Black-Cox mode to 19.88% for the AAA group under the HX-Jumps model.

Second, adding jumps and then endogenous liquidity to the benchmark Black-Cox model each separately reduces the magnitudes of the mean percentage pricing errors except for the AAA group, whose mean percentage error is -17.46% under the DEJD model and 19.88% under the HX-Jumps model. Third, under a given model, there is no monotonic relation between the magnitude of the mean percentage pricing error and the credit rating. Fourth, the mean percentage pricing error of either the DEJD model or the HX-Jumps model is not statistically significantly different from zero, regardless of the rating categories except for the smallest subsample, the "Other" subsample.

Overall, there are four main takeaways from Table 9. First, the Black-Cox model substantially under-estimates the CP spreads, regardless of the credit ratings considered. Second, augmenting the Black-Cox model with jumps significantly improves the model performance, especially for AA–AAA groups on a relative basis. The resulting DEJD model, however, still under-estimates the CP spreads across all rating groups. Third, augmenting the DEJD model with endogenous liquidity substantially improves the pricing performance. In fact, on average, the resulting HX-Jumps model can match the CP spread for the full sample as well as the AAA and AA+ subsamples. Fourth, both the DEJD and HX-Jumps models suffer from the accuracy problem: they both have high mean percentage pricing errors although they are statistically insignificant except for the "Other" rating group.

6 Conclusions

Although short-term corporate debt played an important role in the recent financial crisis, there are very few studies on the determinants of short-term credit spreads. In this paper we examine the determinants of commercial papers using a unique data set of *secondary* market transactions in the Chinese commercial paper market. We propose and empirically test a structural credit risk model with rollover risk, jump risk, and endogenous liquidity, which is particularly suitable for predicting commercial paper spreads. Among other things, this model allows us to decompose CP spreads into a credit component and a liquidity component in a unified manner.

We find that credit and liquidity risks are both important in the determination of short-term yield spreads and that the former is more important for longer-maturity debt. We also find that the Black-Cox (1976) pure-diffusion model substantially under-estimates CP spreads, regardless of credit ratings considered. Not surprisingly, augmenting the Black-Cox model with jumps significantly improves the model performance, especially for AA–AAA groups on a relative basis. However, the resulting model—the double-exponential jump-diffusion (DEJD) model of credit risk—still under-estimates CP spreads across all rating groups. Incorporating endogenous liquidity into the DEJD model substantially improves the model performance except for the AAA group. Furthermore, the resulting model—the He-Xiong (2012) model with jumps—on average, can match the level of CP spreads for either the full sample or the AAA and AA+ subsamples. However, this extended He-Xiong model still has high average percentage pricing errors—which are positive for the full, AAA or AA+ samples but negative for AA and lower rating groups—even though they are insignificantly different from zero.

Overall, this paper provides a comprehensive study on the determinants of short-term credit spreads using *secondary* transaction data and a structural model with both rollover risk and endogenous liquidity. Our results indicate that to better capture the behavior of short-term credit spreads, we need to incorporate a liquidity component that can help raise spreads on the riskiest issues without raising them too much for the safer issues.

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A The Chinese Commercial Paper Market

In the Chinese bond market, commercial papers are widely used by non-financial firms for short-term financing.[10] The standard commercial papers were first introduced to the market in May 2005, followed by the introduction of the super commercial papers in 2010. The major differences between these two types of commercial papers are the maturity at issuance and borrowing capacity. The value of the outstanding standard commercial paper, with a maturity of less than one year, cannot exceed 40% of the issuing firm's net asset. There is no such limit for super commercial papers, for which the maturity is restricted to less than 270 days. Since the borrowing cost of commercial papers is typically lower than that of bank loans with similar maturities, and there is no explicit restriction on the usage of funds raised, the market for commercial papers grows fast since its inception. In 2005, 61 firms raised 142.4 billion RMB with commercial papers. By the end of 2018, the outstanding bond value reached 1.9 trillion RMB, which accounted for 2.3% of the overall bond market.

A.1 Registration and issuance

Commercial papers are issued and traded in the interbank bond market.[11] This is an OTC market, only allowing the participation of institutional investors such as commercial banks, rural credit cooperatives, security firms, insurance companies, mutual funds, and foreign institutions. The market was established in 1997 and regulated by China's central bank, the People's Bank of China. The market significantly dominates bond issuance and trading in China, as the balance of outstanding bonds amounted to 76 trillion (89% of the bond market) at the end of 2018.[12]

[10] Security firms are also allowed to issue commercial papers. However, it is subject to different regulations, and the market size is relatively small. We exclude them from our analysis.

