Price Discovery and Market Segmentation in China's Credit Market

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Abstract

We study the extent of price discovery in the onshore Chinese corporate bond market, focusing in particular on the information content of credit spreads in China. Using Merton's model of default, we construct credit measures of publicly listed firms, using information from their financial statements and stock valuation. We find that, only after the first default in 2014, do credit spreads in China become informative. Compared with the findings in the US credit market, the magnitude of price discovery in the Chinese market is rather limited. We also find that the presence of outside government support for state-owned enterprises (SOEs) in China results in a market segmentation between SOE and non-SOE issuers that is harmful to price efficiency and market stability. Since 2018, the non-SOE issuers have suffered from explosive credit spreads, unprecedented defaults, and shrinking new issuance, while the SOE issuers have remained largely intact. Meanwhile, our default measures show that the non-SOE issuers are in fact stronger in credit quality than their SOE counterparts of the same rating category. Examining the impact of this segmentation on price discovery, we find that non-SOE credit spreads become significantly more informative since 2018, as concerns over credit become front and center for the non-SOE issuers. By contrast, as investors seek safety in SOE bonds, there is no improvement in the information content of SOE credit spreads.

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1 Introduction

From 2008 through 2018, domestic debt securities issued by China's non-financial companies increased by $2.795 trillion, from a negligible level in 2008 to $3 trillion in 2018, second only to the US.[1] As China further opens up its financial system, this onshore credit market has the potential of becoming a key component of the global fixed-income market, offering prospective international investors exposure to the real China. If the rapid growth of China's economy has been the story of our age for the past three decades, then, moving forward, the maturation of China's financial markets and their integration into the global markets can very well be the story of the coming decade.

For the bank-dominated financial system in China, the presence of this market-based credit channel has a profound and potentially long-lasting impact. On the credit-demand side, for non-financial firms in China, it has opened a new channel of debt financing – cheaper and more efficient than the traditional bank loans. Indeed, the emergence of this onshore market has increased the ratio of market-based debt to bank debt from 4.6% in 2008 to 19% in 2018 for non-financial firms in China. On the credit-supply side, for asset managers in China, it has significantly expanded their investment frontier by offering an entirely new asset class – between the lower yielding and lower risk government bonds and the higher yielding and higher risk equity market. Indeed, the growth of the onshore credit market is closely connected with the demand from the fast growing asset-management industry in China.

Focusing on this increasingly important market, our main objective is to evaluate its efficiency and provide empirical evidences on two questions that are central to any credit markets. First, do market prices accurately reflect the fundamental? In other words, do credit spreads in China reflect the credit quality of the bond issuers? Second, what is the impact of the existing frictions in China's economy on credit pricing? Specifically, how and when do differentiation such as the one between state-owned enterprises (SOEs) and non-SOE start to erode credit pricing and threaten the stability of the market? Answers to these questions are of vital importance to the Chinese economy, as it moves toward a market-driven financial system. In particular, for China's young markets to further improve on price discovery, market participants including policy makers need to be better informed about the markets they are involved with and the empirical findings documented in this paper could contribute to such a market-based understanding. Answers to these questions

[1] In a time of accommodative monetary policy, US companies have dramatically increased their borrowing in the form of debt securities. From 2008 to 2018, debt securities issued by U.S. non-financial corporations increased by $2.73 trillion to a record level of $6.28 trillion.

are also important to the existing literature on credit pricing, which has long been focused on mature markets such as the US credit market. The empirical evidences offered in this paper provide insights to the credit-pricing issues that are important to a young market in transition.

Central to our analysis is a measure of credit quality for bond issuers. For this, we base our analysis on the default model of Merton (1974) and focus on the corporate bonds issued by publicly listed firms to take advantage of their publicly available information. Specifically, we measure each issuer's credit quality using Merton's model, with the firm's quarterly financial statements and daily stock prices as the main inputs to the model. Our default measure, the inverse of Merton's distance to default, is higher for firms with lower credit quality. By using the default measure to gauge the information content of credit spreads, we investigate the extend to which credit investors incorporate the information contained in the firm's balance sheet and stock prices (e.g., leverage and return volatility) in their valuation of corporate bonds. For the US market, the link between credit spreads and credit quality has been well established – controlling for credit ratings, a significant portion of the variation in credit spreads can be explained by issuer-level variables known to affect the credit quality of a firm.[2] For the Chinese market, however, this topic has not been systematic studied in the existing literature, and our paper aims at filling the gap.

