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

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Abstract

What drives short-term credit spreads: credit risk, liquidity risk, or both? We investigate this issue using the structural approach to credit risk modeling and a novel data set of *secondary* market transaction prices for Chinese commercial papers (CPs). In particular, we propose and test a structural model with jump risk and exogenous market illiquidity under which the predicted yield spreads can be decomposed into a credit component and a liquidity component. We find that credit risk and, especially liquidity risk, are important determinants of short-term yield spreads. Our model-based decomposition results show that, on average, credit risk and market liquidity account for about 25% and 52% of CP yield spreads, respectively. For comparison, we also examine the drivers of the US CP yield spreads using security-level data. We find that credit risk accounts for a small fraction of the observed yield spreads but liquidity contributes a much greater proportion.

Keywords: Commercial paper, Corporate yield spreads, Corporate debt illiquidity, Jump risk, Credit spread puzzle, Structural credit risk models

JEL classification: G13, G12, G33, E43

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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 global 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 because of data limitations. One exception is an interesting study by Covitz and Downing (2007), who examine a sample of commercial paper (CP) issued by domestic US nonfinancial firms based on regression analysis and conclude that credit risk is the more important determinant of CP spreads than liquidity. As noted by the authors, this finding is somewhat surprising, given the general view that CP spreads are essentially driven by liquidity (Krishnamurthy, 2002). Nonetheless, their study is not focused on the no-arbitrage pricing of CP and, as a result, the relative importance of credit risk or liquidity is based on regression *R*-squared, instead of on a direct decomposition of CP spreads. In addition, the data set used in the Covitz and Downing study consists predominantly of new issues in the primary market. As such, how much of short-term yield spreads is ascribable to credit risk or liquidity risk is still an open question.

In this paper, we shed light on the determinants of short-term corporate credit spreads from at least three new perspectives. First, we employ a novel data set of *secondary* market transactions in Chinese CP, the fastest-growing CP market in the world. This market has four unique features that make it particularly suitable for addressing the main question of this study: (1) Secondary market transactions account for 78% of total daily transaction volumes in this market, compared with 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 the liquidity proxies they use are limited to more traditional ones: trading volume, dollar volume, and CP maturity. (2) The Chinese CP issuers are heterogeneous in terms of creditworthiness, whereas almost all CP issuers in the USA are large, well-capitalized firms. (3) CP in China tends to have a much longer maturity than CP in the USA. For instance, the average maturity is about 248 days for Chinese CP and about 45 days for the USA in our sample. (4) Longer-term corporate debts—for example, medium-term notes (MTNs) and enterprise bonds (EBs)—and CP are traded in the same (interbank) market in China. Taken together, CP in China can be viewed as exactly equivalent to short-term corporate bonds and thus provide an ideal setting to investigate how the relative importance of credit/liquidity changes with the debt maturity.

Second, we quantify liquidity and default risk components in short-term spreads using the structural approach to credit risk modeling (Merton, 1974). In particular, we propose and implement a jump-diffusion structural model that incorporates corporate debt market illiquidity and therefore is particularly suitable for modeling CP spreads. Among other things, this model allows us to decompose yield spreads into a diffusive credit risk component, a jump credit risk component, and a liquidity component.

Third, we show that liquidity is much more important than credit risk in determining CP spreads in China. Moreover, based on a more recent sample of CP issues and more recently developed liquidity measures, we find that this is also the case in the US CP market, a finding opposite of Covitz and Downing (2007). Below we describe our analysis in details.

We first investigate the determinants of Chinese CP yield spreads with regressions. Explanatory variables we use include distance-to-default or DD (Kealhofer, 2003), credit ratings, the Amihud (2002) illiquidity measure, and a trading cost (TC) measure. We find that while DD and credit rating explain about 7.6% of CP spread variations, the two liquidity measures have an unconditional R^2 of 27.3% and an incremental R^2 of 20.0%. These results indicate that illiquidity is much more important than credit risk in explaining variations in the Chinese CP spreads. As a robust check, we find that the credit-related variables indeed become more important than liquidity in explaining variations in spreads on MTNs and EBs that have longer maturities than CP.

Importantly, our regression results also provide evidence on the potential role of structural models in the determination of short-term credit spreads. Specifically, we find that DD—a credit-risk-related variable suggested by structural models—subsumes equity volatility and has incremental explanatory power for spreads over credit ratings. In addition, the regression results indicate that jump risk matters. Thus, we examine the predictive power of structural models for short-term credit spreads in the second part of our empirical analysis.

In order to quantify the relative importance of credit risk, especially jump risk, and liquidity in a unified manner, we first propose a structural model with both jumps and debt market illiquidity. In this model, the underlying asset return follows a double-exponential jump-diffusion (DEJD) process. Corporate bond investors are subject to a Poisson liquidity shock, as well as a proportional transaction cost when they are hit by the shock and need to sell their bond holdings. Default boundary is assumed to be flat and exogenous, and therefore there is no rollover risk in the sense of He and Xiong (2012). That is, jumps and liquidity affect yield spreads separately and directly in the standard manner in this model. As a result, its predicted yield spreads can be decomposed into a diffusion credit component, a jump credit component, and a liquidity component. The model is essentially a simplified He and Xiong (2012) model augmented with jumps (DEJ) in the underlying asset return process and is termed the HX-DEJ model for convenience.

Next, we examine the ability of the HX-DEJ model as well as its special cases to predict spreads. To this end, we follow the credit spread puzzle literature by utilizing default data for model calibration and then deriving the model prediction of spreads (Huang and Huang, 2012). However, one challenge we face in doing this is the short history of corporate defaults in China. To tackle this issue, we depart from the recorded corporate debt defaults and instead focus on distressed issuers.[1] Among other things, calibration with historical distress rates allows us to see whether there exists a credit spread puzzle in the Chinese CP market.

We begin with our baseline model, the Black and Cox (1976) model—a special case of the HX-DEJ model that only accounts for the diffusion (credit) risk. The consensus is that purely diffusive structural models substantially underpredict short-term spreads. Indeed, the Black–Cox model-implied average CP spread is 9 basis points (bps), accounting for only 6.3% of the observed spread (143 bps). Additionally, the model-implied median spread is 0 whereas its empirical counterpart is 119 bps. Moreover, the model has substantial pricing errors with a mean pricing error (MPE) of −1.34% and a mean percentage pricing error (MPPE) of −92.17%. The model does predict lower-rated CP spreads better than higher-rated ones. For instance, the MPE is −0.82% for AAA issues and −2.16% for AA issues.

1 We are grateful to Zhiguo He for making this suggestion.

Next, we consider the DEJD model of risky debt, another special case of the HX-DEJ model that extends the Black–Cox model to include jumps in the underlying asset return process. As expected, the DEJD model markedly improves the pricing performance. For instance, the average and median model-implied spreads are now 35 and 19 bps, respectively, and the MPE is −1.09%. But the DEJD model still underpredicts CP spreads, explaining about 24.5% of the spread. This result mirrors the finding of Huang and Huang (2002, 2012) that the credit spread puzzle in the USA is robust to the DEJD model.

We then examine yet another special case of the HX-DEJ model, the simplified He and Xiong (2012) model that assumes exogenous default boundary and thus has no rollover risk—termed the HX model. We find that the HX model, a pure-diffusion model, significantly outperforms the DEJD model. For instance, the average and median spreads implied by the HX model are 98 and 51 bps, respectively, and its MPE of −0.45% is less than half of that of the DEJD model (−1.09%). On average, the HX model can account for around 68.5% of the CP spread. In other words, we find that liquidity is much more important than jumps. The intuition behind this result is that jump risk is more or less incorporated by the model calibration to default data but liquidity is not. Yet liquidity alone is inadequate at filling the gap between the Black–Cox model-implied and observed spreads.

Lastly, we implement the HX-DEJ model. Its mean spread, median spread, and MPE are 110 bps, 73 bps, and −0.34%, respectively. On average, the model can account for about 76.9% of the observed spread, which can be decomposed to a diffusive credit component (1.4%), a jump risk component (23.1%), and a liquidity component (52.4%). Clearly, augmenting the HX model with jumps improves the model performance. The HX-DEJ model, however, still underestimates the average CP spread and especially the median spread. Nonetheless, our results from structural models show that market illiquidity accounts for a much higher proportion of Chinese CP spreads than credit risk.

For comparison, we redo the analysis using a sample of individual CP issues in the USA (which is detailed in Appendix A). The regression results indicate that the explanatory power of both credit risk variables and traditional liquidity proxies is comparable to that derived from the Chinese sample. Therefore, although the structure of the US CP market prevents us from inferring the secondary market liquidity, the discrepancy between the main finding of Covitz and Downing (2007) and ours is likely attributable to the difference in the liquidity measures used, rather than the differences between the US and Chinese CP markets. More importantly, our calibration of structural models to the US CP data confirms that credit risk explains only a small proportion of CP yield spreads and that market illiquidity is a much more important determinant. Overall, our findings from the US market are qualitatively the same as our main results. To some extent, this is not surprising given that on average US CP issues have much shorter maturities than their Chinese counterparts.

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 novel data set of CP *secondary* market transaction prices. Second, we propose a structural model of credit risk with jump risk and market illiquidity that is suitable for decomposing CP spreads. Third, we conduct one of the first empirical studies of structural models using CP data and study two important yet quite different CP markets. We document the evidence of a credit spread puzzle in both the Chinese and US CP markets. We show that liquidity risk can help mitigate the puzzle and is much more important than credit risk in determining CP spreads in these two markets.

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

2. Related Literature

This paper is most directly related to the literature on structural models of credit risk. However, it departs from this literature in two main aspects. First, this paper contributes to the theoretical literature by proposing a new structural model that extends the He and Xiong (2012) model to allow for jumps in the underlying asset return process. Although for tractability and comparison, we implement a simplified version of the proposed model that assumes exogenous default boundary, the model nonetheless incorporates both exogenous liquidity and jumps and allows us to quantify the impact of these two features on credit spreads. The proposed model can also be considered to be an extension of the DEJD model of risky debt to allow for exogenous liquidity. In addition to Huang and Huang (2002, 2012), the DEJD model is used in several other studies, such as Cremers, Driessen, and Maenhout (2008); Bao (2009); Chen and Kou (2009); Bai, Goldstein, and Yang (2020); and Huang, Shi, and Zhou (2020). One limitation of the proposed model implemented in the empirical analysis is that it has no rollover risk, an important feature of the He and Xiong (2012) model (see also He and Milbradt, 2014).

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 CP (short-term debt claims) and examines the performance of the proposed structural model and its three special cases in predicting CP spreads. The only other empirical study of individual CP issues that we are aware of is Covitz and Downing (2007), who investigate the determinants of CP spreads in the USA using regressions and do not implement any structural models in their analysis. We study both the Chinese and US CP markets using not only regressions but also structural models. Moreover, we examine whether there exists a credit spread puzzle in the CP market. Furthermore, we contribute to this literature in terms of its methodology by calibrating structural models to distress rates as estimated from the secondary corporate debt market, instead of default rates published by rating agencies. This calibration approach has potential applicability to studies on the emerging credit markets.

Other studies of the credit spread puzzle include Bao (2009); Chen, Collin-Dufresne, and Goldstein (2009); Chen (2010); Bhamra, Kuehn, and Strebulaev (2010); Christoffersen, Du, and Elkamhi (2017); Feldhütter and Schaefer (2018); McQuade (2018); Du, Elkamhi, and Ericsson (2019); Shi (2019); and Bai, Goldstein, and Yang (2020). A related literature focuses on implications of structural models under the risk-neutral measure only. See, for example, 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); and Huang, Shi, and Zhou (2020).

One of our main findings is that liquidity plays a very important role in CP spreads. Krishnamurthy (2002) argues that CP spreads in the USA are essentially entirely due to liquidity, whereas Covitz and Downing (2007) find that credit risk is more important than liquidity in the determination of such spreads. We go beyond the traditional liquidity measures used in Covitz and Downing (2007) in our analysis. Specifically, we construct liquidity measures by following the literature on corporate bond illiquidity; see, for example, Bao, Pan, and Wang (2011); Chen, Lesmond, and Wei (2007); Dick-Nielsen, Feldhütter, and Lando (2012); Han and Zhou (2016); Helwege, Huang, and Wang (2014); He, Khorrami, and Song (2019); and Longstaff, Mithal, and Neis (2005). We provide evidence that such constructed liquidity measures have stronger explanatory power for CP spreads than the traditional ones.

Lastly, our paper is also related to the literature on the Chinese corporate debt market. Amstad and He (2019) and Mo and Subrahmanyam (2018) provide a comprehensive overview of this market. Chen *et al.* (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 (2021) focus on the segmentation of the Chinese corporate bond market. However, none of these studies focus on the Chinese CP and MTN markets as we do. Ding, Xiong, and Zhang (2022) present robust evidence of overpricing in the primary markets of CP and MTNs in China and attribute the overpricing to competition among underwriters. We focus on the secondary market of CP in this paper. In addition, we study their secondary prices using structural credit risk models.

3. Data

3.1 The Chinese CP Market

Before describing data we use, we provide some background information about the Chinese CP market. CP is widely used by non-financial firms for short-term financing in China.[2] There are two types of CP: standard “short-term CP” and “super short-term CP” (SCP), first introduced to the market in May 2005 and in late 2010, respectively. Standard CP and SCP mainly differ in the maturity at issuance and borrowing capacity. Standard CP has a maturity of less than 1 year and its outstanding amount cannot exceed 40% of the issuing firm’s net asset value. The latter restriction does not apply to SCP, however, which has a maturity of 270 days or less. We include both standard CP and SCP in this study.

CP is issued and traded in the China interbank bond market (CIBM) (see Amstad and He (2019) for an in-depth overview of this market), an OTC market accessible only to institutional investors, such as commercial banks, credit cooperatives, securities firms, insurance companies, mutual funds, and foreign institutions. CIBM was established in 1997 and regulated by the People’s Bank of China (PBC, China’s central bank). The market dominates bond issuance and trading in China, of which the outstanding amount accounts for 86.8% of the total domestic bond market at the end of 2020.[3] The China Foreign Exchange Trade System (CFETS) offers a centralized trading system for bonds including CP.[4] The Shanghai Clearing House provides unified depository and clearing services to CP investors.