[11] See Amstad and He (2019) for an in-depth overview of the interbank bond market in China.

[12] Another important bond market in China is the exchange market, i.e., the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The exchange market is regulated by the China Security Regulatory Commission, the counterpart of SEC in China. A variety of bond products, including corporate bonds,

Bond issuance in the interbank bond market is based on a registration system. The National Association of Financial Market Investors (NAFMII), a self-regulation industry organization under the central bank's guidance, makes the registration rules and oversees the registration process. With a book building process, the offering interest rate is determined by underwriters based on bids collected from market investors. Since the maturity is quite short, typically firms issue commercial papers to repay bank loans or other bonds, and fund their working capitals. In 2018, 827 firms, including both SOEs and privately-owned enterprises, issued 2,918 commercial papers, raising 3.1 trillion RMB. This accounted for 7.2% of the total bond issuance in the Chinese market. The maturity of an average bond was 0.66 years, and it was offered at 4.94% per year.

A.2 Trading and investors

The interbank bond market is an OTC market in nature. However, the China Foreign Exchange Trade System offers a centralized trading system for bonds including commercial papers. Similarly, the Shanghai Clearing House provides unified depository and clearing services to commercial paper investors. All the participants in the interbank bond market are allowed to invest in commercial papers. As of the end of 2018, the largest investor was non-legal-person investor (mutual funds, wealth management products, trusts, etc.), which held 69.9% of the outstanding commercial papers. The second and third largest investors were commercial banks and security firms, holding 23.1% and 4.3%, respectively. Commercial papers are among the most liquid products in the bond market. In 2018, the spot transaction volume amounted to 7.0 trillion RMB, which could be translated to an annual turnover rate of 4.1.

government bonds, and financial bonds, is available on this market. By the end of 2018, the value of outstanding bonds in the exchange market is 9.2 trillion RMB.

A.3 Credit rating and defaults

NAFMII asks for standard commercial paper issuers to be rated AA- or above. For super commercial papers, two ratings from different rating agencies are mandatory with one at AA or above. Note that the distribution of the Chinese rating scale is upward skewed, these rating requirements seems not to be very binding in many cases. Among the 2,918 bonds issued in 2018, 51.6% were rated AAA, 34.5% were rated AA+, and 13.5% were rated AA. Only 5 bonds (0.2%) are rated AA-. Credit enhancements were also seldom seen as 36 (1.2%) issuances provided enhancements like guarantees or collaterals. Though Chinese regulators are striving to eliminate implicit government guarantees in the bond market, the overall bond default rate remains relatively low in China. It is the same case for commercial papers. The first real default in the commercial paper market occurred in November 2015, as Sunnsy Group failed to repay its 2 billion RMB bond. From 2014 to 2018, only 62 commercial papers of 42.2 billion outstanding amount defaulted, representing a default rate of 0.53% in terms of bond number and 0.29% in terms of value. Moreover, 10 of these defaulted bonds of 4.6 billion outstanding amount were fully recovered by November 2019.

Table 1: Trading Activity in the Chinese CP Market

This table reports average trading volumes for different segments in the Chinese commercial paper market, as well as their average shares of total daily trading volumes. The "Primary Market" includes new issues, and the "Secondary Market" is for paper traded after its issuance date in the primary market. The volumes are reported in billion RMB and shares are expressed in percent. The figures below each average volume/share are the corresponding standard deviations.

		Days to Maturity						
		1-30	31-60	61-90	91-180	181-270	271-360	Sum
Primary Market	Volume (bn)							
	Mean	2.27	2.34	2.27	3.06	6.25	3.31	19.50
	SD	2.62	2.23	2.58	3.26	4.59	2.94	
	% of Total							
	Mean	4.08	4.49	4.35	5.96	11.93	6.95	37.76
	SD	4.8	4.01	4.31	6.46	8.77	6.99	
	No. Issues	1.17	1.12	1.31	1.76	4.73	3.69	13.78
Secondary Market	Volume (bn)							
	Mean	3.39	3.61	3.59	10.64	13.39	5.97	40.60
	SD	2.09	2.22	2.37	6.13	7.63	3.78	
	% of Total							
	Mean	6.72	7.18	7.03	20.34	25.37	11.95	78.58
	SD	3.98	4.02	3.99	7.2	8.51	7.25	
	No. Issues	23.85	23.1	20.22	60.83	61.46	34.37	223.82