Focusing first on the market's capacity for price discovery, our empirical findings paint the picture of a market in transition. Prior to 2014, China's credit market was absent of default events, with wide spread belief that bond investors will always be paid in full. Not surprisingly, credit spreads during this pre-default period are found to be rather uninformative. Using quarterly panel regressions of credit spreads on credit measures and controlling for credit ratings and other bond characteristics, our result shows that, prior to 2014, credit spreads bear no statistically significant relation with the default measures. In other words, in the pre-default era, credit pricing is de-coupled from the issuer-level credit information. Post 2014, as the credit market grows out of the pre-default era, we see an improvement in the information content of credit spreads in China. From 2014 to 2018Q1, the first wave of defaults occurs mostly to privately held firms, but its impact is felt in the pricing of bonds issued by public firms. Repeating the same panel regression for this time period, we now find a statistically significant relation between credit spreads and default measures, indicating that as defaults start to occur, concerns over credit risk begin to take hold. Controlling for ratings, a one standard deviation increase in our default measure translates to an increase in credit spread of about 15 bps. Compared with the findings in the US market, the

[2]Among others, empirical studies on the determinants of credit spreads include Collin-Dufresne et al. (2001), Campbell and Taksler (2003) and Bao et al. (2011).

explanatory power of the default measure remains rather limited. The adjusted R-squared of the panel regression remains the same after the inclusion of the default measures, while, for the US market, the default measures can explain as much as 45% of the variation in credit spreads in the US market.[3] In other words, the occurrences of defaults do bring the credit market pricing in line with the fundamental credit risk, but the capacity for price discovery remains limited in the Chinese credit market.

Focusing next on the market segmentation between non-SOE and SOE issuers, our empirical findings raise serious concerns with respect to this market structure, which forces non-SOE issuers with no outside government support to compete against SOE issuers in the same market. Among important frictions in the Chinese economy, the co-existence of SOE and non-SOE is near top of the list. The inefficiency of China's SOEs, their preferential access to banks loans, and their outside government support have been widely documented in the academic literature and popular press. Likewise, the contribution of China's non-SOEs to the country's economy has also been widely reported.[4] The impact of this friction on China's credit market, however, has not been examined in the existing literature, and our empirical evidences can be summarized as follows.

First, we document a severe segmentation between the pricing of non-SOE and SOE bonds that arises sharply post 2018, amidst the second and much more severe wave of defaults. The significance of this second wave of defaults is not in its magnitude, which remains small by the US standard, but in that the public non-SOE issuers, who remain largely intact during the first wave, are severely hit during this period. At the peak in 2018Q4, the public non-SOEs, which are larger and more important companies in the economy relative to the private firms, account for 30% of the total default amount in the credit market. At the same time, the public SOE issuers remain mostly intact. Behind this wave of credit-market stress is the sequence of credit-tightening policies in China. Specifically, the continued campaign on financial deleveraging, followed by the April 2018 release of "New Regulations on Asset Management," has severely weakened the demand for corporate bonds from the asset-management industry in China and shrunk the financing and re-financing channels of corporate issuers. Compared with their SOE counterparts, the non-SOE issuers are more vulnerable due to their lack of outside support from central and local governments. Akin to a run on the non-SOE issuers, investors seek safety in SOE bonds and shun non-SOE bonds.

[3]While it is well known that credit spreads have a non-trivial liquidity component, default measures constructed using models of Merton (1974) and Black and Cox (1976) can explain as much as 45% of the cross-sectional variation in credit spreads, as documented by Bao (2009).

[4]A widely used expression is that non-SOEs contribute 60% of China's GDP, and are responsible for 70% of innovation, 80% of urban employment and provide 90% of new jobs.

Controlling for credit ratings and other bond and firm characteristics, the difference in credit spread between non-SOE and SOE bonds fluctuates around an average level of 20 bps prior to 2018Q2, indicating a moderate premium enjoyed by SOE issuers because of their perceived outside government support. Since 2018, this premium doubles to 40 bps during the first two quarters, and then explodes quickly to 90 bps in 2018Q3, 140 bps in 2018Q4, and 167 bps in 2019Q1. Amidst this unprecedented explosion in SOE premium (or non-SOE discount), new issuance by non-SOEs, which in 2017Q1 accounts for 44% of the total new issuance in the corporate bond market (excluding Chengtou bonds), drops to a mere 10% in 2019Q3. This segmentation between non-SOE and SOE bonds occurs not only for public firms but also private firms, but the development in the public sample is the most dramatic and alarming, as the public non-SOE issuers represent the larger and more important firms in China's economy.[5] Defaults are part and parcel in any credit markets and investors in China's credit market should be relieved that defaults are finally occurring in this market. But the presence of the implicit government support for SOEs and the resulting segmentation between non-SOE and SOE is harmful to the stability of China's credit market.