2 Security firms can also issue CP but they are subject to different regulations; this market is relatively small so is not included in this study.

3 Unless otherwise noted, source of statistics cited in Section 3.1 is WIND.

4 As an institution directly affiliated with the PBC, CFETS (also known as the National Interbank Funding Center) plays a similar role to Financial Industry Regulatory Authority in the USA in terms of serving and monitoring the over-the-counter bond market.

Bond issuance in the CIBM is based on a registration system. The National Association of Financial Market Investors (NAFMII), a self-regulatory organization for the China interbank market under the central bank's guidance, makes the registration rules and oversees the registration process. NAFMII requires that standard CP issuers be rated AA- or above. For SCP, two ratings from different rating agencies are mandatory with at least one at AA or above. These rating requirements seem to be not strictly binding in many cases, however, given that the distribution of the Chinese rating scale is upwardly skewed.

CP market has grown significantly since its inception, partly because borrowing costs of CP are typically lower than those of bank loans and there is no explicit restriction on the usage of funds raised from issuing CP. For example, 61 firms raised 142.4 billion RMB with CP in 2005, and 15 years later, 1,206 firms (including both state-owned enterprises (SOEs) and privately owned enterprises) issued 4,840 CPs, raising 5.0 trillion RMB in 2020. Figure 1 shows annual issuance volumes of corporate bonds (divided into seven categories) in China from 2012 to 2020. CP issuance volume is the largest every year in this period.

CP is also among the most liquid products in the Chinese bond market. For instance, among eight different categories of bonds (including government bonds) traded in the interbank market, CP has the highest turnover ratio in 2015, 2016, and 2020 and the second highest in 2017–9, according to a recent study by NAFMII and ICMA (2021).

All participants in the CIBM are allowed to invest in CP. Figure 2 illustrates the investor base for CP. At the end of 2020, asset managers (e.g., mutual funds, wealth management products, insurance companies, and trust firms) hold 63.0% of the outstanding CP, followed by depository institutions (e.g., commercial banks and credit cooperatives) with 30.5%. Other investors in this market include policy banks (2.1%), securities firms (2.0%), and foreign investors (1.8%).

Although Chinese regulators have been striving to eliminate implicit government guarantees in the credit market, corporate default rates remain relatively low in China. The first actual default in the CP market occurred in November 2015 when Sunnsy Group failed to repay its 2 billion RMB debt. From 2014 to 2020, 115 CP issues with 100.4 billion outstanding amount defaulted, representing a default rate of 0.55% by the number of issues or 0.04% based on the outstanding amount. Moreover, twenty-five of these defaulted issues with 20.2 billion outstanding amount were fully repaid by December 2021.

3.2 CP Data

CP data we use are obtained from the CFETS, the main source of data on Chinese CP. Our data set consists of end-of-day transaction summaries of all corporate debts traded in the CIBM. A noteworthy feature of this data set is that it contains daily volume-weighted average prices, which are used in our calculation of yield spreads and liquidity measures. Our sample period is from May 2014 to December 2020. We choose this beginning of the sample period because, firstly, transaction data before 2014 are relatively sparse and unreliable according to CFETS and secondly, the first default of publicly issued bonds in China did not occur until March 7, 2014, when Shanghai Chaori Solar defaulted on its one billion RMB bond.[5]

5 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. Geng and Pan (2021) document that prior to the Chaori default, corporate debt pricing in

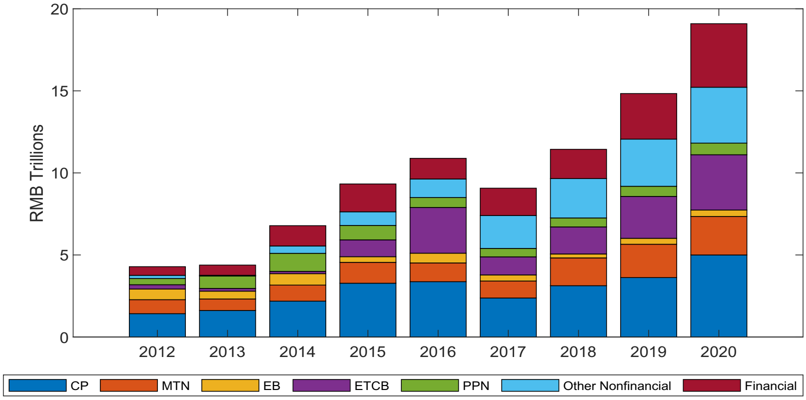

Figure 1. Chinese corporate bond issuance by type.

Notes: This figure displays the annual issuance volume of corporate bonds in China from 2012 to 2020. The total issuance amount is divided into seven categories: CPs, MTNs, EBs, exchange-traded corporate bonds (ETCB), private placement notes (PPN), other nonfinancial corporate bonds, and financial bonds.

Data source: China Wind Bond Overview.

Table I provides summary statistics on trading activities in the Chinese CP market. We partition the data into six maturity categories: 1–30, 31–60, 61–90, 91–180, 181–270, and 271–365 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.[6] We find that, on average, secondary market transactions account for more than 76% of total daily transaction volumes. This finding stands in stark contrast to the US CP market, in which the proportion is about 8.34% according to Covitz and Downing (2007) and primary market transactions completely dominate. The intense transaction activity in the Chinese CP market is largely attributable to the regulatory constraint imposed on money market funds (MMFs) (i.e., the overall duration of their portfolio cannot exceed 120 days). On the other hand, the overall term structure of CP yields is upward sloping, thus rolling down the yield curve is on average profitable. Not surprisingly, in response to the regulatory constraint, fund managers actively adjust their portfolios to make full use of the upper limit on the duration. This high-frequency rebalancing of their portfolios makes the trading volume evenly distributed across different maturity buckets.[7] Indeed, we find that CPs with even less than 30 days to maturity are still actively traded, with their

China is decoupled from issuers' fundamental default risk (with the widespread belief that bond investors will always be paid in full).

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

7 For example, when a fund manager finds that the overall duration of her portfolio has fallen to 118 days, she could purchase a 270-day CP to reach for yield. However, since it is fairly costly to carry out a transaction with a small size in the corporate bond market (Bessembinder, Maxwell, and Venkataraman, 2006; Edwards, Harris, and Piwowar, 2007; Goldstein, Hotchkiss, and Sirri, 2007), the overall portfolio duration is likely to exceed 120 days after the purchase. It follows that the fund manager also needs to buy a 30-day CP or sell a 180-day CP to make the portfolio duration barely below 120 days, depending on fund flows and cash holdings.

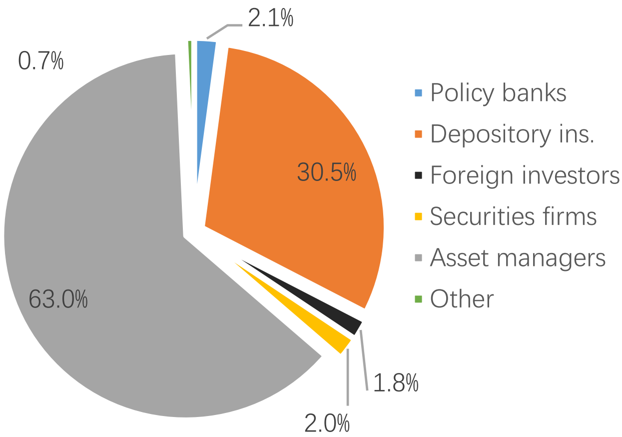

Figure 2. Investor base of CP in China.
Notes: This figure illustrates the investor base for Chinese CPs at the end of 2020. Asset managers include mutual funds, wealth management products, insurance companies, and trust firms. Depository institutions include commercial banks and credit cooperatives. Remaining investors in this market include policy banks, securities firms, foreign investors, and "other."
Data source: Wind Information.

volume making up 11.48% of all secondary transactions, even though the average initial maturity of CPs is 248 days.

Another notable difference from the US CP market arises from the primary market. Rather than concentrating on the shortest maturities—1–4 days as reported in Covitz and Downing (2007)—primary issues in China have maturities evenly spread across ranges. If the decision of the 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* liquidity.

We match the CP pricing data to the WIND IBQ database to obtain the characteristics of each issue, including the name of the issuer, coupon rate, face value, issuance date, maturity date, credit rating, redemption features, and so on. Panel A of Table II shows that the total issuance amount of CPs is more than 21.0 trillion RMB (about 3.3 trillion USD) over the period 2014–20. For comparison, the total issuance amount of non-financial public debts is 61.5 trillion RMB during this sample period. In other words, CP accounts for a market share of about 34.2% in terms of issuance size.

We extract CP credit ratings from the six rating agencies that dominate the CIBM: ChengXin, DaGong, JinCheng, LianHe, PengYuan, and Shanghai Brilliance (XinShiJi). To assign a single categorical rating to each issue-month observation, we follow the market convention of lowest-rating principle (e.g., Collin-Dufresne, Goldstein, and Martin, 2001). That is, when there are multiple ratings available for the same issue in a given month, we take the lowest one.[8]

8 Chen *et al.* (2019) adopt the same principle in their study of the pledgeability effect on corporate bond prices in China. For a comprehensive review of the rating agencies in China, see Amstad and He (2019).

Table I. Trading activity in the Chinese CP market

This table reports average trading volumes for different segments in the Chinese CP market, as well as their average shares of total daily trading volumes, over the period May 2014–December 2020. 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 percentages. 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	1.96	2.19	2.46	3.76	6.31	3.12	19.81
	SD	1.68	2.03	2.59	3.56	4.46	2.97	
	% of total							
	Mean	5.04	5.41	5.48	7.79	12.88	6.65	43.24
	SD	6.43	6.84	6.01	7.25	9.15	6.72	
	Number of issues	1.21	1.47	1.70	2.68	5.88	3.36	16.31
Secondary market	Volume (bn)							
	Mean	3.82	3.71	3.60	9.88	11.02	4.50	36.52
	SD	2.51	2.40	2.44	5.94	7.08	3.43	
	% of total							
	Mean	8.80	8.16	7.73	20.18	22.35	9.53	76.74
	SD	7.18	5.32	4.85	7.76	9.79	6.61	
	Number of issues	25.94	24.07	20.70	57.52	52.93	24.42	205.57

Panel B of Table II summarizes the issue-level information over our sample period. A majority of CPs in the final sample have an initial maturity of 9–12 months. The average issuance size is 12.86 billion RMB. Most CP issuers in China are covered in only three rating categories—AAA, AA+, and AA—which reflect the extreme skewness of Chinese credit ratings. Only about 3% of CP in our final sample are rated AA- or below. As discussed in Amstad and He (2019), the AA rating is generally seen as the lowest investment-grade level in China. Attaching a numerical value to each credit rating as in $AAA = 1, \cdots, A+ = 5$, we obtain an average rating of 1.84 for CP issues in the sample. Note that the average ratings of MTNs and exchange-traded corporate bonds issued during the same period are 1.78 and 2.09, respectively. Thus, CP issuers as a group are not different from firms issuing longer-term debts in terms of creditworthiness,[9] which is in sharp contrast with the US CP market. Finally, the average turnover of CP in our sample is 262%, much higher than that of the entire CP universe (64.1%).

As public information in financial statements is essential to any quantitative assessment of credit risk, we limit our analysis to CP issued by publicly listed firms. After merging with (quarterly) financial statements and equity data from WIND, we obtain a sample consisting of 2,829 CP issued by 434 companies. Panel C reports summary statistics for CP issuers in

9 Based on private conversations with some licensed bond underwriters, it is even easier to issue CPs compared with longer-term public debts.

Table II. Descriptive statistics for CP issuance and issuers

Panel A reports the number of CPs issued, the number of issuing companies, and the total issuance amount for each year in China over the period May 2014–December 2020. Panel B provides issue-level information for all CPs used in model specification and regression analyses. Panel C summarizes the (quarterly) financial metrics of CP issuers that have observations included in the final data sample. Maturity is the issue's initial time to maturity in years. Issuance Amount is the issue's amount outstanding in billions of RMB. Issuance Yield is the promised (annualized) interest rate at issuance. Rating is a numerical translation of credit rating: 1 = AAA and 5 = A+. Turnover is the issue's annualized trading volume scaled by the amount outstanding. Leverage denotes the ratio of the book value of debt to the sum of the book value of debt plus the market value of equity. Equity Volatility is the annualized volatility of daily log equity returns for a quarter. Payout Ratio is the ratio of payment to outside stakeholders over the past 1 year divided by the asset value. Equity market capitalization is defined as the product of share price and shares outstanding in billions of RMB. Return on Assets is a firm's income before extraordinary items divided by the mean of total assets at the start and end of the quarter. Interest Coverage is EBIT divided by the interest expense.

Panel A: CP issuance and issuers by year

Year	2014	2015	2016	2017	2018	2019	2020
Number of issues	1,481	2,521	2,614	2,057	2,868	3,367	3,210
Number of issuers	822	993	960	702	826	951	1,027
Issuance amount (bn)	2,136	3,257	3,328	2,247	3,091	3,453	3,505

Panel B: Characteristics of CP issues

	Obs	Mean	Std Dev	25th	50th	75th
Maturity (year)	3,074	0.68	0.26	0.5	0.75	0.75
Issuance amount (bn)	3,074	12.86	13.52	5	10	17
Issuance yield	3,074	3.96	1.45	2.9	3.75	5
Rating	3,074	1.84	0.94	1	2	3
Turnover	3,074	2.62	3.25	1.48	2.13	2.94

Panel C: Characteristics of CP issuers

	Obs	Mean	Std Dev	25th	50th	75th
Leverage	12,266	0.58	0.17	0.47	0.59	0.70
Equity volatility	11,194	0.43	0.44	0.27	0.37	0.51
Payout ratio	12,161	0.02	0.01	0.01	0.02	0.03
Market cap (bn)	11,637	31.07	76.12	6.97	13.76	28.00
Return on assets (%)	12,452	1.81	5.14	0.49	1.45	3.10
Interest coverage	11,363	7.12	15.67	1.64	3.04	6.33

our final sample. Quasi-market leverage equals book debt/(book debt + market equity), which averages out at 58%. The average equity volatility is comparable to that reported in Giannetti, Liao, and Yu (2015). CP issuers in our sample have larger than average equity market capitalization (31.07 versus 27.36 billion RMB). They also tend to be profitable with a mean quarterly ROA of 1.81% when compared with an average of 1.32% for the full A-share universe during the same period.