Table 2: Transaction Cost Measures and Effective Bid-Ask Spread

Panel A shows descriptive summary statistics (in basis points) for our low-frequency transaction cost measures: Roll (1984)'s measure, Hasbrouck (2009)'s measure, Effective tick (Goyenko, Holden, and Trzcinka 2009; Holden 2009), Fong, Holden, and Trzcinka (2017)'s measure (FHT), High-low spread estimator ($HLsprd$) (Corwin and Schultz 2012), and Close-High-Low estimator (CHL) (Abdi and Ranaldo 2017). The comprehensive measure for effective bid-ask spread, TC, is defined as an equally weighted linear combination of these six measures. Panel B shows the principal component analysis loadings on each of the six measures, along with the cumulative explanatory power of the components. Monthly liquidity measures are computed based on daily transaction prices and volumes provided by CFETS.

Panel A: Descriptive statistics (bp)

	Mean	10%	25%	50%	75%	90%
Roll	75	0	3	44	103	182
Hasbrouck	80	7	16	34	76	160
EffectiveTick	46	2	8	22	50	110
FHT	85	12	23	46	94	163
HLsprd	48	0	1	4	29	118
CHL	168	8	25	60	151	384
TC	75	10	21	45	89	158

Panel B: Principal component loadings

	PC1	PC2	PC3	PC4
Roll	0.45	−0.41	0.01	0.12
Hasbrouck	0.42	−0.04	0.03	−0.36
EffectiveTick	0.35	0.26	0.07	−0.46
FHT	0.44	0.03	0.02	−0.31
HLsprd	0.31	0.40	−0.22	0.51
CHL	0.32	0.45	−0.19	0.33
Cumulative	0.44	0.63	0.77	0.87

Table 3: Regression of CP Spreads on Credit Risk Determinants

This table reports results from six specifications of regressions of commercial paper (CP) spreads on credit risk related variables. Explanatory variables used include the risk-free rate (rf_t), firm-i's leverage ratio ($Lev_{i,t}$), equity volatility ($\sigma^E_{i,t}$), distance-to-default ($DD_{i,t}$), credit ratings ($Rating_{i,t}$), the slope of yield curves ($Slope_t$), the equity market index ($CSI300_t$), the option-implied volatility, the slope of its "smirk" ($Jump_t$).

	Dependent variable: CP spreads					
	$M1$	$M2$	$M3$	$M4$	$M5$	$M6$
Intercept	0.009	0.023***	0.012	0.012	0.012	0.012
	(0.68)	(5.22)	(0.87)	(0.65)	(0.68)	(0.63)
rf_t	0.244		0.531**	0.303	0.451*	0.565
	(0.97)		(2.11)	(1.34)	(1.74)	(1.35)
$Lev_{i,t}$	−0.004		−0.009	−0.007	−0.008	−0.010
	(−0.59)		(−1.04)	(−0.67)	(−0.71)	(−0.76)
$\sigma^E_{i,t}$	0.021***		0.009	−0.009	−0.016	−0.021
	(2.75)		(0.97)	(−0.84)	(−1.24)	(−1.64)
$DD_{i,t}$		−0.002***	−0.003***	−0.003***	−0.004***	−0.004***
		(−2.66)	(−2.60)	(−2.93)	(−3.01)	(−3.06)
$Rating_{i,t}$				0.010***	0.011***	0.011***
				(9.19)	(10.17)	(9.07)
$Slope_t$					−0.501	−0.590
					(−0.88)	(−0.72)
$CSI300_t$					−0.061*	−0.081**
					(−1.70)	(−1.99)
$CIVIX_t$						−0.046
						(−1.52)
$Jump_t$						0.125***
						(3.56)
$\bar{R}^2$	0.005	0.037	0.044	0.043	0.048	0.064
Obs	5755	5755	5755	5755	5755	4920

Table 4: The Explanatory Power of Liquidity Measures for CP Spreads

This table reports results from regressions of commercial paper (CP) spreads on a variety of illiquidity measures. They include six transaction cost proxies: measures of Roll (1984) and Hasbrouck (2009), the effective tick of Goyenko, Holden, and Trzcinka (2009); Holden (2009), the Fong, Holden, and Trzcinka (2017) measure ($FHT_{i,t}$), the Corwin and Schultz (2012) high-low spread estimator ($HighLow_{i,t}$), and the Abdi and Ranaldo (2017) close-high-low estimator ($CHL_{i,t}$); and two price impact proxies: $Amihud_{i,t}$ and $PS_{i,t}$, representing those of Amihud (2002) and Pástor and Stambaugh (2003), respectively.