Second, this market segmentation between non-SOE and SOE is not driven by the fundamentals of the firms. Using our default measures, we find that the SOEs are in fact weaker in credit quality than their non-SOE counterpart in the same rating category. Prior to the 2014 default, the difference in default measure between the SOE and non-SOE samples is economically small and of marginal statistical significance. After the first default in 2014, the default measures of these two samples of firms start to diverge, with non-SOEs becoming significantly healthier than their SOE counterparts. In other words, as investors become more mindful of credit risk, the non-SOE issuers are compensating for their lack of outside government support by providing healthier balance sheets and better performing stocks. As the credit market condition worsens in 2019, however, the difference in credit quality between these two samples starts to shrink steadily, pointing to the possibility that the credit-market stress caused by market segmentation has begun to hurt the balance sheets and equity performance of the non-SOEs. The segmentation in the credit market hurts not only the credit pricing of non-SOEs, but also spills over to their equity pricing and firm fundamentals.

Third, this market segmentation has also caused a segmentation in price discovery. Repeating the same quarterly panel regressions from 2018Q2 to 2019Q2, we find a marked improvement in the information content of non-SOE credit spreads. A one standard deviation increase in default measure is associated with a widening of credit spread in the order of 165

[5]For the private firms, the segmentation actually shows up earlier during the first wave of defaults, and further deepens after 2018Q2, when the second wave of defaults hits the market. We also examine the potential segmentation between private and public firms, and between local and central government SOEs.

bps. Moreover, the inclusion of our default measures also improves the explanatory power for credit spreads by 6.2% in adjusted R-squared. This result is consistent with the observation that, during this severe segmentation, investors are forced to be more discriminating against the non-SOE bonds because of the perceived vulnerability. Conversely, counting on the outside government support, investors holding the SOE bonds are less pressured to differentiate the SOE bonds, making the SOE prices less efficient. Indeed, the relation between credit spreads and default measures is statistically insignificant for SOE bonds during this period and the economic significance of the estimate is about one-tenth of the non-SOE sample.

Overall, our empirical results contribute to the existing literature by offering insights into a young but important market that is very much in transition. While the information content of credit spreads has been widely studied and documented for the mature US credit market, our understanding of credit spreads in China remains rather limited. Our paper is the first to document the improving informativeness of credit spreads in China after the first default in 2014. Our paper is also the first to document the segmentation between non-SOE and SOE issuers in the Chinese credit market. Our results show that, while the segmentation remains mostly dormant during calm market conditions, it has the potential of breaking open rather rapidly, threatening the stability of the market. Moreover, the presence of the severe segmentation also has differing impact on market efficiency – the pricing of non-SOE bonds becomes more efficient amidst market turmoil, while there is no improvement in the pricing of SOE bonds as investors seek safety in such bonds.

Our paper is related to the still growing literature on the Chinese credit market. Overviews on this market can be found in Hu et al. (2019) and Amstad and He (2019). Recent empirical studies include Mo and Subrahmanyam (2019) on China's credit bond liquidity, Chen et al. (2018) on the value of pledgeability in Chinese corporate bonds, Wang et al. (2015) on the pricing effects caused by China's yield-chasing retail investors, and Jin et al. (2018) on the value of implicit government guarantee in SOE bonds. We compliment their studies by focusing explicitly on the information content of the credit spreads and documenting the asset pricing implication of the severe market segmentation between SOE and non-SOE issuers. Bai and Zhou (2018) and Liu et al. (2017) investigate the importance of government guarantee in the pricing of Chengtou bonds, and Chen et al. (2019) study the link between the growth of Chengtou bonds and the 2009 stimulus package in China. We exclude such bonds in our study because Chengtou bonds are issued not by corporations but by local government financing vehicles, further weakening the link between credit pricing and fundamental credit quality.[6]

[6] It is interesting to observe that in the presence of unprecedented defaults by non-SOEs, we have not yet observed a real default by Chengtou bonds.