Figure 3 displays the structure of public debts held by public firms in our sample at the end of 2020.[10] Clearly, CP is an important source of these firms' public debts, accounting for a fraction of 13.6%. EBs, exchange-traded corporate bonds, and MTNs together account for 78.7%, convertible bonds 5.7%, and private placement notes 2.0%.

3.3 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 in the case of the US market, CPs in China do not carry a coupon, but the interest is calculated on an actual/365 basis. CP credit spreads can therefore simply be 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 fixed repo rate (FR007) as well as swaps with a fixed rate versus it,[11] where the swap rates are means of the bid and ask rates from major swap dealers' quoted rates and cover maturities from 1 month to 10 years. The term structure of risk-free zero rates is then constructed via standard bootstrapping techniques. Finally, we remove the upper 1% and lower 1% tails of the credit spreads in order to avoid the influence of outliers (Campbell and Taksler, 2003).

Figure 4 presents the face-value-weighted average CP yield spreads for different rating/maturity categories. Note that the term structure of yield spreads is generally upward sloping for all rating classes. If MMFs engage in reaching-for-yield behavior, they are supposed to exhaust the 120-day upper limit on portfolio duration. Also, the average CP spreads here are much higher than average CP spreads in the USA. For example, for AAA issuers, it ranges from 71 bps for maturities of 1–60 days to 109 bps for maturities of 301–365 days. One reason is that on average, US CP has much shorter maturity. Another reason is that credit ratings in China are often too high. Despite the upward bias in rating assignment, the CP yield spread does monotonically decrease with the credit rating in each maturity category as shown in Figure 4. This result indicates that credit ratings can still serve as a useful measure of default risk in this market. Geng and Pan (2021) also show that China's domestic ratings contain information above and beyond the issuer's financial state of health, such as an implicit government guarantee. These findings justify the use of credit ratings as a proxy for default risk in our empirical analysis in Section 5.

10 Note that banks still dominant lending in China. Even in our sample of listed firms, which have better access to the public market, the size of their bank loans is eleven times that of their public debts.

11 Interbank fixing repo rates (including FR001, FR007, and FR014) are based on the repo trading rate for the interbank market between 9:00 a.m. and 11:30 a.m. and are 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 account for more than 70% of the trading volumes of all interest rate swaps, and swaps based on the 3-month SHIBOR constitute the second-largest market.

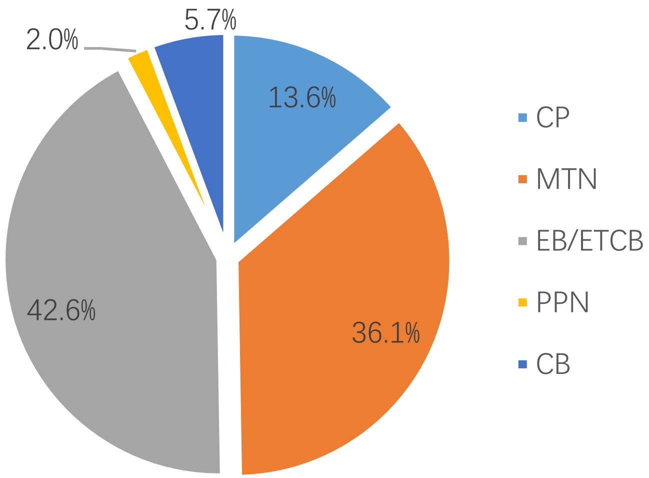

Figure 3. Public debt structure of the sample firms.
Notes: This figure displays the structure of public debts held by listed firms in our sample at the end of 2020. Public debts are divided into five categories: CP, MTNs, EBs and exchange-traded corporate bonds (EB/ETCB), private placement notes (PPN), and convertible bonds (CB).
Data source: Wind Information.

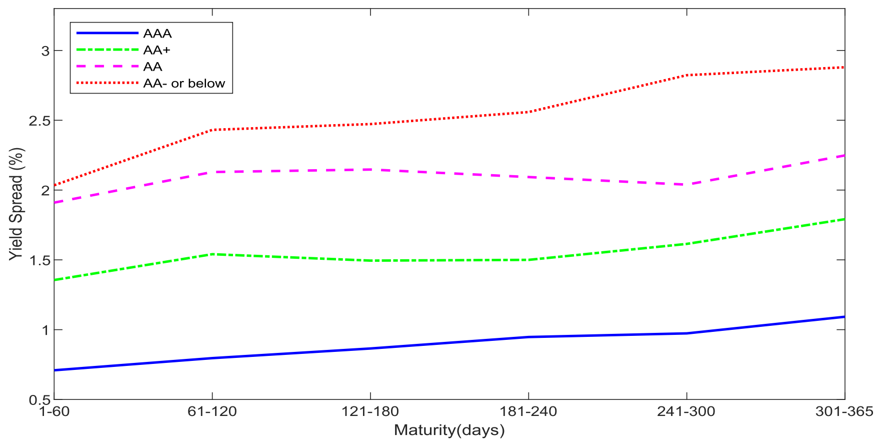

Figure 4. Term structure of average CP yield spreads.
Notes: This figure plots the par-value-weighted average yield spread of CPs against maturity over the period from May 2014 to December 2020. Yield spreads are calculated as the annualized continuously compounded money market yield less the zero yield of comparable maturity as implied from general collateral repurchase agreements and interest rate swaps.

3.4 Liquidity Measures

How to measure CP liquidity? Because of the sparseness of secondary market transactions in the US CP market, Covitz and Downing (2007) use issuance size and time to maturity as liquidity proxies. On the other hand, studies on the US corporate bond market tend to employ liquidity measures based on intra-day and daily transaction data. We consider both of these types of liquidity variables.

Given that our data on CP are not transaction data, we focus on six measures related to effective bid–ask spreads that can be estimated based on daily data. We find that the average bid–ask spread estimates of these six measures range from 46 to 168 bps in our CP sample in an analysis detailed in Online Appendix IA.A. Compared with summary statistics for the same measures as reported by Schestag, Schuster, and Uhrig-Homburg (2016), who conduct a comprehensive analysis of dozens of liquidity measures using US data, the overall TC in the Chinese CP market is generally comparable to that in the US corporate bond market. We use the average of these six measures as a TC factor, denoted TC. This measure does not only serve as our primary liquidity variable in regression analysis but also provides a comprehensive and robust estimate of effective bid–ask spreads, which is a key model input when we quantify the liquidity component in CP yield spreads in Section 5.3. We also consider the Amihud (2002) and Pástor and Stambaugh (2003) price impact measures that more directly incorporate the volume information. These two measures are shown to offer additional explanatory power for corporate bond yield spreads in the US relative to transaction cost measures (see e.g., Dick-Nielsen, Feldhütter, and Lando, 2012; Rossi, 2014; He, Khorrami, and Song, 2019).

4. Structural Models of Credit Risk

In this section, we introduce the four credit risk models to be implemented in our empirical analysis. We first review the general framework that underlies these models. We then specify each of the models. Lastly, we discuss the implementation of these models.

4.1 Modeling Framework

To place 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 an 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 $T/2$.

Following Black and Cox (1976), we assume that there exists an exogenous firm value threshold K, called default boundary, such that default is triggered by covenant violation when the market value of the firm's assets, denoted A, falls below K. In other words, the default time is defined as $\tau^* = \inf\{t : A_t \leq K\}$. Given that CPs are zero-coupon debts, we assume that investors recover $R \times f \times e^{-r(\tau-\tau^*)}$ upon default, where r is the risk-free rate, R the recovery rate of the face value, and $\tau = t + T$ the debt maturity date.

To quantify the liquidity component in CP spreads, we follow Amihud and Mendelson (1986) and He and Xiong (2012) and assume that each bond investor is subject to a Poisson liquidity shock with intensity ξ. Liquidity shocks bring about liquidity needs, which have to be covered by selling bonds in the illiquid secondary market at a fractional cost of k. It follows that the time-t price of a debt with τ years to maturity is given by

$$d_t(\tau) = e^{-(r+\xi k)\tau} f \times \Big(1 - \pi(\tau)\Big) + e^{-r\tau} f \times R \times G(\xi k, \tau), \tag{1}$$

where $\pi(\tau)$ denotes the risk-neutral default probability over horizon τ, and $G(z, \tau) = \{E^{\mathbb{Q}}[\exp(-\int_0^{\tau^*} z)], \tau^* \leq \tau\}$ is the price of an Arrow–Debreu default claim with the discount rate equal to z. Note that transaction cost k enters bond pricing through its product with the liquidity shock intensity ξ. As illustrated in He and Xiong (2012), $r+\xi k$ is a liquidity-adjusted discount rate with ξk representing the liquidity adjustment. Liquidity shocks do not affect the firm's fundamentals; however, given the exogenous default boundary K, ξk do not enter $\pi(\tau)$. Once $d_t(\tau)$ is known, the time-t credit spread on the bond is

$$cs(\tau) = -\frac{\log\left(d_t(\tau)/f\right)}{\tau} - r. \tag{2}$$

Note that the setting here is similar to He and Xiong (2012) except that we focus on zero-coupon bonds with an exogenous default boundary. Below we consider four specific models.

4.2 A Jump-Diffusion Model with Exogenous Liquidity

We begin with our proposed model, which incorporates exogenous liquidity as described in Section 4.1 into the known DEJD model of credit risk. Among other things the proposed model allows us to decompose yield spreads into a pure-diffusion credit component, a jump-risk credit component, and a liquidity component. Given the importance of jump risk to short-term credit spreads (e.g., Duffie and Lando, 2001), such a model-based decomposition makes it possible to quantify the relative contribution of jumps and liquidity to yield spreads.

We focus on the DEJD model because it is a first-passage-time credit risk model that allows for analytically tractable solutions for default probabilities. In this model, the dynamics of the firm's asset value A_t under the risk-neutral measure are specified as

$$\frac{\mathrm{d}A_t}{A_t} = (r-\delta)\mathrm{d}t + \sigma \mathrm{d}W_t + \mathrm{d}\left[\sum_{i=1}^{N_t}(Z_i - 1)\right] - \lambda\zeta \mathrm{d}t, \tag{3}$$

where r is as defined before, δ is the payout rate, and σ the asset volatility. W is a one-dimensional standard Brownian motion. N is a Poisson process with a constant intensity λ. The Z_is are i.i.d. random variables and $Y \equiv \ln(Z_1)$ has a double-exponential distribution with the following density:

$$f^{\mathrm{DE}}(y|p_u, p_d, \eta_u, \eta_d) = p_u \eta_u e^{-\eta_u y} 1_{\{y \geq 0\}} + p_d \eta_d e^{\eta_d y} 1_{\{y<0\}}, \tag{4}$$

where $\eta_u, \eta_d > 0$, and $p_u, p_d \geq 0$ with $p_u + p_d = 1$. The mean percentage jump size ζ is

$$\zeta = \mathbf{E}[e^Y - 1] = \frac{p_u \eta_u}{\eta_u - 1} + \frac{p_d \eta_d}{\eta_d + 1} - 1. \tag{5}$$

As noted before, incorporating exogenous liquidity into the DEJD model leads to our proposed model, also termed the HX-DEJ model. Let $\pi_{\mathrm{HX-DEJ}}$ and $G_{\mathrm{HX-DEJ}}$ be the default probability and the price of an Arrow–Debreu default claim in this model, respectively. Given the fixed exogenous default boundary, $\pi_{\mathrm{HX-DEJ}}$ equals its counterpart in the DEJD model, denoted π_{DEJD}. Once $\pi_{\mathrm{HX-DEJ}}$ and $G_{\mathrm{HX-DEJ}}$ are known, the price and credit spread of a zero-coupon bond are given by Equations (1) and (2), respectively.

To better understand the proposed model and its implied decomposition of yield spreads, we now consider three special cases of the model. In the first case, we shut down the jump component in the right-hand side of Equation (3) and assume that the underlying asset follows a log-normal process. The resultant model is a pure-diffusion model with exogenous liquidity and, in fact, is a simplified version of the He and Xiong (2012) model. However, unlike their original model, here the default boundary is exogenous and therefore there is no rollover risk. As a result, there is no interaction between default risk and liquidity, which affect spreads separately in this simplified He–Xiong model. For convenience, it is still termed the He–Xiong or HX model. As such, our proposed model can be considered to be an extension of the HX model to allow for a DEJ component in the underlying process.

Given that the default boundary is exogenous and fixed, the default probability under the HX model is the same as that under the Black–Cox (1976) model [see Equation (10)]. The price of an Arrow–Debreu default claim, denoted G_{HX}, is

$$G_{\mathrm{HX}}(\xi k,\tau) = N\Big(h_1(g(\xi k))\Big)\left(\frac{K}{A_t}\right)^{\frac{\nu-g(\xi k)}{\sigma^2}} + N\Big(h_2(g(\xi k))\Big)\left(\frac{K}{A_t}\right)^{\frac{\nu+g(\xi k)}{\sigma^2}}, \tag{6}$$

where $N(\cdot)$ is the cumulative standard normal density function and

$$h_{1,2}(\nu) = \frac{\log(K/A_t)\mp\nu\tau}{\sigma\sqrt{\tau}}, \tag{7}$$

$$g(\xi k) = \sqrt{\nu^2 + 2\xi k\sigma^2}, \tag{8}$$

$$\nu = r - \delta - \sigma^2/2. \tag{9}$$

In the second case, we turn off liquidity shocks ($\xi = 0$) and obtain the DEJD model of credit risk, a pure default-risk model. As such, our proposed model can also be interpreted as an extension of the DEJD model to allow for exogenous liquidity. We can calculate π_{DEJD} numerically through an inverse Laplace transform (see, e.g., Huang and Huang, 2012). Similarly, G_{DEJD} as well as $G_{\mathrm{HX-DEJ}}$ can be computed numerically (e.g., Huang, Shi, and Zhou, 2020).