	Dependent variable: CP spreads							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.017***	0.008**	0.012***	0.011***	0.016***	0.011***	0.017***	0.018***
	(11.92)	(2.33)	(5.05)	(3.41)	(12.54)	(3.06)	(11.99)	(9.96)
$Roll_{i,t}$	3.309***							
	(2.90)							
$Hasbrouck_{i,t}$		3.672**						
		(2.48)						
$EffTick_{i,t}$			8.225**					
			(2.30)					
$FHT_{i,t}$				5.871**				
				(2.38)				
$HighLow_{i,t}$					2.934***			
					(6.67)			
$CHL_{i,t}$						4.279**		
						(2.07)		
$Amihud_{i,t}$							16.968	
							(1.44)	
$PS_{i,t}$								−0.736
								(−0.36)
$\bar{R}^2$	0.154	0.164	0.040	0.165	0.005	0.062	0.018	0.002
Obs	4582	4543	4582	4581	4582	4582	4582	4582

Table 5: Regressions of CP Spreads on Liquidity- and Credit-Related Variables

This table reports results from nine specifications of regressions of commercial paper (CP) spreads on liquidity- and credit-related variables. Liquidity variables used include the CP offer amount ($OfferAmt_i$), trading volume ($volume_{i,t}$), time-to-maturity ($Mat_{i,t}$), the initial maturity ($InitMat_i$), the average trading cost ($TC_{i,t}$), price impact proxy $Amihud_{i,t}$. Credit-related variables used include distance-to-default ($DD_{i,t}$), credit ratings ($Rating_{i,t}$), the slope of yield curves ($Slope_t$), the equity market index ($CSI300_t$), the option-implied volatility ($CIVIX_t$), and the slope of its "smirk" ($Jump_t$). Additional variables used include the year end dummy ($YearEnd$), and the difference between the interest rates on interbank loans and on short-term government debt (TED_t).

	Dependent variable: CP spreads								
	M1	M2	M3	M4	M5	M6	M7	M8	M9
Intercept	0.005*	0.002	−0.003	0.008**	0.013***	−0.000	0.016***	0.001	0.004
	(1.66)	(0.37)	(−0.49)	(2.50)	(2.77)	(−0.11)	(2.60)	(0.30)	(0.45)
$OfferAmt_i$	−0.156***			−0.030					
	(−6.01)			(−0.77)					
$Volume_{i,t}$	−0.004			0.018**					
	(−0.95)			(2.56)					
$Mat_{i,t}$	−0.010			−0.024***					
	(−1.43)			(−2.58)					
$InitMat_i$	0.024***			−0.002					
	(3.11)			(−0.38)					
$TC_{i,t}$		2.273***	3.172***	3.284***		3.198***		3.347***	3.359***
		(2.81)	(2.98)	(3.03)		(2.90)		(3.01)	(3.06)
$Amihud_{i,t}$			0.005***	0.006***		0.005***		0.005***	0.005***
			(3.06)	(2.71)		(3.25)		(2.92)	(2.79)
$DD_{i,t}$					−0.002***	−0.001***	−0.002***	−0.001**	−0.002***
					(−2.98)	(−2.62)	(−2.83)	(−2.41)	(−2.58)
$Rating_{i,t}$					0.007***	0.003**	0.007***	0.003*	0.004**
					(6.35)	(1.99)	(5.25)	(1.65)	(2.39)
$Jump_t$							0.068***	0.039***	0.049***
							(3.08)	(4.06)	(2.79)
$Slope_t$									0.028
									(0.10)
$CSI300_t$									−0.034*
									(−1.71)
YearEnd									0.008
									(0.77)
SCP									0.005
									(1.50)
$CIVIX_t$									−0.031**
									(−2.05)
TED_t									0.176
									(0.55)
$\bar{R}^2$	0.007	0.214	0.261	0.270	0.034	0.261	0.041	0.272	0.275
Obs	5755	4543	4543	4543	4543	4543	3853	3853	3853