The rest of our paper is organized as follows. Section 2 summarizes the data used in our study and details the construction of our default measures. Section 3 reports our main empirical results, and Section 4 concludes.

2 Data

2.1 The Corporate Bond Sample

Excluding financial bonds, the Chinese credit market for non-financial companies stands at RMB 22 trillion by the end of June 2019. As shown in the top panel of Figure 1, the credit instruments in this market are categorized into four groups: corporate bonds, Chengtou bonds, commercial papers, and other instruments including private placement bonds, convertible bonds, and asset-backed securities. The group of corporate bonds, similar in structure to the US corporate bonds, is the main focus of our paper. It is made up of three types of bonds: Medium-Term Notes account for the largest portion and are traded in the inter-bank market; Corporate Bonds are the second largest and are exchange traded; and Enterprise Bonds, traded in both markets, account for only a very small portion of our sample. By June 2019, the total amount outstanding of our corporate bond sample is RMB 7 trillion, accounting for 31% of the credit market. Chengtou bonds, as shown in Figure 1 to be an important component of the credit market, are excluded from our analysis because of their unique association with local governments in China. Issued by local government financing vehicles (LGFV), Chengtou bonds enjoy a rather special status in China's credit market and are not the best credit instruments for our purpose. We exclude commercial papers from our analysis due to their short duration, and the other credit instruments due to their non-standard structures and limited market size.

We further sort the corporate bond sample by issuer type into four groups along two dimensions. First, we consider whether the bond issuer is publicly listed or privately held. This differentiation is important because public firms are in general larger and more important to the economy. More importantly, being public firms, they disclose quarterly financial statements and are monitored by equity investors as well as bond investors. For our purpose, such publicly available information is essential for us to measure the credit quality of the bond issuers. Although private firms issuing bonds in China are also required to disclose financial statements, the quality of the issuer-level information cannot be compared with what public firms can offer. Moreover, the lack of equity market information makes it impossible for us to construct credit quality measures.

Second, we consider whether the bond issuer is a state-owned enterprise (SOE) or non-

SOE. Unlike SOEs, the non-SOEs are perceived to be vulnerable because of their lack of outside government support. This differentiation turns out to be the most important segmentation in our data, especially under credit-market stress. When necessary, we further differentiate the SOEs into local and central government SOEs (LSOEs and CSOEs).

The bottom panel of Figure 1 outlines the overall size of our corporate bond sample, and summarizes the relative size of the four issuer types. The publicly listed issuers, including both public SOE and public non-SOE, account for 30% of the corporate sample, while the privately held issuers account for the rest. This pattern is contrary to what is observed in the US corporate bond market, where larger public firms generally have better access to the corporate bond market. Another stark contrast to the US market is the dominance of the SOE issuers. Within the public sample, a significant gap exists between public SOE and public non-SOE. The ratio in amount outstanding of public SOE to public non-SOE bonds is 10 in 2010. As the credit market expands in size and diversity, this ratio has decreased steadily to a level close to 2 in 2016, but then the improvement flattens out. Not surprisingly, the gap within the private sample is even more astounding: the ratio of SOE to non-SOE is 54 in 2010 and then decreases to 5 in 2016. The fact that the privately-held SOEs continue to dominate the market share is an unhealthy situation for this market. In a way, their presence sucks the oxygen out of an otherwise healthy market.

2.2 Bond-Level Data

Data used in this paper are from the Wind database. Our bond data includes quarterly bond prices with bond characteristics and bond trading variables. For each bond and during each quarter, we calculate its yield to maturity using the last transaction price of this bond in the quarter. Following the convention in the Chinese market, we use the yield curve of the Chinese Development Bank (CDB) bonds as the reference curve to calculate credit spreads. Specifically, credit spread is measured as the difference between the corporate bond yield and CDB yield of the same maturity.