In the third case, we exclude both jumps and liquidity shocks and obtain the Black–Cox (1976) model, a pure diffusion model of credit risk. In this model, the Arrow–Debreu default claim price $G_{\mathrm{BC}}(r,\tau) = G_{\mathrm{HX}}(r,\tau)$ and the risk-neutral default probability $\pi_{\mathrm{BC}}(\tau) = G_{\mathrm{HX}}(\xi k,\tau)|_{\xi=0}$. For completeness, the formula for $\pi_{\mathrm{BC}}(\tau)$ is (see e.g., Bao, 2009):

$$\pi_{\mathrm{BC}}(\tau) = N(h_1(\nu)) + (K/A_t)^{2\nu/\sigma^2} N(h_2(\nu)), \tag{10}$$

It follows from Equations (1) and (2) that the Black–Cox credit spread is

$$cs_{\mathrm{BC}}(\tau) = -\frac{\log\Big(1-\pi_{\mathrm{BC}}(\tau)(1-R)\Big)}{\tau}. \tag{11}$$

To summarize, our proposed model incorporates jumps and liquidity into the Black–Cox model. These two features affect spreads directly and separately, however, given that the default boundary is exogenous. As a result, the model admits a straightforward decomposition of spreads into a credit component and a liquidity component. Moreover, as discussed in Section 5.3, calibrating the model to default data first before using it to predict spreads helps mitigate the concern that the liquidity–default interaction is missing in the model.

4.3 Implementation

4.3.a. Firm fundamentals

We consider two alternative approaches to estimating parameters on firm fundamentals: asset value A_t, asset volatility σ, and four jump parameters $\{\lambda, p_u, \eta_u, \eta_d\}$. With the first approach, we identify these parameters progressively, starting with A_t and σ, two parameters relevant to all models. Following Bao (2009), we implement a rolling estimation of the Black–Cox model using the method of Jones, Mason, and Rosenfeld (1984), namely, we match model-implied values of market leverage and equity volatility to their empirical counterparts. Next, we use high-frequency equity returns to pin down the values of λ and p_u for each debt issuer. Finally, we obtain the estimates of η_u and η_d using the moment condition that equalizes the empirical and model-implied fourth moments of equity returns. This estimation scheme has merits in quantifying the incremental contribution of jumps to credit spreads. On the other hand, it is subject to the criticism that, if the DEJD model is the correct specification, A_t and σ are essentially estimated from a misspecified model. To address this concern, we also implement an alternative, "decremental" estimation approach: we directly estimate the DEJD model using generalized method of moments (GMM) from the get-go. We can then set the jump parameters to zero to derive the implications from the Black–Cox model. Another main difference between these two estimation schemes lies in the data required: whereas the second scheme uses the average CP spreads as one of the moment conditions, the first estimation scheme does not require any data on CP spreads.

We discuss these two estimation schemes in detail in Online Appendix IA.C.1. Following the literature, we focus on the first scheme in our main analysis (Section 5). We implement the second scheme in Online Appendix IA.C.3.

4.3.b. Jump risk premium

We adopt the specification used in Huang and Huang (2012) that the transformation from $\mathbb{P}$-measure jump parameters to $\mathbb{Q}$-measure ones is controlled by a single parameter,

$$\gamma = \frac{\lambda\zeta}{\lambda^{\mathbb{P}}\zeta^{\mathbb{P}}}. \tag{12}$$

The jump risk premium parameter γ is identified using index option data. Until December 23, 2019, options on the Shanghai Stock Exchange (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 first assume that the SSE 50 Index returns follow a DEJD process and employ a MCMC estimator for joint options and index returns data (Eraker, 2004).[12] Next, we convert the estimated γ for levered equity to an equivalent one for the underlying asset value. To allow for time-varying jump risk premium, we perform this estimation year by year. As shown in Online Appendix IA.C.2, our estimates of γ range from 1.42 in 2017 to 3.01 in 2015, with the latter coinciding with the stock market turmoil in China.

4.3.c. Liquidity parameters

The implementation of the HX-DEJ model requires estimates of the fractional TC k and liquidity shock intensity ξ. The former can be calibrated to our transaction cost measure TC,

12 To reduce the computational burden, we follow Pan (2002) and select near-the-money short-dated option contracts for our estimation.

which varies across CP issues and over time. We find that the distribution of TC in our sample is highly skewed to the right, with a mean of 86 bps and median of 49 bps. Intensity ξ is identified by targeting the average turnover rate in the Chinese CP market, as in the calibration analysis of He and Xiong (2012). Given the substantial temporal variation in the aggregate trading intensity, we calibrate ξ to the marketwide turnover rate year by year. The estimated ξ ranges from 42.9% in 2014 to 88.9% in 2016. See Online Appendix IA.C.2 for the details of our calibration of k and ξ.

4.3.d. Default boundary and recovery rates

A common practice to assess structural model performance in the literature is calibrating to $\mathbb{P}$-measure default probabilities. However, how to implement this idea poses a serious empirical challenge in the setting of Chinese credit markets. On the one hand, it typically requires a default sample for decades to obtain a reliable estimate of physical default rates. On the other hand, defaults of public debts did not occur in China until 2014, thus the realized default rate is still kept at an unreasonably low level and still converging to the stationary rate.[13] Moreover, many *de facto* defaults in China take the form of distressed exchanges, which is often not taken into account by domestic rating agencies.

To tackle these empirical issues, we focus on a broad collection of distressed bonds rather than relying on default rates published by rating agencies. In China, distressed bonds carry severe penalties on asset managers which are comparable to nominal defaults (missed payments and bankruptcies). In fact, many commercial banks, wealth management products, and insurance companies in China instruct their portfolio managers to initiate the selloff procedure of a bond once its clean price falls below 80% of its face value. Calibrating a model to the historical distress rate therefore largely reflects the equilibrium effect of physical default risk on corporate bond pricing. Thus, we treat default rates and distress rates the same in the estimation of default boundary K.

We collect a sample of 1,419 firms whose public debt prices have fallen below 80 in the secondary market over the 2014–20 period. Using this broader definition of "default" dramatically expands the list of defaulting issuers (from the 210 based on nominal defaults as defined by Wind Information). Given our short sample period, we calculate distress rates for horizons up to 3 years only. Figure 5 shows the term structure of historical distress rates by rating category.[14] Note that the distress rate monotonically increases with the investment horizon and decreases with credit rating. The only exception lies in issuers rated as AA- or below, whose 3-year distress rate (2.87%) is lower than the 2-year rate (2.90%) and also lower than the 3-year rate of AA-rated bonds. The reasons for this anomalous pattern are that (1) the number of AA- firms issuing public debts in China is rather small and (2) the cohorts for the 3-year horizon are substantially fewer than cohorts for the 2-year

13 For example, the average cumulative default rate in China up to 2019 is 0.71% at the 1-year horizon, which is substantially lower than the global default rate reported by Moody's (1.01%) over the same period. In addition, unlike global rating agencies, the domestic agencies in China do not take loan defaults into account when maintaining their databases, possibly because most defaults of bank loans in China are distressed exchanges and rating agencies do not have access to this part of information.

14 We adopt the Moody's procedures and calculate cumulative distress rates by averaging the multi-period distress rates of cohorts formed at monthly intervals.

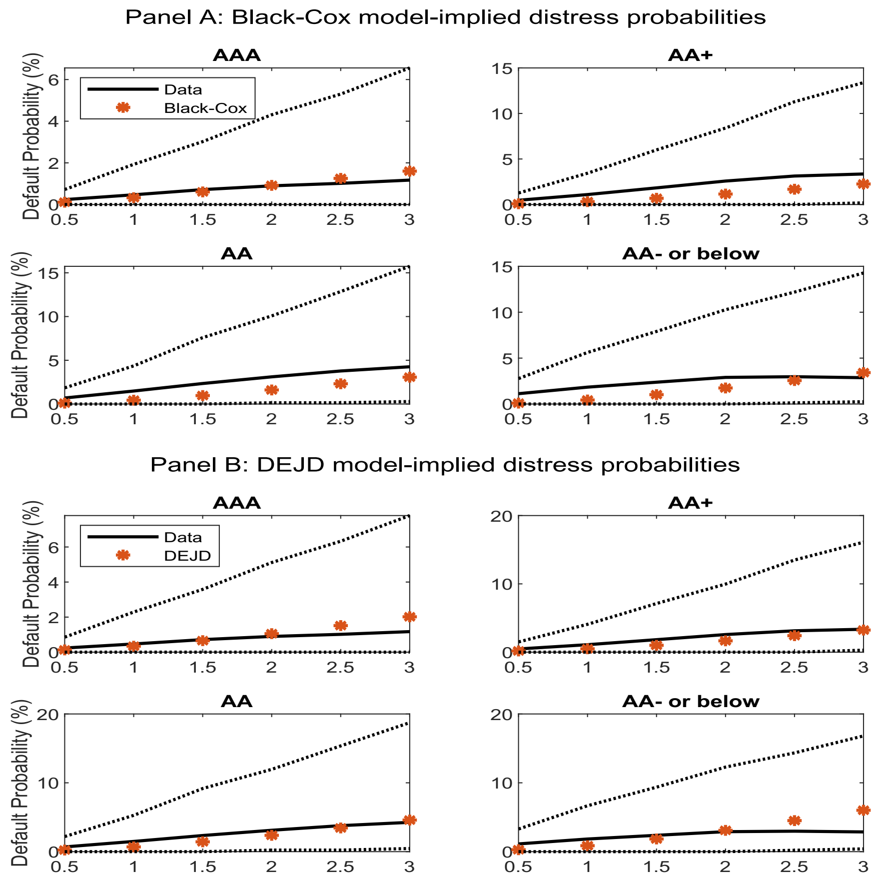

Figure 5. Term structures of corporate debt distress rates in China.

Notes: This figure shows the Black–Cox model-implied (Panel A) and DEJD model-implied (panel B) $\mathbb{P}$-measure probabilities of distress by rating class. Asterisk markers show the average model-implied distress probability across firms and time for each rating and maturity bin. The model-implied distress probability here is the model-implied default probability. The solid lines show the corresponding historical distress frequency from 2014 to 2020. The 95% confidence interval (dotted line) is computed based on the 10,000 simulations.

horizon in our short sample period. Given the apparently problematic estimate of the AA- default rates, we restrict our default boundary estimation to AAA, AA+, and AA groups.

Specifically, we calibrate a structural model to match the term structure of P-measure distress rates for different rating categories and determine the (fractional) default boundary $d \equiv K/F$ as follows (Feldhütter and Schaefer, 2018):

$$d = \underset{d}{\operatorname{argmin}} \sum_{\tau=1}^{6} \sum_{R=1}^{3} \frac{1}{\tau/2} \left|\pi^{\text{Model}}(\tau/2; d, R) - \pi^{\text{Data}}(\tau/2; R)\right|, \tag{13}$$

where $\pi^{\text{Model}}(T; d, R)$ is the $\mathbb{P}$-measure default probability implied by a model for T-year bonds with rating class R, with $\text{Model} = \{\text{BC, DEJD, HX, HX} - \text{DEJ}\}$ and $R = \{1 = \text{AAA}, 2 = \text{AA+}, 3 = \text{AA}\}$; $\pi^{\text{Data}}(T; R)$ is the T-year average distress rate for rating class R. Because our modeling of debt market frictions does not accommodate the liquidity-driven-default channel, the BC and HX models share the same estimate of default boundary and the DEJD and HX-DEJ models do so as well. We find that $d_{\mathrm{BC}} = d_{\mathrm{HX}} = 0.681$, which is close to 0.60 used by Huang and Huang (2012) and 0.66 estimated by Davydenko (2012) using a sample of US defaulted firms. As expected, incorporating jump risk lowers the default boundary estimate: $d_{\mathrm{DEJD}} = d_{\mathrm{HX-DEJ}} = 0.527$.

We estimate the recovery rate in accordance with our broad definition of corporate defaults. Based on our definition, only 10.7% of distressed firms eventually default on their obligations of debt repayment. Regarding these nominal defaulters, we take the recovery rate 0.175 as published by Wind Information. Then we calculate the average clean price for the remaining distressed firms—when their bond prices fall below 80 for the first time—and obtain an estimate of 0.654. Therefore, the ultimate recovery rate used in our model implementations is $0.107 \times 0.175 + 0.893 \times 0.654 = 0.603$.

5. Empirical Results

In this section, we present our empirical results. We consider regressions of CP spreads first, which are followed by regression analysis of the determinants of MTNs and EBs. We then investigate the pricing performance of the structural models reviewed in Section 4.

5.1 Determinants of CP Spreads: Evidence from Regressions

Panel A of Table III 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 (e.g., Ericsson, Jacobs, and Oviedo, 2009). Model M2 is closer to the Merton model in that it examines the DD, a nonlinear function of the aforementioned three variables that in theory directly determines the risk-neutral default probability. The results from these two regression models show that individual equity volatility is significantly positive and DD is significantly negative. Model M3, a combination of M2 and M1, indicates that DD subsumes equity volatility, which lends support to the functional form of the model spread.

Interestingly, augmenting M3 with credit ratings ($\mathrm{Rating}_{i,t}$) slightly strengthens the impact of DD (model M4). This result implies that DD contains incremental information about spreads over credit ratings. M5 and M6 consider other explanatory variables included in the benchmark regression model of Collin-Dufresne, Goldstein, and Martin (2001). Including the slope of yield curves and the equity market return ($\mathrm{CSI300}_t$) does not drive out DD and Rating (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/probability. Augmenting M5 with these two variables raises the adjusted R^2 from 8.4% to 9.0% (M6). In particular, Jump 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 (Duffie and Lando, 2001; Zhou, 2001).