Table 6: Spreads on MTNs and EBs on Credit- and Liquidity-Related Variables: 1-3 Years

This table reports results from nine specifications of regressions of 1-3 years MTNs and enterprise bonds (EBs) spreads on liquidity- and credit-related variables. Liquidity variables used include the CP offer amount ($OfferAmt_i$), trading volume ($volume_{i,t}$), time-to-maturity ($Mat_{i,t}$), the initial maturity ($InitMat_i$), the average trading cost ($TC_{i,t}$), price impact proxy $Amihud_{i,t}$. Credit-related variables used include distance-to-default ($DD_{i,t}$), credit ratings ($Rating_{i,t}$), the slope of yield curves ($Slope_t$), the equity market index ($CSI300_t$), the option-implied volatility ($CIVIX_t$), and the slope of its "smirk" ($Jump_t$). Additional variables used include the year end dummy ($YearEnd$), and the difference between the interest rates on interbank loans and on short-term government debt (TED_t).

	Dependent variable: Spreads on short-term MTNs and EBs						
	M1	M2	M3	M4	M5	M6	M7
Intercept	0.015***	0.017***	0.015***	0.013***	0.017***	0.015***	0.015***
	(7.14)	(11.98)	(6.84)	(7.09)	(6.75)	(7.81)	(3.60)
$TC_{i,t}$	2.207***	2.323***		1.830***		1.703***	1.704***
	(3.67)	(3.64)		(3.49)		(3.05)	(3.03)
$Amihud_{i,t}$		0.017***		0.007		0.007	0.007
		(2.72)		(1.21)		(1.26)	(1.24)
$DD_{i,t}$			−0.003***	−0.002***	−0.003***	−0.003***	−0.003***
			(−5.47)	(−6.21)	(−5.77)	(−6.74)	(−5.90)
$Rating_{i,t}$			0.008***	0.006***	0.008***	0.006***	0.006***
			(8.07)	(7.03)	(7.47)	(6.51)	(6.26)
$Jump_t$					0.024***	0.022***	0.021***
					(3.92)	(3.97)	(3.66)
$Slope_t$							0.217*
							(1.83)
$CSI300_t$							−0.006
							(−0.79)
YearEnd							−0.001
							(−0.53)
$CIVIX_t$							0.005
							(0.82)
TED_t							−0.327
							(−1.22)
$\bar{R}^2$	0.240	0.248	0.093	0.278	0.098	0.304	0.304
Obs	2123	2123	2123	2123	1883	1883	1883

Table 7: Spreads on MTNs and EBs on Credit- and Liquidity-Related Variables: 3-5 Years

This table reports results from nine specifications of regressions of 3-5 years MTNs and enterprise bonds (EBs) spreads on liquidity- and credit-related variables. Liquidity variables used include the CP offer amount ($OfferAmt_i$), trading volume ($volume_{i,t}$), time-to-maturity ($Mat_{i,t}$), the initial maturity ($InitMat_i$), the average trading cost ($TC_{i,t}$), price impact proxy $Amihud_{i,t}$ Credit-related variables used include distance-to-default ($DD_{i,t}$), credit ratings ($Rating_{i,t}$), the slope of yield curves ($Slope_t$), the equity market index ($CSI300_t$), the option-implied volatility ($CIVIX_t$), and the slope of its "smirk" ($Jump_t$). Additional variables used include the year end dummy ($YearEnd$), and the difference between the interest rates on interbank loans and on short-term government debt (TED_t).