We only include fixed-rate bonds in the form of medium-term notes, corporate bonds, and enterprise bonds issued by non-financial listed companies. Bonds without any trading during a quarter are excluded from that quarter. Bonds with less than one year to maturity are excluded from our sample. Bonds whose issuer has less than 10 trading days in the equity market during a quarter or has missing financial statements during a quarter are excluded from that quarter. Defaulted bonds are excluded from our data sample retroactively. We adopt this conservative treatment because we are not sure of the accuracy of the official default dates. This is particularly troubling as we observe, for some bonds, extremely large yield spreads even before the actual default date. Moreover, in China, default occurs at the bond level. But we also exclude other, not yet defaulted, bonds issued by the same firm, once the firm has defaulted on at least one bond. The reasoning is similar – we are not sure of the accuracy of the official default dates and the defaulted bonds usually have a spillover effect on other existing bonds issued by the same firms. This treatment has the effect of cutting down extremely large credit spreads and under-biases our results. In practice, this treatment has a rather negligible effect on our results, given the limited number of defaulted issuers in our sample (18 issuers for the public non-SOE sample, and 2 issuers for the public SOE sample). Finally, we winsorize the credit spreads at 1% and 99% on three time periods.

Since our main focus is on the corporate bonds issued by public firms, we choose our sample period to start from January 1, 2010 through June 30, 2019. Prior to 2010, there are not enough public issuers for us to perform our empirical analysis. We perform our empirical tests over three time periods. Period I, from 2010 through 2013, is the pre-default period. Period II, from 2014 through 2018Q1, captures the first wave of defaults, which occurred mostly to private firms in industries suffering from overcapacity. Period III, from 2018Q2 to 2019Q2, captures the second and much more severe wave of defaults.

Table 1 summarizes our bond sample for each of the four groups. Overall, there are 325 public non-SOE issuers with 750 bonds , 363 public SOE issuers with 1107 bonds, 382 private non-SOE issuers with 1248 bonds, and 1511 private SOE issuers with 5209 bonds. Table 2 further summarizes our sample by period, and, as we can see, the numbers of issuers and bonds vary over time as well. In addition to credit spreads, the bond-level variables reported in the summary tables include bond characteristics such as rating, maturity, age, issuance size and coupon rate; and bond trading variables such as number of trading days per quarter (TradingDays), percent of zero trading days per quarter (ZeroDays) and quarterly turnover. In addition, we also control for issuers' industry in our analysis using the 11 industry categorization from Wind.

For credit ratings, we merge our sample with the rating dataset of Wind, and update any changes in rating by the major rating agencies in China.[7] We convert the letter grades into numerical grades by assigning 1 to AAA, 2 to AA+, 3 to AA, 4 to AA-, and so on. In China, AAA is the top grade, with AA+ and AA in the middle, and AA- is generally of low quality, and very few bonds are below AA-. As shown in Tables 1 and 2, the average credit ratings varies across the four sub-samples, as well as over the three time periods. Indeed, credit rating is the most important control variable in all of our empirical analysis.

A non-trivial amount of the corporate bonds in China are issued with embedded option-

[7]The major rating agencies in China includes CCXI, China Lianhe, DaGong Gloabl, and Shanghai Brilliance.

ality. For example, a 2+1 bond is issued with a three-year maturity, but, at the end of the second year, investors have the option to sell back the bond at its face value while the bond issuer can choose to modify the coupon rate within a pre-set range to make the bond more or less attractive. We use the dummy variable Embed to single out the bonds with this optionality. As shown in Table 1, the average value of this dummy is 62% for public non-SOE, 39% for public SOE, 55% for private non-SOE, and 29% for private SOE. Clearly, the non-SOE issuers are more eager to extend the maturity of their bonds by offering more optionality. As shown further in Table 2, there is an increasing trend in the issuance of such bonds. For example, the ratio of bonds with optionality increases from 36% in Period I to 54% in Period II, and to 70% in Period III for the private non-SOE sample. Throughout our analysis, we control for this optionality since the embedded option has the effect of making bonds more expensive and lowering yields.

Another well established feature in China's bond market is the difference between the inter-bank market, populated by large institutional investors, and the exchanges, populated by small and medium-size investors. Unlike the US corporate bond market, which is dominated by the over-the-counter trading, the inter-bank market, which is similar to the OTC market in the US, and the exchanges both claim significant market share in bond trading. We use the dummy variable Exch to indicate whether the observed bond price is from exchange trading. As shown in Table 1, exchange-traded bonds account for 70% for public non-SOE, 55% for public SOE, 46% for private non-SOE, and 19% for private SOE. Given that Medium-Term Notes trade exclusively on the inter-bank market, Corporate Bonds trade exclusively on the exchanges, and Enterprise Bonds only account for a small fraction of our sample, this differentiation in trading venue is very much aligned with the listing venue. Throughout our analysis, we use the Exch dummy to control for potential differences in investor behavior between these two markets.