To assess the relative importance of liquidity- and credit-related variables in explaining the CP spreads, we estimate ten regression models and report the results in panel B of Table III. Model M1 includes four traditional liquidity proxies considered in Covitz and Downing (2007): CP offer amount, trading volume, time to maturity, and the initial maturity. We find that, while $\mathrm{OfferAmt}_i$ and $\mathrm{InitMat}_i$ are significant with expected signs, the four proxies explain little variation in the spread with an $\overline{R}^2$ of merely 1.4%. In contrast, the

Table III. The determinants of CP spreads: evidence based on regressions

This table reports results from different specifications of regressions of CP spreads on credit–risk variables (panel A) or credit- and liquidity-related variables (panel B) based on a sample of Chinese CP issues over the period May 2014–December 2020. 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 TC ($TC_{i,t}$), and price impact proxy $Amihud_{i,t}$. Credit-related variables used include the risk-free rate (rf_t), firm-i's leverage ratio ($Lev_{i,t}$), equity volatility ($\sigma^E_{i,t}$), DD ($DD_{i,t}$), 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 ($YearEnd_t$), the SOE dummy equal to one if the issuer is state-owned (SOE_i), and the difference between the interest rates on interbank loans and short-term government debt (TED_t). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A						Panel B									
	Regressions of spreads on credit risk determinants						Regressions of spreads on liquidity- and credit-related variables									
	M1	M2	M3	M4	M5	M6	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
Intercept	–0.003	0.020***	0.007	0.000	0.001	0.011	0.002	0.005	0.002	–0.004*	0.007**	0.006**	–0.005	0.010**	–0.005	–0.004
	(–0.39)	(7.98)	(0.60)	(0.03)	(0.10)	(0.65)	(1.06)	(1.44)	(0.41)	(–1.75)	(2.44)	(2.40)	(–1.62)	(2.35)	(–1.53)	(–0.64)
rf_t	0.509***		0.613***	0.448***	0.463***	0.422**										
	(3.28)		(4.01)	(2.96)	(3.01)	(2.28)										
$Lev_{i,t}$	–0.002		–0.008	–0.004	–0.004	–0.004										
	(–0.38)		(–1.01)	(–0.45)	(–0.46)	(–0.48)										
$\sigma^E_{i,t}$	0.014***		0.006	–0.001	–0.004	–0.003										
	(3.32)		(1.04)	(–0.28)	(–0.62)	(–0.41)										
$OfferAmt_i$							–0.158***			–0.068**						
							(–7.32)			(–2.53)						
$Volume_{i,t}$							–0.003			0.007**						
							(–0.68)			(1.99)						
$Mat_{i,t}$							–0.005			–0.012**						
							(–1.08)			(–1.99)						
$InitMat_i$							0.025***			0.015***						
							(4.33)			(3.47)						
$TC_{i,t}$								3.962***	3.922***	3.905***		3.881***	4.540***		4.559***	4.512***
								(3.27)	(3.34)	(3.30)		(3.25)	(3.81)		(3.62)	(3.29)
$Amihud_{i,t}$									0.025***	0.024***		0.018***	0.003		0.014***	0.014***

(continued)

Table III. Continued

	Panel A						Panel B									
	Regressions of spreads on credit risk determinants						Regressions of spreads on liquidity- and credit-related variables									
	M1	M2	M3	M4	M5	M6	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
									(11.49)	(9.93)		(9.33)	(0.10)		(6.09)	(6.08)
$DD_{i,t}$		–0.003***	–0.003***	–0.003***	–0.003***	–0.003***					–0.002***	–0.002***	–0.002***	–0.002***	–0.003***	–0.002***
		(–4.73)	(–2.96)	(–3.11)	(–3.11)	(–3.05)					(–3.85)	(–3.49)	(–3.81)	(–3.98)	(–3.77)	(–2.76)
$Rating_{i,t}$				0.013***	0.013***	0.014***					0.014***	0.007***	0.008***	0.014***	0.008***	0.004***
				(11.60)	(11.93)	(10.74)					(13.89)	(8.78)	(9.97)	(12.50)	(8.44)	(3.36)
$DD_{i,t} \times TC_{i,t}$													–0.596***		–0.597***	–0.600***
													(–7.78)		(–7.56)	(–7.51)
$Jump_t$						0.068***								0.054***	0.024**	0.033***
						(3.17)								(3.04)	(2.09)	(2.69)
$CIVIX_t$						–0.038										–0.006
						(–1.64)										(–0.64)
$Slope_t$					–0.204	–0.012										–0.009
					(–0.78)	(–0.05)										(–0.06)
(HTML translation failed)					–0.046*	–0.049*										–0.001
					(–1.81)	(–1.87)										(–0.10)
$YearEnd_t$																0.003
																(0.97)
SOE_i																–0.002
																(–0.45)
TED_t																0.585***
																(3.40)
$\overline{R}^2$	0.005	0.032	0.038	0.081	0.084	0.090	0.014	0.238	0.273	0.276	0.076	0.276	0.433	0.082	0.445	0.448
Obs.	7691	7691	7691	7691	7691	6860	7691	5821	5821	5821	7691	5821	5821	6902	5118	5118

TC alone, TC_i, is significantly positive with an R^2 of 23.8% (M2). Augmenting M2 with $Amihud_{i,t}$ raises the $\overline{R}^2$ to 27.3% (M3). Augmenting M3 with the four traditional liquidity proxies has only a marginal impact on $\overline{R}^2$ and weakens the impact of OfferAmt and InitMat (M4). These results indicate that the four traditional liquidity proxies have little explanatory power for CP spreads in China.

Given the results in panel A of Table III, we use DD and Rating as our baseline credit variables and, in addition, consider Jump. M5 shows that both DD and Rating are significant with expected signs albeit with a relatively low $\overline{R}^2$ of 7.6%. Augmenting M5 with TC and Amihud raises the $\overline{R}^2$ substantially to 27.6% (close to $\overline{R}^2$ of 27.3% under M3) and weakens the impact of Rating, although the variable and DD_i are still significant (M6). Taken together, 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. So far we have treated credit and liquidity variables separately. To examine the impact of their interaction, we estimate M7 that augments M6 with DD $\times$ TC. This interaction term is indeed significantly negative, indicating that illiquidity exacerbates the effect of default risk on CP spreads as implied by the He and Xiong (2012) model. Next, we include Jump. The results from M8 and M9—M5 and M7 augmented with Jump, respectively—show that Jump is significantly positive and raises $\overline{R}^2$ from 7.6% for M5 to 8.2% for M8 and from 43.3% for M7 to 44.5% for M9. Lastly, we augment M9 with more market-wide variables, including Slope, CSI300, CIVIX, and TED, along with control dummies YearEnd and SOE (M10). Among these variables, only TED is significant and has an expected positive sign. In particular, while SOE has an expected, negative effect on yield spreads, the dummy is insignificant in the presence of other credit variables. This result is consistent with findings by Geng and Pan (2021), which suggest that rating agencies have taken debt issuers' nature into account. Moreover, M10 has an $\overline{R}^2$ of 44.8%, very close to M9's 44.5%.

To summarize, there are two main takeaways from our regression analysis. First, both credit risk and liquidity variables are important in determining CP spreads, but the latter have much stronger explanatory power for such spreads. Second, the interaction of these two sets of variables is also very important and has strong explanatory power for CP spreads.

The dominance of liquidity variables as shown in Table III is reconcilable with the findings of Covitz and Downing (2007) through three alternative explanations. First, as we aim to argue, the sparsity of secondary market transactions in the US CP market confines their analysis to the four traditional liquidity proxies, which underestimate the explanatory power for CP spreads. Second, the relative importance of liquidity and credit risk in the primary market somehow dramatically differs from that in the secondary market. Third, the moderate R^2 values generated by credit variables are unique to the Chinese CP market.

To explore the latter two explanations, we first examine if credit variables capture a substantially larger portion of variations in *new issue* yield spreads of Chinese CP than in the secondary market (see Online Appendix IA.B.1). It turns out that, while some explanatory variables (e.g., credit rating) show greater significance in the primary market, the overall explanatory power of credit risk variables seems to be of the same magnitude as documented in the secondary market in Table III. Next, we conduct an analysis of individual CP issues in the USA over the same period in Appendix A. Among other things, we estimate regression models similar to those in Table III and find little evidence that credit risk plays a significantly larger role in determining CP spreads in the US market. For instance, the $\overline{R}^2$ as achieved by specification M6 is 9.0%, 7.9%, and 8.4% for the Chinese secondary market, Chinese primary market, and US market (dominated by primary market transactions), respectively. Therefore, while the different market structure prevents us from implementing dynamic liquidity measures for the US market, at least issuers' fundamental default risk appears to play a similar (and rather limited) role in shaping CP yield spreads in both markets.

5.2 Determinants of Spreads on MTNs and EBs

Intuitively, credit-related variables become more important in determining longer-maturity spreads. 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 debt maturity. Doing so also helps validate the credit- and liquidity-related variables used earlier. Below we briefly describe our analysis of MTNs and EBs and summarize the main findings (see Online Appendix IA.B.2 for the details of the analysis).

We examine MTNs and EBs with maturities of 1–3 years first. As expected, when we move from CP to these longer maturity instruments, the credit variables become relatively more important than the liquidity proxies. The jump risk, however, becomes less important relative to the other credit variables: The incremental explanatory power of Jump_t over DD_i and Rating_i becomes weaker than it does for CP spreads. The credit–liquidity interaction, $\text{DD}_i \times \text{TC}_i$, is still highly significant and has strong incremental explanatory power over TC_i, DD_i, Rating_i, and Jump_t.

Next, we repeat the above analysis using MTNs and EBs with maturities of 3–6 years. The explanatory power of the credit variables is much stronger than for the short-term MTNs and EBs. The jump risk, Jump_t, is also less significant and has a much lower coefficient than its counterpart for short-term MTNs and EBs. Interestingly, the incremental explanatory power of $\text{DD}_i \times \text{TC}_i$ over TC_i, DD_i, Rating_i, and Jump_t is much weaker than its counterparts for the CP or short-term MTNs and EBs. This is not surprising to some extent, given that the four variables together capture almost 50% of the spread variation here. Lastly, as in the case of CP spreads, the market-wide variables and control dummies (e.g., YearEnd and SOE) together show little incremental explanatory power over the credit and liquidity variables for spreads on MTNs and EBs.

Figure 6 summarizes the explanatory power ($\overline{R}^2$) of credit- or liquidity-related proxies for spreads on CP, short-term MTNs-EBs, and medium-term ones. Credit variables considered include DD_i and Rating_i with (in blue) and without Jump_t (in navy blue). Liquidity proxies include TC with (in orange) and without Amihud_i (in crimson). The light and dark green bars depict the joint explanatory power of the two sets of variables with and without the interaction between DD and TC, respectively. Note from the figure that as debt maturity becomes longer, the liquidity proxies together have a relatively stable $\overline{R}^2$ of around 25%, the credit-risk proxies have an increasing $\overline{R}^2$, and the incremental $\overline{R}^2$ of DD $\times$ TC decreases.

5.3 Pricing Performance of Structural Models

Sections 5.1 and 5.2 provide regression-based evidence on the role of credit and liquidity variables in capturing spread variations. In this subsection, we perform a yield spread accounting within the structural framework using the four models reviewed in Section 4. We implement each of the models as described in Section 4.3 and calculate the model-

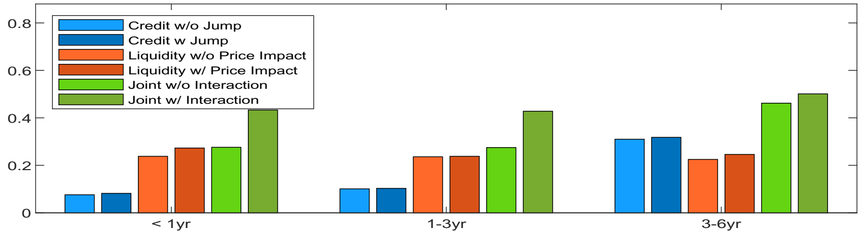

Figure 6. Explanatory power of corporate yield spread determinants.
Notes: This figure plots the adjusted R^2s in panel regressions of yield spreads on credit- or liquidity-related proxies. The former proxies considered include DD and credit ratings with (in blue) and without *Jump* (in navy blue). Liquidity-related variables considered include TC (the TC) with (in orange) and without the Amihud (2002) measure of price impact (in crimson). The light and dark green bars depict the joint explanatory power of the two sets of variables, with or without the interaction between DD and TC. Corporate debt issues included are divided into three groups: CP (with maturities less than 1 year), short-maturity MTNs and EBs (with maturities of 1–3 years), and intermediate-maturity MTNs and EBs (with maturities of 3–6 years).

predicted spread of every CP issue in our sample. We then focus on three aspects of the pricing performance of these models. First, we examine the empirical distributions of the model-predicted spreads and, in particular, the ability of the models to predict the mean and median spreads. Second, we quantify the contributions of default and liquidity risks to the level of CP yield spreads. Third, we analyze the pricing errors of the models.

5.3.a. Quantiles of observed and predicted CP spreads

To get a broad picture of the pricing performance of the models, we tabulate the quantiles of observed CP spreads as well as the model-predicted spreads by credit ratings in Table IV. Consider the full sample first. Not surprisingly, the pure-diffusion Black–Cox model substantially underestimates CP spreads, especially given that here $d_{\mathrm{BC}} = 0.681$. For instance, the model-implied mean spread is 9 bps, accounting for only 6.3% of the average observed spread of 143 bps. The median of the model spreads is 0 (119 bps in the data). The distribution of the model spreads is more right-skewed than the empirical distribution. Thus, we need to evaluate the model performance by going beyond its predictive power for the mean spread.

As expected, the DEJD model improves the pricing performance markedly, especially at the right tail. For instance, the predicted average and median spreads are 35 and 19 bps, respectively; the Black–Cox, DEJD, and observed spreads at the 90th percentile are 0, 71, and 273 bps, respectively. But the left tail DEJD spreads are still way below their empirical counterparts. For example, the DEJD spread at the 10th percentile is 4 bps versus 34 bps in the data. In other words, the model spreads are still more right-skewed than the data. The model still substantially underpredicts the average spread, accounting for about 24% of the spread; namely, there is a credit spread puzzle in this CP market. The reason why jumps alone have such a limited ability to raise the spread is that their impact on credit risk is to some extent balanced out by the low default boundary of $d_{\mathrm{DEJD}} = 0.512$, as a result of first calibrating the model to low average default rates.