	Dependent variable: Spreads on 3–5 years MTNs and EBs						
	M1	M2	M3	M4	M5	M6	M7
Intercept	0.019***	0.019***	0.010***	0.010***	0.010***	0.011***	0.008*
	(7.56)	(7.47)	(6.04)	(3.21)	(5.50)	(3.36)	(1.87)
$TC_{i,t}$	1.858***	1.905***		1.219**		1.369**	1.355**
	(2.91)	(3.01)		(2.42)		(2.41)	(2.30)
$Amihud_{i,t}$		−0.002		−0.002		−0.001	−0.001
		(−0.78)		(−0.87)		(−0.67)	(−0.71)
$DD_{i,t}$			−0.001***	−0.001***	−0.001***	−0.001***	−0.000**
			(−5.43)	(−4.53)	(−4.65)	(−3.74)	(−2.26)
$Rating_{i,t}$			0.007***	0.006***	0.007***	0.006***	0.006***
			(7.30)	(6.22)	(6.71)	(6.12)	(6.26)
$Jump_t$					0.011*	0.013*	0.007
					(1.70)	(1.85)	(1.29)
$Slope_t$							0.150
							(1.41)
$CSI300_t$							0.003
							(0.48)
YearEnd							−0.002
							(−1.22)
$CIVIX_t$							0.019***
							(3.67)
TED_t							−0.158
							(−1.22)
$\bar{R}^2$	0.239	0.239	0.378	0.427	0.375	0.439	0.463
Obs	1183	1183	1183	1183	999	999	999

Table 8: Distributions of Observed and Predicted Credit Spreads

This table reports summary statistics of observed and predicted yield spreads for a sample of commercial papers during May 2014–December 2018. The predicted spreads are generated from the Black-Cox (1976) model, the double-exponential jump diffusion (DEJD) model, and the He-Xiong (2012) model with double-exponential jumps (HX-Jumps). N denotes the number of observations in each rating category. All entries are expressed in percentage points.

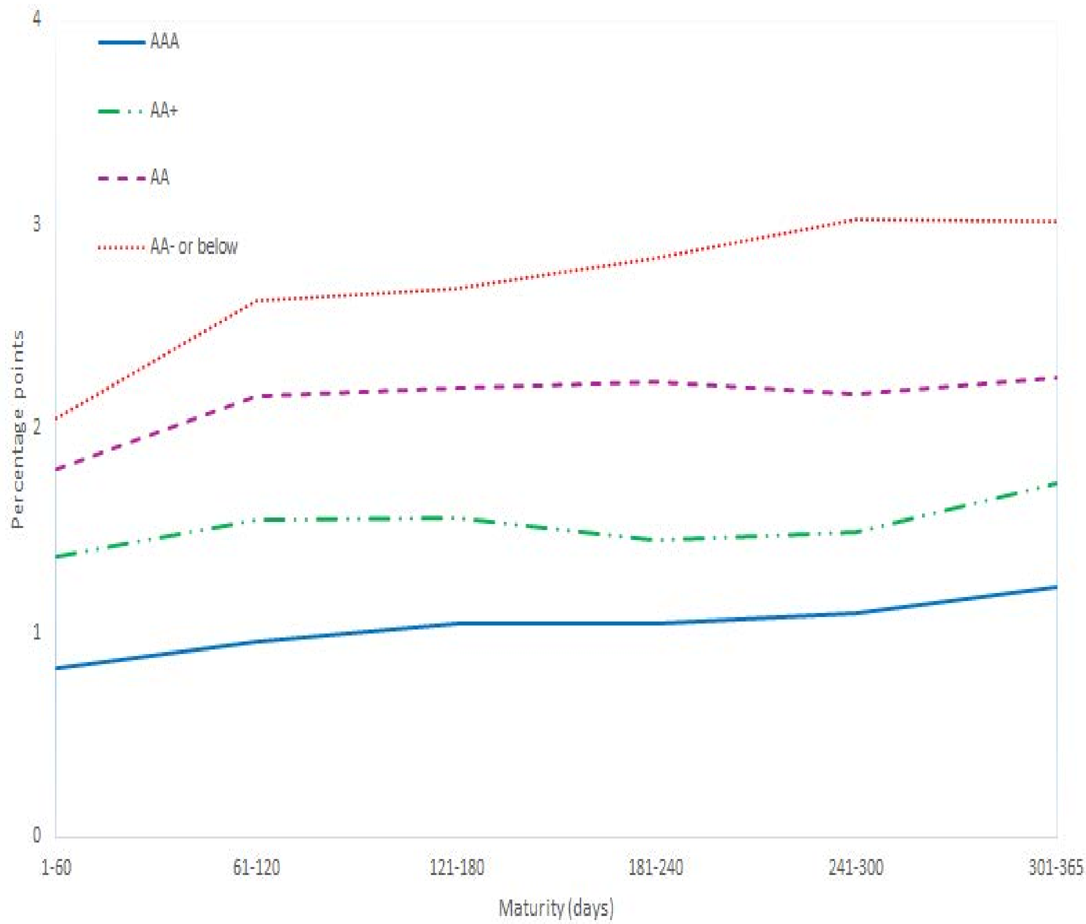
		Mean	10%	25%	50%	75%	90%	N
all	Observed Spread	1.53	0.45	0.80	1.34	1.96	2.88	5478
	Black-Cox Spread	0.32	0.00	0.00	0.00	0.03	0.96	
	DEJD Spread	1.07	0.06	0.20	0.48	1.08	2.62	
	HX-Jumps Spread	1.62	0.27	0.46	0.85	1.62	3.43	
AAA	Observed Spread	0.99	0.32	0.53	0.92	1.34	1.71	2405
	Black-Cox Spread	0.22	0.00	0.00	0.00	0.02	0.70	
	DEJD Spread	0.71	0.05	0.19	0.39	0.71	1.55	
	HX-Jumps Spread	1.02	0.21	0.36	0.62	1.11	2.11	
AA+	Observed Spread	1.55	0.62	1.04	1.45	1.90	2.51	1344
	Black-Cox Spread	0.31	0.00	0.00	0.00	0.02	0.90	
	DEJD Spread	1.06	0.06	0.20	0.52	1.12	2.71	
	HX-Jumps Spread	1.59	0.31	0.51	0.93	1.67	3.93	
AA+	Observed Spread	2.11	0.94	1.35	1.94	2.69	3.50	1383
	Black-Cox Spread	0.48	0.00	0.00	0.00	0.13	1.68	
	DEJD Spread	1.44	0.05	0.23	0.72	1.65	3.71	
	HX-Jumps Spread	2.68	0.40	0.77	1.40	2.56	5.32	
Other	Observed Spread	2.76	1.34	1.92	2.68	3.63	4.18	346
	Black-Cox Spread	0.39	0.00	0.00	0.00	0.03	0.97	
	DEJD Spread	1.98	0.09	0.25	0.71	1.84	4.57	
	HX-Jumps Spread	2.65	0.47	0.76	1.29	2.36	5.03	

Table 9: Pricing Errors of Structural Models

This table reports means of pricing errors and percentage errors of structural models for a sample of commercial papers during May 2014–December 2018. Pricing errors are reported as the difference in percentage between predicted and observed yield spreads, and percentage pricing errors the difference between predicted and observed yield spreads divided by the observed spread. The predicted spreads are generated from the Black-Cox (1976) model, the double-exponential jump diffusion (DEJD) model, and the He-Xiong (2012) model with double-exponential jumps (HX-Jumps). p-values are computed from the t-test (in parentheses) and Wilcoxon signed-rank test (in braces), respectively.

	all	AAA	AA+	AA	Other
Panel A: Mean pricing error (%)					
Black-Cox	−1.09	−0.72	−1.17	−1.30	−2.11
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
DEJD	−0.70	−0.41	−0.75	−0.92	−1.42
	[0.000]	[0.084]	[0.139]	[0.000]	[0.000]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
HX-Jumps	−0.30	−0.17	−0.38	−0.35	−0.84
	[0.161]	[0.531]	[0.594]	[0.000]	[0.000]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
Panel B: Mean percentage error (%)					
Black-Cox	−66.87	−72.31	−75.04	−56.00	−48.46
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
DEJD	−20.63	−17.46	−31.12	−8.55	−46.15
	[0.158]	[0.466]	[0.317]	[0.756]	[0.000]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
HX-Jumps	10.31	19.88	10.84	−2.60	−18.85
	[0.556]	[0.507]	[0.801]	[0.454]	[0.004]
	{0.023}	{0.000}	{0.015}	{0.000}	{0.000}
N	5478	2405	1344	1383	346

Figure 1: Term Structure of Average Commercial Paper Yield Spreads



This figure plots the par value weighted average yield spread of commercial papers against maturity over the period from May 2014 to December 2018. Yield spreads are calculated as the annualized continuously compounded money market yield less the zero yield of comparable maturity as implied from general collateral repurchase agreements and interest rate swaps.