Incorporating a liquidity premium into the Black–Cox model also improves the pricing performance. The average and median HX model-implied spreads are 98 and 51 bps,

Table IV. Quantiles of observed and predicted credit spreads

This table reports summary statistics of observed and predicted yield spreads for a sample of CPs during May 2014–December 2020. The predicted spreads are generated from the Black and Cox (1976) model, the DEJD model, a simplified He and Xiong (2012) model (HX), and the HX-DEJ. *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	1.43	0.34	0.61	1.19	1.83	2.73	7,672
	Black–Cox spread	0.09	0.00	0.00	0.00	0.00	0.00	
	DEJD spread	0.35	0.04	0.09	0.19	0.37	0.71	
	HX spread	0.98	0.15	0.26	0.51	1.11	2.19	
	HX-DEJ spread	1.10	0.26	0.42	0.73	1.31	2.23	
AAA	Observed spread	0.89	0.25	0.42	0.74	1.22	1.68	3,810
	Black–Cox spread	0.07	0.00	0.00	0.00	0.00	0.00	
	DEJD spread	0.21	0.03	0.06	0.13	0.24	0.40	
	HX spread	0.68	0.11	0.19	0.33	0.68	1.46	
	HX-DEJ spread	0.73	0.20	0.31	0.48	0.82	1.36	
AA+	Observed spread	1.66	0.65	1.03	1.46	1.92	2.52	1,929
	Black–Cox spread	0.08	0.00	0.00	0.00	0.00	0.00	
	DEJD spread	0.41	0.07	0.14	0.25	0.40	0.71	
	HX spread	1.12	0.23	0.36	0.61	1.18	2.24	
	HX-DEJ spread	1.28	0.41	0.57	0.88	1.42	2.28	
AA	Observed spread	2.31	1.02	1.43	2.06	2.78	3.70	1,718
	Black–Cox spread	0.15	0.00	0.00	0.00	0.00	0.06	
	DEJD spread	0.56	0.08	0.18	0.37	0.69	1.22	
	HX spread	1.53	0.34	0.58	1.04	1.82	3.31	
	HX-DEJ spread	1.70	0.64	0.89	1.37	2.08	3.03	
AA− or below	Observed spread	3.32	1.95	2.57	3.26	4.09	4.51	215
	Black–Cox spread	0.04	0.00	0.00	0.00	0.00	0.03	
	DEJD spread	0.81	0.08	0.22	0.55	1.04	1.73	
	HX spread	1.39	0.41	0.68	1.24	1.97	2.56	
	HX-DEJ spread	2.00	0.76	1.17	1.70	2.68	3.31	

explaining about 69% and 43% of their observed counterparts, respectively. The improvement at the tails, especially the right tail, is significant: the HX spread at the 10th and 90th percentiles is 15 and 219 bps, respectively. Overall, the HX model predicts much higher spreads than the DEJD model, let alone the Black–Cox model, and also leads to a heavier right tail in the spread distribution compared with the DEJD model. This pattern is attributable to the fact that transaction costs tend to rise dramatically for high leverage and/or high asset volatility firms. Consequently, the model implies that corporate debts with a higher level of default risk are likely to have a greater incremental liquidity component in their yield spreads. The above results indicate that incorporating liquidity can raise the short-term spreads much more effectively than incorporating jumps. The reason is that unlike jumps, the role of exogenous liquidity is not attenuated by the model calibration to default rates.

Now let's turn to the HX-DEJ model. Note that $d_{\text{HX-DEJ}} = 0.512 \ll d_{\text{HX}} = 0.682$. Thus, the HX-DEJ spread on a CP issue can be lower than its HX spread. The top panel of Table IV shows that the HX-DEJ model does raise the HX spread for the full sample, especially at the left tail relatively. For instance, the spread increase is 11 (= 26 − 15) and 4 (=223 − 219) bps at the 10th and 90th percentiles, respectively. The average and median HX-DEJ spreads are 110 and 73 bps, accounting for about 77% and 61% of their counterparts in the data, respectively. Taken together, the HX-DEJ model improves the overall pricing performance significantly but still underestimates the average and median spreads. The model-implied spreads are still right skewed albeit less so than the HX spreads.

Next, consider the subsamples by credit ratings. The results for AAA or AA+ issues show similar patterns to those for the full sample. The results for the AA subsample display a slightly different pattern: the HX-DEJ spread is slightly below the HX spread at the 90th percentile. The results for the "AA- or below" subsample (effectively "high-yield" issues) also show patterns different from those for the other groups. The HX-DEJ model significantly improves the performance of the HX model across all percentiles, but it still underestimates the average and median spreads. One possible reason is that the estimated default boundary is too low for issues rated AA- or below. Another possible reason is that this subsample is small (consisting of 215 observations only).

5.3.b. More on the mean and median of predicted CP spreads

Figure 7 visualizes the explanatory power of different models for either the mean (top panel) or the median CP spread (bottom panel). Consider the mean spread first. The portion of the observed spread attributable to the Black–Cox model decreases from about 8% for AAA to 1% for "AA- or below." The portion attributable to the DEJD model is relatively stable across different rating groups and is about 24%. The HX model explains about 76% for AAA, to 68% for AA+, 66% for AA, and 42% for "AA- or below." The HX-DEJ model explains 82% for AAA, 77% for AA+, 74% for AA, and 60% for "AA- or below" issues; namely, the underprediction of the mean spread is more severe for lower rating groups.

Consider the median spread next. The Black–Cox spread is basically zero, regardless of the rating groups. The predicted portion of the median spread by the DEJD model is relatively stable across different rating groups and is around 17%. The HX model-implied portion ranges from 38% for "AA- or below" to 51% for AA issues. The portion explained by the HX-DEJ model is 65% for AAA, 60% for AA+, 67% for AA, and 52% for "AA- or below" issues.

Taken together, here are the main takeaways from Figure 7. First, all the models underestimate the mean and median spreads, regardless of the rating groups. Second, the median spread is harder to explain than the average spread. Third, the DEJD model can explain a relatively stable portion of the average spread (around 24%) or the median spread (about 19%), across all rating groups. Fourth, the HX model can explain about 69% of the mean spread overall, with the explained portion higher for higher rating groups. Lastly, the HX-DEJ model can explain 77% of the mean spread and 61% of the median spread. The explained portion of the mean spread is higher for higher rating groups.

5.3.c. Time-series evidence and the decomposition of CP spreads

Having presented the cross-sectional evidence of the model performance, we now examine the performance in time series. Panel A of Figure 8 plots the monthly average of CP spreads

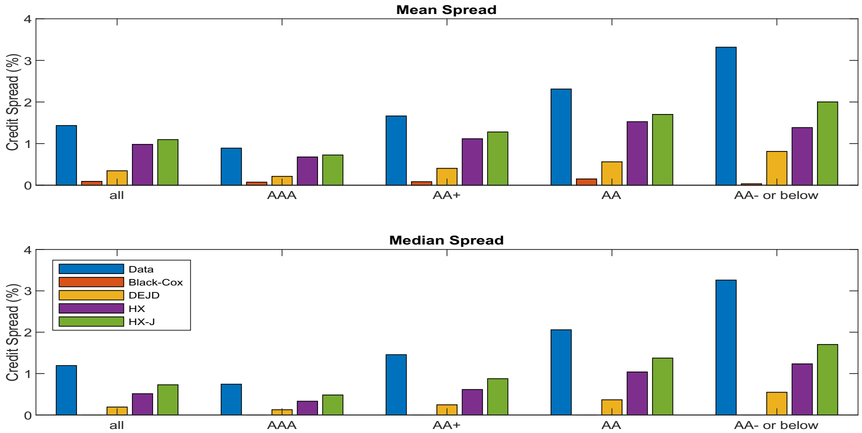

Figure 7. Mean and median of predicted CP yield spreads in China.

Notes: This figure plots the mean and median of CP yield spreads by rating category. The five bars in each rating category, in turn, represent yield spreads in the data (blue) and those generated by the Black–Cox (1976) model (orange), the DEJD model (yellow), a simplified He and Xiong (2012) model (HX in purple), and the He–Xiong model with double-exponential jumps (HX-J in green). Note that the Black–Cox median spread is virtually zero for all rating groups. The sample period spans from May 2014 to December 2020.

over time for both the observed (in solid blue) and predicted spreads. We omit the Black–Cox model in the figure as its spreads are too low. The DEJD and HX-DEJ models tract the trend of the observed spread reasonably well, so does the HX model except in late 2015 when the model spread has a large spike. While the DEJD spread (in red) is always below the observed spread, the HX (in yellow) and HX-DEJ (in purple) spreads occasionally are higher than the observed one. The gap between the observed and predicted spreads is wide until late 2019 when the observed spread drops substantially. This sharp decline in the spread is mainly owing to the deleveraging campaign by the central government. As a result, the HX and HX-DEJ spreads have been much closer to the observed spread since late 2019.[15]

The implication of Panel A is consistent with estimated correlations between the average predicted and observed spreads, which are 0.02 for Black–Cox, 0.58 for DEJD, 0.26 for HX, and 0.61 for HX-DEJ. We also run a panel regression of the observed spreads on the predicted spreads by each model and find that the R^2 is 0.0 for Black–Cox, 9.0% for DEJD, 6.1% for HX, and 14.6% for HX-DEJ.

Next, we focus on the HX-DEJ yield spread (denoted by $cs_{\mathrm{HX-DEJ}}$) and decompose it into a diffusive (credit) component ($cs^{\mathrm{D}}_{\mathrm{HX-DEJ}}$), a jump risk component ($cs^{\mathrm{J}}_{\mathrm{HX-DEJ}}$), and a liquidity component ($cs^{\mathrm{L}}_{\mathrm{HX-DEJ}}$). We denote the average of a variable by a bar (e.g., $\overline{cs}_{\mathrm{HX-DEJ}}$). Panel B of Figure 8 plots the average observed CP spread (solid blue line), $\overline{cs}_{\mathrm{HX-DEJ}}$ (dashed orange line), and its jump component $\overline{cs}^{\mathrm{J}}_{\mathrm{HX-DEJ}}$ (yellow dotted line) and liquidity component $\overline{cs}^{\mathrm{L}}_{\mathrm{HX-DEJ}}$ (purple dash-dotted line). The diffusive component $\overline{cs}^{\mathrm{D}}_{\mathrm{HX-DEJ}}$

15 See Online Appendix IA.D for a subsample analysis. The ability of the DEJD model to capture the CP spread would be much greater if the model is not first calibrated to distress data (see Online Appendix IA.E).

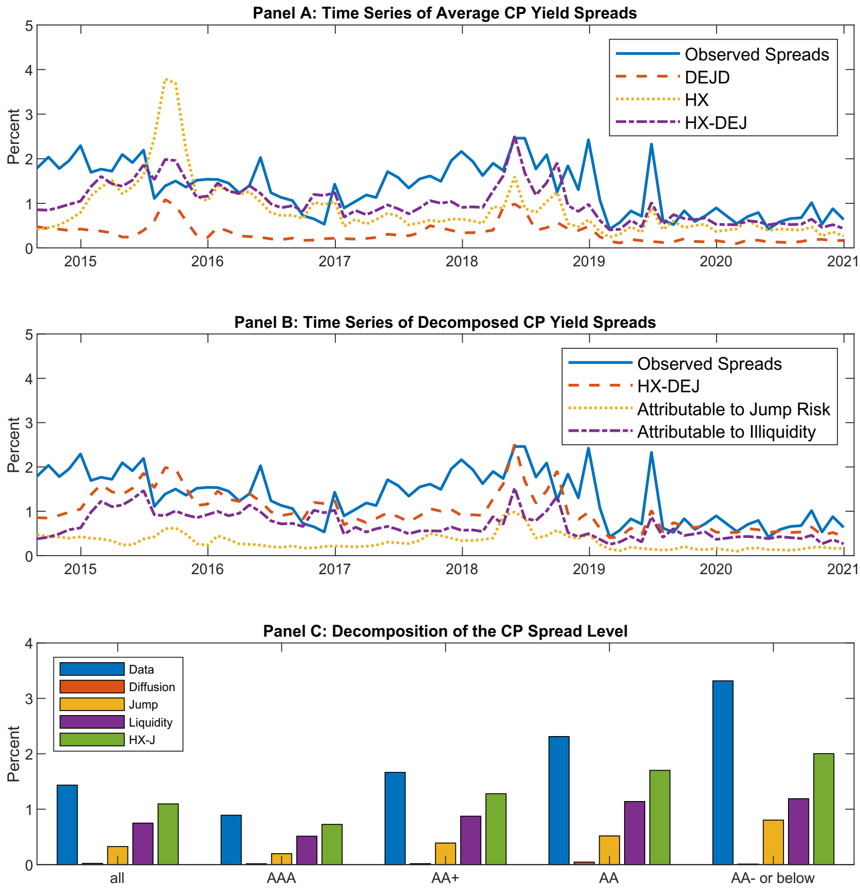

Figure 8. Structural decomposition of CP yield spreads.

Notes: Panel A plots the monthly means of CP yield spreads over time for the data (solid blue line) as well as three credit risk models for the full sample. The latter include the DEJD model (DEJD in red), a simplified He–Xiong (2012) model (HX in yellow), and the He–Xiong model with double-exponential jumps (HX-DEJ in purple). Panel B plots the jump risk (yellow dotted line) and liquidity (purple dash-dotted line) components of the average HX-DEJ model-implied yield spread (orange dashed line) for the full sample. Panel C illustrates the decomposition of the average HX-DEJ model-implied yield spread (in green) into its diffusive credit risk (in orange), jump risk (in yellow), and liquidity (in purple) components for each rating group. The sample period spans from May 2014 to December 2020.

is too small to include in the figure. We find that $\overline{cs}^{\mathrm{L}}_{\mathrm{HX-DEJ}}$ dominates $\overline{cs}^{\mathrm{J}}_{\mathrm{HX-DEJ}}$ especially for AAA and AA+ issues and also exhibits sharper fluctuations. It follows that $\overline{cs}^{\mathrm{L}}_{\mathrm{HX-DEJ}}$ captures the time variation in the CP spread more adequately than $\overline{cs}^{\mathrm{J}}_{\mathrm{HX-DEJ}}$ does.