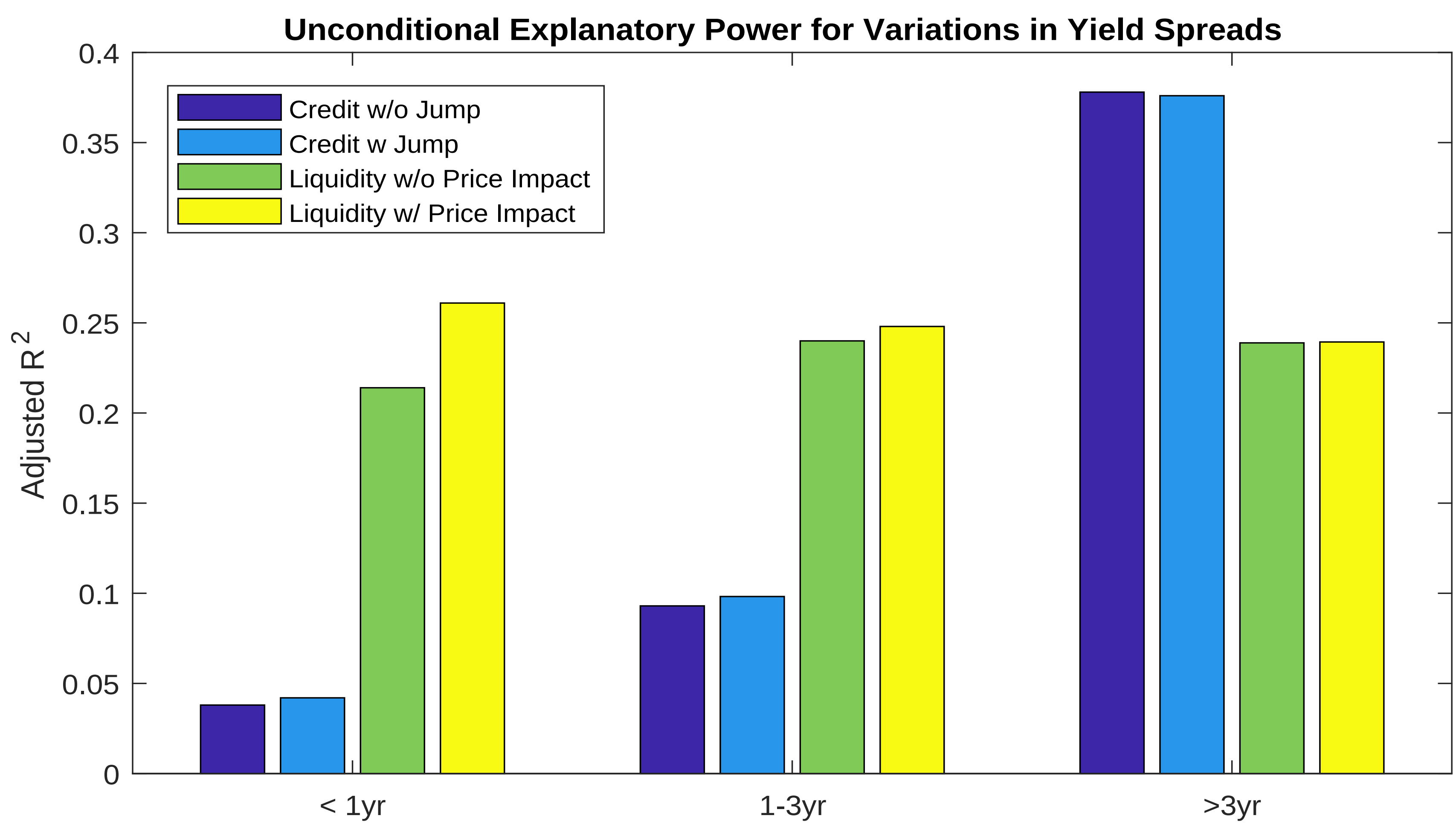


Figure 2: Unconditional Explanatory Power for Variations in Corporate Yield Spreads

This figure plots the unconditional explanatory power of credit- or liquidity-related proxies for variations in corporate yield spreads with different maturities. Credit-related variables considered include DD (distance-to-default) and credit ratings with (in blue) and without $Jump$ (in navy blue). Liquidity-related variables considered include TC (the average trading cost) with (in yellow) and without the Amihud (2002) measure of price impact. Corporate debt issues included are divided into three groups: commercial paper (with maturities less than 1 year), short-maturity MTNs and enterprise-bonds (with maturities between 1 and 3 years), and intermediate-maturity MTNs and enterprise-bonds (with maturities between 3 and 5 years).