Table V reports the quantiles of $cs^{\mathrm{D}}_{\mathrm{HX-DEJ}}$, $cs^{\mathrm{J}}_{\mathrm{HX-DEJ}}$, and $cs^{\mathrm{L}}_{\mathrm{HX-DEJ}}$. As expected, $cs^{\mathrm{D}}_{\mathrm{HX-DEJ}}$ is often zero, regardless of credit ratings and quantiles of spreads. Regarding $cs^{\mathrm{J}}_{\mathrm{HX-DEJ}}$, it shows greater magnitude than $cs^{\mathrm{D}}_{\mathrm{HX-DEJ}}$, especially for lower credit ratings. In addition, it is still low at the left tail but matters greatly at the right tail. The ratio, $\overline{cs}^{\mathrm{L}}_{\mathrm{HX-DEJ}}/(\overline{cs}^{\mathrm{D}}_{\mathrm{HX-DEJ}}+\overline{cs}^{\mathrm{J}}_{\mathrm{HX-DEJ}})$, is over 2 for AAA through AA and about 1.5 for “AA- or below,” indicating the dominance of the liquidity component.

Table V. Structural decomposition of CP yield spreads based on the He and Xiong (2012) model with jumps

This table presents a structural decomposition of yield spreads for a sample of CPs during May 2014–December 2020. Based on the He and Xiong (2012) model with DEJ—a fully fledged model termed the HX-DEJ model, corporate yield spreads are decomposed into a diffusive (credit) component, a jump risk component, and a liquidity component. *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	1.43	0.34	0.61	1.19	1.83	2.73	7,672
	Diffusive component	0.02	0.00	0.00	0.00	0.00	0.00	
	Jump component	0.33	0.04	0.09	0.19	0.36	0.69	
	Liquidity component	0.75	0.14	0.24	0.46	0.90	1.61	
	HX-DEJ spread	1.10	0.26	0.42	0.73	1.31	2.23	
AAA	Observed spread	0.89	0.25	0.42	0.74	1.22	1.68	3,810
	Diffusive component	0.02	0.00	0.00	0.00	0.00	0.00	
	Jump component	0.20	0.03	0.06	0.12	0.24	0.39	
	Liquidity component	0.51	0.11	0.18	0.30	0.54	1.08	
	HX-DEJ spread	0.73	0.20	0.31	0.48	0.82	1.36	
AA+	Observed spread	1.66	0.65	1.03	1.46	1.92	2.52	1,929
	Diffusive component	0.02	0.00	0.00	0.00	0.00	0.00	
	Jump component	0.39	0.06	0.13	0.25	0.40	0.69	
	Liquidity component	0.87	0.22	0.34	0.56	0.97	1.74	
	HX-DEJ spread	1.28	0.41	0.57	0.88	1.42	2.28	
AA	Observed spread	2.31	1.02	1.43	2.06	2.78	3.70	1,718
	Diffusive component	0.04	0.00	0.00	0.00	0.00	0.00	
	Jump component	0.52	0.07	0.18	0.35	0.66	1.11	
	Liquidity component	1.14	0.33	0.53	0.87	1.42	2.14	
	HX-DEJ spread	1.70	0.64	0.89	1.37	2.08	3.03	
AA− or below	Observed spread	3.32	1.95	2.57	3.26	4.09	4.51	215
	Diffusive component	0.01	0.00	0.00	0.00	0.00	0.00	
	Jump component	0.80	0.08	0.21	0.54	1.00	1.73	
	Liquidity component	1.19	0.41	0.66	1.08	1.70	2.10	
	HX-DEJ spread	2.00	0.76	1.17	1.70	2.68	3.31	

On average, cs^{D}_{HX-DEJ}, cs^{J}_{HX-DEJ}, and cs^{L}_{HX-DEJ} account for 1.8%, 30.0%, and 68.2% of cs_{HX-DEJ} for the full sample. Similar decompositions hold for AAA, AA+, and AA subgroups. For "AA- or below" issues, the decomposition is 0.5%, 40.0%, and 59.5%. In terms of the proportion of the observed spread, cs^{D}_{HX-DEJ}, cs^{J}_{HX-DEJ}, and cs^{L}_{HX-DEJ}, on average, account for 1.4%, 23.1%, and 52.4%, respectively, for the full sample; that is, the two credit risk components together explain about 24.5% of the observed spread. The liquidity proportion of the observed spread decreases as the rating decreases, and is 57.3% for AAA, 52.4% for AA+, 49.4% for AA, and 35.8% for "AA- or below" issues.

5.3.d. Pricing errors

Table VI reports the MPEs (Panel A) and MPPEs (Panel B) of the four structural models by credit ratings. We make several observations from Panel A. First, all the models have

Table VI. Pricing errors of structural models

This table reports means of pricing errors and percentage errors of structural models for a sample of CPs during May 2014–December 2020. Pricing errors are reported as the difference (in percentages) 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 and Cox (1976) model, the DEJD model, a simplified He and Xiong (2012) model (HX), and the HX-DEJ. *P*-values are computed from the *t*-test (in parentheses) and Wilcoxon signed-rank test (in braces), respectively.

	All	AAA	AA+	AA	AA− or below
Panel A: MPE (%)					
Black–Cox	−1.34	−0.82	−1.58	−2.16	−3.28
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
DEJD	−1.09	−0.68	−1.26	−1.75	−2.50
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
HX	−0.45	−0.21	−0.55	−0.78	−1.93
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
HX-DEJ	−0.34	−0.17	−0.38	−0.61	−1.31
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
Panel B: Mean percentage error (%)					
Black–Cox	−92.17	−91.92	−93.33	−90.81	−98.98
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
DEJD	−70.26	−67.85	−72.81	−72.58	−77.52
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
HX	21.34	52.57	−9.05	−13.52	−54.90
	[0.150]	[0.062]	[0.042]	[0.039]	[0.000]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
HX-DEJ	33.74	68.86	0.44	−7.80	−38.24
	[0.029]	[0.019]	[0.912]	[0.010]	[0.000]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}

significantly negative MPEs, across all rating groups. The MPE ranges from −3.28% for the "AA- or below" group from the Black–Cox model to −0.17% for the AAA group from the HX-DEJ model. Furthermore, the underprediction of the spread for a given model is worse for lower-rated issues. Second, although incorporating jumps into the Black–Cox model reduces the magnitudes of the MPEs, incorporating market illiquidity improves the performance much more significantly. Third, jumps and market illiquidity together can reduce the magnitude of the MPEs even further.

The MPPEs reported in Panel B show that, on average, both the Black–Cox and the DEJD models have extremely large negative relative pricing errors. The HX model reduces the MPPEs substantially for AA+, AA, and “AA- or below” issues. Its MPPEs for the full sample or the AAA subsample are actually positive but insignificant under the *t*-test but are significantly different from zero based on the Wilcoxon signed-rank test (owing to the right-skewed HX-implied spreads). The HX-DEJ model improves the performance for AA+, AA, and AA− or below issues even further. For instance, the MPPE of the HX-DEJ model for AA+ issues is only 0.44%, which is quite impressive given the low observed spreads for such issues. However, relative to the HX model, the HX-DEJ model lowers the model performance for the full sample or the AAA subsample. Overall, the four models all have high MPPEs in terms of the magnitude. This finding is similar to that of Eom, Helwege, and Huang (2004) based on US corporate bond data.

To summarize, there are three main takeaways from Table VI. First, both the Black–Cox and the DEJD models substantially underestimate the CP spreads, regardless of the credit ratings considered. Second, incorporating liquidity into either of these two models significantly improves the model performance and helps mitigate the credit spread puzzle substantially. The resulting HX model or HX-DEJ model, however, still underestimates the average CP spread across different rating groups. Third, all of the four models suffer from an accuracy problem in that they all have high absolute MPPEs.

5.3.e. Discussion

Given the evidence of a credit spread puzzle in the CP market documented in Section 5.3, one question that arises is how to raise the HX-DEJ model-implied spread. One way is to add rollover risk by endogenizing the default boundary. However, given that it is still a default risk, the effect of rollover risk on CP spreads may be weakened once the model is first calibrated to default data; namely, the effectiveness of this channel is an empirical question. Another channel is to increase the impact of liquidity, which is not affected by the calibration to default data. For instance, in our calibration of parameter k, we only take into account the information on effective bid–ask spreads, owing to the difficulty in quantifying the effect of another liquidity dimension, while k in the original HX model should be broadly interpreted as encompassing both transaction costs and the price impact of trades. Thus, once the adjustment of the effective discount rate to the price impact is built in, the model-implied spreads are likely to have a nontrivial increase. Alternatively, we can use a simplified He and Milbradt (2014) model that assumes an exogenous default boundary. In this case, *endogenous* liquidity can help raise the model-implied credit spread. One implementation of such a variant of the He and Milbradt model can be found in Huang, Nozawa, and Shi (2021).

6. Conclusions

Although short-term corporate debt played an important role in the recent financial crisis, there is very limited empirical research examining what drives the prices of such debt. In this paper, we investigate the determinants of short-term corporate yield spreads within the structural framework of default risk, using a novel data set of *secondary* market transactions in the Chinese CP market. In particular, we propose and test a structural model with jump risk and exogenous liquidity, suitable for analyzing short-term yield spreads and especially for quantifying the relative importance of credit and liquidity risks in determining such spreads.

We find that credit and liquidity risks are both important drivers of short-term yield spreads and that the latter is much more so than the former. Credit risk, however, is more important for longer-maturity debt. For instance, as a special case of the proposed model, the Black–Cox (1976) pure-diffusion model of credit risk predicts extremely low CP spreads, regardless of the credit ratings considered. Augmenting the model with a DEJ component in the underlying asset return process significantly improves the model performance. The resulting DEJD model of corporate debt pricing, however, can merely account for about 24.5% of the CP spreads on average. In contrast, augmenting the Black–Cox model with exogenous market illiquidity can raise the proportion to about 68.5%.

Our proposed model incorporates this exogenous liquidity into the DEJD model and is a simplified He and Xiong (2012) model augmented with a DEJ component. The resultant HX-DEJ model further improves the model performance. On average, the model can account for 76.9% of the CP spread in the full sample, 82.0% for AAA, 77.1% for AA+, 73.6% for AA, and 60.2% for BBB. These findings provide evidence that liquidity risk comprises a much more important component of short-term spreads than jump risk. The model also captures the time series of the mean and median spreads reasonably well. On the other hand, it still underpredicts the spread on average and gives rise to large positive (negative) MPPEs for "safer" (riskier) issues.

For comparison, we also conduct an analysis using security-level data in the US CP market, which is different from the Chinese CP market in several aspects. The main findings are similar to those from the Chinese CP market. Specifically, on average the DEJD, HX, and HX-DEJ models account for 22%, 54%, and 71% of the observed spread, respectively. Importantly, credit risk accounts for a small proportion of CP spreads in the USA (about 22% for the full sample), although the proportion attributable to credit risk is higher for lower-rated CP issuers, ranging from 0.9% for AAA to 23.1% for BBB issuers. In contrast, liquidity can explain a much greater proportion of the CP spreads, with about 49% for the full sample.

Overall, this paper provides a comprehensive study on the determinants of short-term credit spreads using a structural model with both jump risk and liquidity risk, with security-level data in both the Chinese and the US CP markets. We find that there is a credit spread puzzle in both markets and that market liquidity shows much greater importance than credit risk in explaining these CP spreads. Our results also indicate that to better fit the distribution 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. A related question worth studying concerns the impact of rollover risk, an important feature missing in the proposed model. We leave these questions to future research.

Appendix A: Evidence from the US CP Market

To investigate whether the limited explanatory power of credit-related variables is limited to the Chinese CP market, we examine the US CP market in this Appendix.

A.1 Data

We compile a data set of individual CP yield spreads using holdings data of MMFs in the USA. The holdings information at the security level is collected by the SEC at a monthly frequency and available to the public through EDGAR. We retrieve data from Form N-MFP—which discloses portfolio holdings of every MMF at the CUSIP level since 2011—and aggregate them to the security level by computing volume-weighted prices for $1 face value. For comparison, we focus on securities in the "Non-Financial Company CP" category that are traded by prime funds over the period May 2014–April 2020.

For each CP issue, we manually link it to a public firm in CRSP and Capital IQ through CUSIP or issuer names if possible, given that CP may not share the first six digits of CUSIP with their issuers. We then extract the information about issuers' firm fundamentals. After matching the equity and accounting information to the CP observations, we obtain a panel of 9,925 issue-month CP spread observations with 5,823 CPs issued by 115 firms.

Panel A of Table AI summarizes our US CP sample. Consistent with the finding of Covitz and Downing (2007), the median day to maturity is 25. The average trade size is \$70.83 million, with the interquartile range of [7.25, 94.87]. The average credit rating of CP issuers is between A and A−. We calculate the CP yield spread over the comparable-maturity general collateral repo rate as in Section 3. However, about 30% of CP transactions in our sample have negative spreads. For instance, the 25th percentile of CP spreads is −1.0 bps; the median of AAA spreads is −1.6 bps, the 25th percentile of AA spreads is −1.7 bps, and the 10th percentiles of A and BBB spreads are −1.6 and −2.4 bps, respectively. In contrast, if we measure spreads relative to Treasury bills, the negative spread observations almost vanish. As a result, below we focus on the CP-Treasury spreads.

Descriptive statistics of CP issuers are reported in Panel B of Table AI. The distribution of CP issuers' leverage ratios is rather similar to that of investment-grade corporate bond issuers, but the former's equity volatility appears substantially smaller than that of the latter. As expected, CP issuers are on average large, value firms. Both the median of market capitalization (\$49.01 billion) and that of market-to-book ratio (3.51) are larger than the 80th percentile cutoff for NYSE firms as of December 2020. Overall, results in Table AI indicate that, unlike the case of the Chinese CP market, CP issuance in the USA is concentrated in a small group of large and financially healthy firms with high credit quality, which are not properly representative of corporate bond issuers in the USA.

A.2 Regression Analysis of CP Spreads in the USA

Table AIII reports the regression results from seven models, including the six models used in panel A of Table III. The first column (M1) shows that the risk-free rate, firm leverage, and volatility all have significant coefficients with expected signs, with an $\overline{R}^2$ of 1.8% (higher than that of 0.5% as reported from the Chinese market). Results in Columns 2–4 confirm our finding in Section 5.1 that DD and credit ratings seem to summarize information on the firm fundamental default risk. Likewise, Columns M5 and M6 indicate that similar to our baseline results, the proxy for jump risk offers nontrivial additive explanatory power for CP yield spreads, whereas the yield curve slope and market index returns do not. Note that VIX is significant, possibly because VIX captures information on the US financial markets above and beyond variations in risk-neutral variance, for example, funding liquidity and investor sentiment. The overall $\overline{R}^2$ as achieved by all these explanatory variables is 8.4% (M6), slightly lower than its counterpart in the Chinese CP market (9.0%).

Finally, as it is infeasible to implement dynamic liquidity measures for the US market, we consider the dollar trading volume and time to maturity as examined by Covitz and Downing (2007).[16] Consistent with their finding, Column M7 shows that a rise in trading

16 As we have no access to the issuance information of each CP issue, we are unable to determine the total amount outstanding nor identify whether a particular transaction is in the primary or secondary market.

Table AI. Summary statistics for CP transactions and issuers in the US market

Panel A provides transaction-level information for all nonfinancial CP used in the model specification and regression analyses. Panel B summarizes the financial metrics of CP issuers that have observations included in the final sample. Maturity is the CP's time to maturity in days. Volume is the trade size of the CP in million of dollars of face value. Rating is a numerical translation of credit rating. Yield is the annualized yield to maturity at the transaction date. Spread over repo and Spread over Treasury are CP yield spreads against the general collateral (GC) repurchase rate and Treasury-bill rate, respectively. Variables shown in Panel B are defined in Table II. The sample period spans from May 2014 to April 2020.

Panel A: Characteristics of CP transactions

	Obs	Mean	Std Dev	25th	50th	75th
Maturity (day)	9,925	45.45	54.23	10.00	25.00	57.00
Volume (mm)	9,925	70.83	121.97	7.25	38.99	94.87
Rating	9,925	6.48	4.68	4.00	4.00	7.00
Yield	9,920	1.71	1.47	1.02	1.76	2.31
Spread over repo	9,920	0.17	1.35	−0.01	0.06	0.17
Spread over Treasury	9,920	0.28	1.36	0.08	0.18	0.32

Panel B: Characteristics of CP issuers

	Obs	Mean	Std Dev	25th	50th	75td
Leverage	2,050	0.38	0.20	0.25	0.33	0.42
Equity volatility	2,050	0.19	0.08	0.13	0.17	0.23
Market cap (bn)	2,050	105.21	154.29	20.64	49.01	164.97
Market-to-book	2,050	10.88	105.36	1.83	3.51	6.48
Return on assets	2,050	2.38	1.85	1.14	2.12	3.33
Interest coverage	1,990	9.50	10.05	3.20	6.72	12.93

volume significantly decreases CP spreads and the *Maturity* variable seems to lose its significance when controlling for *Volume* and other variables.

A.3 Evidence Based on Structural Models

In this subsection, we quantify the contribution of credit and liquidity risks to CP spreads in the USA using the Black–Cox, DEJD, HX, and HX-DEJ models. We first discuss the estimation of the model parameters and then analyze the pricing performance of the models.

We estimate A_t and σ using the same method as described in Section 4.3. For the remaining parameters, we take their estimates from the recent literature when necessary. Specifically, we use $d = 0.82$ (Bai, Goldstein, and Yang, 2020; Huang, Nozawa, and Shi, 2021) and $R = 0.378$ (Feldhütter and Schaefer, 2018). For jump parameters, $\{\lambda, p_u, \eta_u, \eta_p\}$, we use the estimates from Huang, Shi, and Zhou (2020). Transaction cost k in the HX model is calibrated to the average bid–ask spread in each rating class as implied by the Roll (1984) model. Liquidity shock intensity ξ is chosen to be consistent with the average turnover rate in the US secondary CP market. We estimate the latter to be 0.22, much lower than the rate of 0.70 for

Table AII. Calibration of the DEJD and HX models in the US market

This table reports the parameter values used in model calibration for the US CP issues. Default boundary is as estimated by Bai, Goldstein, and Yang (2020) and Huang, Nozawa, and Shi (2021). Recovery rate is from Feldhütter and Schaefer (2018). Parameters in the DEJD model, $\{\lambda, p_u, \eta_u, \eta_p\}$, are the calibrated estimates of Huang, Shi, and Zhou (2020). Parameter k in the He and Xiong (2012) model is calibrated to the average bid–ask spread in each rating class as implied by the Roll (1984) model. Liquidity shock intensity ξ is calibrated to the aggregate turnover rate in the US secondary CP market.

Default parameters		Jump parameters			Liquidity parameters		
Parameter	Value	Parameter	Rating	Value	Parameter	Rating	Value
Default boundary (d)	0.82	λ	AAA	0.119	k	AAA	25.7
			AA	0.092		AA	31.1
Recovery rate (R)	37.8%		A	0.113		A	44.9
			BBB	0.123		BBB	60.1
		p_u		0.5	ξ		0.22
		η_u		3			
		η_d		3			

the corporate bond market as estimated by He and Milbradt (2014).[17] Table AII summarizes the estimates of $\{d, R, \lambda, p_u, \eta_u, \eta_p, k, \xi\}$ that we use.

We then implement each structural model to calculate its model-implied spreads for our US sample. Panel A of Figure A1 plots the average model spread versus the data for each model by credit ratings of CP issuers. The Black–Cox model-implied mean spreads are virtually zero, regardless of rating categories. The DEJD model raises the mean spread to 4.7, 0.1, 2.7, 3.2, and 6.3 bps for All, AAA, AA, A, and BBB groups, respectively. These spreads amount to 22.4%, 0.9%, 14.4%, 18.4%, and 23.1% of their empirical counterparts of 21.0, 10.9, 18.8, 17.4, and 27.3 bps, respectively. In other words, the DEJD model accounts for only a small proportion of the average CP spread and the proportion is higher for lower rating issuers. These results provide evidence that there exists a credit spread puzzle in the US CP market. The HX model raises the proportions of the mean spread to 53.8%, 52.3%, 58.0%, 56.9%, and 48.4%, respectively, and the proportion is lower for lower-rated issuers except for the AAA group (much smaller than the AA, AA, or BBB groups). The HX-DEJ model increases those proportions further to 71.0%, 53.2%, 73.9%, 80.5%, and 63.4%, thereby helping mitigate the credit spread puzzle substantially.

Panel B shows that the two pure-credit risk models severely underpredict the median spread. In contrast, the two models incorporating liquidity can raise the median dramatically, say, to 61.9% (HX) and 68.8% (HX-DEJ) of the observed median for the full sample.

Panel C decomposes the HX-DEJ model-implied mean spread to its diffusion ($\overline{cs}^{\mathrm{D}}_{\mathrm{HX-DEJ}}$, which is zero across all rating groups), jump ($\overline{cs}^{\mathrm{J}}_{\mathrm{HX-DEJ}}$), and liquidity ($\overline{cs}^{\mathrm{L}}_{\mathrm{HX-DEJ}}$)

17 As we are lack of information on whether a particular CP purchase by MMF is from the primary or secondary market, we estimate the aggregate turnover based on the following assumption: we assume that for each CP issue, its transactions occurred on its first appearance date in our sample take place in the primary market and any transactions occurred afterward in our sample take place in the secondary market.

Table AIII. Regression of CP yield spreads in the US market

This table reports results from seven specifications of regressions of CP spreads on explanatory variables in the US market. Explanatory variables used include the risk-free rate (rf_t), firm i's leverage ratio ($Lev_{i,t}$), equity volatility ($\sigma^E_{i,t}$), DD ($DD_{i,t}$), credit ratings ($Rating_{i,t}$), the slope of yield curves ($Slope_t$), the return on S&P 500 index ($SP500_t$), the option-implied volatility (VIX_t), the slope of its "smirk" ($Jump_t$), the logarithm of total transaction volumes ($Volume_{i,t}$), and the time to maturity of the paper ($Maturity_{i,t}$). The sample period spans from May 2014 to April 2020. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: CP spreads							
	M1	M2	M3	M4	M5	M6	M7
Intercept	0.002	0.002*	0.005	0.004	0.009*	−0.002	−0.004
	(1.06)	(1.76)	(1.30)	(1.18)	(1.86)	(−0.45)	(−0.76)
rf_t	−0.122		−0.128	−0.129	−0.280*	−0.248**	−0.242**
	(−1.14)		(−1.19)	(−1.19)	(−1.93)	(−1.97)	(−1.99)
$Lev_{i,t}$	−0.001		−0.002	−0.002	−0.002	−0.001	−0.001
	(−1.13)		(−1.32)	(−1.20)	(−1.18)	(−1.04)	(−0.64)
$\sigma^E_{i,t}$	0.006***		−0.002	−0.001	−0.002	−0.000	0.001
	(3.29)		(−0.70)	(−0.34)	(−0.58)	(−0.13)	(0.15)
$DD_{i,t}$		−0.006***	−0.006***	−0.007***	−0.006***	−0.007***	−0.005***
		(−3.39)	(−3.27)	(−3.32)	(−3.58)	(−3.06)	(−2.85)
$Rating_{i,t}$				0.009***	0.007***	0.006***	0.007***
				(3.83)	(3.15)	(2.86)	(2.65)
$Slope_t$					−0.182**	−0.051	−0.035
					(−2.37)	(−0.43)	(−0.29)
$SP500_t$					−0.002	0.011	0.011
					(−0.23)	(1.44)	(1.47)
VIX_t						0.001*	0.001*
						(1.83)	(1.87)
$Jump_t$						−0.122*	−0.124*
						(−1.90)	(−1.95)
$Volume_{i,t}$							0.005
							(1.05)
$Maturity_{i,t}$							−0.008
							(−1.20)
$\overline{R}^2$	0.018	0.033	0.041	0.047	0.058	0.084	0.093
Obs	8,280	8,280	8,280	8,280	8,280	8,280	8,280

components. The proportions (%) of the mean *observed* spread attributable to ($\overline{cs}^{\mathrm{J}}_{\mathrm{HX-DEJ}}$, $\overline{cs}^{\mathrm{L}}_{\mathrm{HX-DEJ}}$) are (22.4, 48.6) for All (slightly lower than their counterparts for Chinese CP), (0.9, 52.3) for AAA, (14.4, 59.9) for AA, (18.4,62.1) for A, and (23.1,40.3) for BBB issuers.

To summarize, we find that credit risk accounts for a small fraction of CP spreads over the Treasury in the USA, especially for CP issuers rated A or higher. To explain such short-term spreads, it is necessary to incorporate liquidity into structural models as in He and Xiong (2012) or He and Milbradt (2014). The HX-DEJ model proposed here, however, still underestimates the average CP spread, regardless of CP issuers' credit ratings.

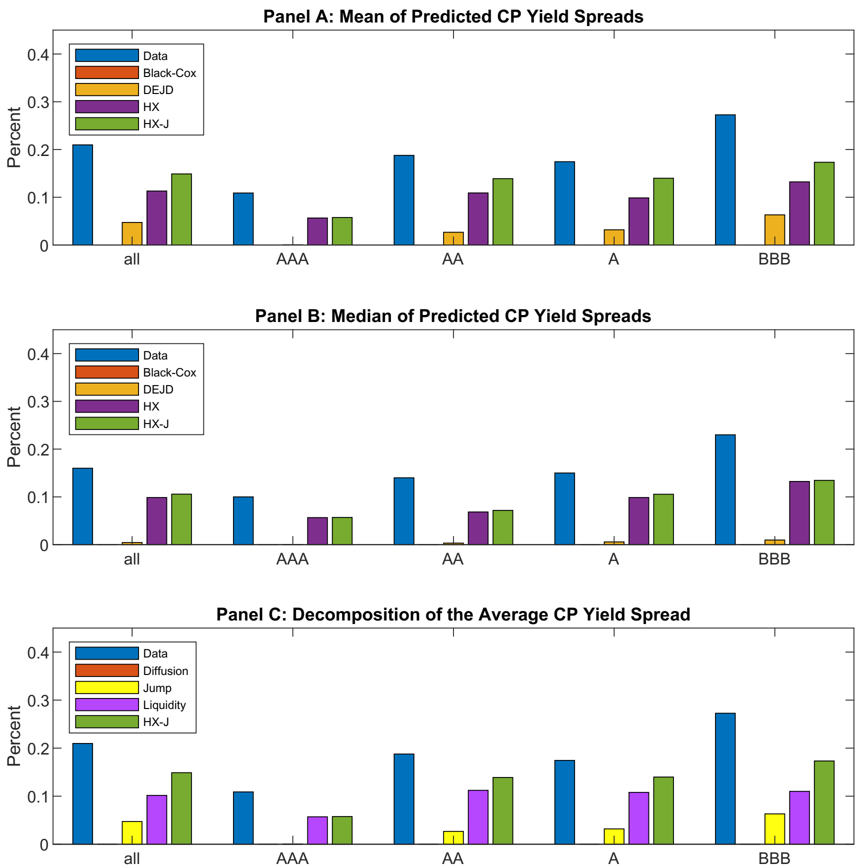

Figure A1. Mean, median, and decomposition of predicted CP yield spreads in the USA.
Notes: This figure plots the mean (panel A), median (panel B), and decomposition (panel C) of CP yield spreads over the Treasury by rating category in the US market. Ratings used here are ratings of CP issuers. In panels A and B, the five bars in each rating category, in turn, represent yield spreads in the data (blue) and those generated by the Black and Cox (1976) model (orange), the DEJD model (yellow), a simplified He and Xiong (2012) model (HX in purple), and the He–Xiong model with double-exponential jumps (HX-DEJ in green). Note that the Black–Cox model-implied mean and median spreads are virtually zero for all rating groups. Panel C illustrates the decomposition of the average HX-DEJ model-implied yield spread (green) into its diffusive credit risk (orange), jump risk (yellow), and liquidity (purple) components for each rating group. The sample period spans from May 2014 to April 2020.

Supplementary Material

Supplementary data are available at *Review of Finance* online.

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