Comparing the non-SOE and SOE samples further, we see that SOE bonds in general have higher ratings, larger issuance size (RMB 2 billion vs 1 billion for the public sample), and with longer maturity and older in age. Because of these differences in bond characteristics, a direct comparison between their credit spreads is therefore not meaningful. For this reason, we will later compare their bond pricing after controlling for credit ratings and other bond characteristics.

The bond trading variables give us a sense of the overall liquidity condition of the market. TradingDays counts the number of trading days per quarter. As we can see, corporate bonds are on average infrequently traded across the board. As shown in Table 1, for bonds in our sample, the average number of trading days per quarter is 16 for public non-SOE, 10 for public SOE, 10 for private non-SOE, and 9 for private SOE. Moreover, there is a dramatic decrease in trading activity over the three time periods, as shown in Table 2. Part of this decreasing trend is due to the crackdown of agent-holding transactions.[8]

2.3 Issuer-Level Equity Data

Focusing on the sample of bonds issued by publicly listed firms, both public non-SOE and public SOEs, we merge the bond data by issuer with equity data from Wind. As shown in Table 3, there are in total 326 public Non-SOE issuers and 369 public SOE issuers, with the numbers varying over the three sub-sample periods.

For each of these firms and during each quarter, we collect information on the total market value of its equity. EquitySize denotes the logarithm of the equity value. As shown in Table 3, the average size of the firms in our public non-SOE sample is RMB 12.39 billion, smaller than the average number of RMB 18.65 billion for the public SOE sample. Compared with the universe of stocks in the Chinese equity market, these firms are larger in size. In fact, a large majority of our equity sample is from the mainboard and they are evenly distributed in the Shanghai and Shenzhen stock exchanges.

To measure the credit quality of a firm, the two most important inputs are leverage and volatility. For each firm, we use its daily stock returns during the quarter to calculate its quarterly equity volatility. As shown in Table 3 the annualized volatility for the public firms in our sample is on average 41% for non-SOE and 38% for SOE. To calculate firm leverage, we collect information on the firm's short- and long-term debt and its total asset, using quarterly financial statements. Leverage is calculated as the ratio of total current liabilities plus half of the total non-current liabilities to the total asset value. As shown in Table 3, the average leverage for non-SOEs is 48%, slightly lower than the 50% for the SOEs.

2.4 Construction of Default Measures

We use Merton (1974) structural model of default to construct our default measure. The key concept of the model is the distance-to-default, which computes how many standard deviations a firm is away from the default boundary. A lower distance-to-default indicates that the firm is closer to the default boundary, and therefore has a higher probability of default. Under the Merton model, the firm's total asset follows a geometric Brownian motion,

$$dV_t = \mu \, V_t \, dt + \sigma_A \, V_t \, dZ_t \, ,$$

[8]This topic is covered in Mo and Subrahmanyam (2019) extensively.

where V_t is the time-t value of the firm's total asset, Z_t is a Brownian motion, μ is the constant growth rate, and σ_A is the constant volatility. According to the Merton model, the value of the firm's equity is the European call option on the firm's asset with strike price K equalling the firm's liability.

Using this insight and following the approach of Moody's KMV (Kealhofer and Kurbat (2001)), we estimate the firm's asset value V and its corresponding asset volatility σ_A by solving the following non-linear equations simultaneously,

$$\begin{aligned} E_t &= V_t\, N(d_1) - e^{rT}\, K N(d_2) \\ \sigma_E &= \frac{V}{E}\frac{\partial E}{\partial A}\sigma_A\,, \end{aligned} \tag{1}$$

where E_t is the time-t value of the firm's equity, r is the riskfree rate, σ_E is the equity volatility, and

$$d_1 = \frac{\ln(V_t/K) + (r + \sigma_A^2/2)\,T}{\sigma_A\sqrt{T}}\,; \quad d_2 = \frac{\ln(V_t/K) + (r - \sigma_A^2/2)\,T}{\sigma_A\sqrt{T}}\,,$$

where T is the time-horizon of interest.

The key inputs to the model are calibrated as follows. We fix the time horizon $T = 1$ to focus on the distant-to-default over a one-year horizon. For each quarter, we use the average growth rate of the asset value in the past three years for μ; the default boundary K equals the firm's current liabilities plus one half of its long-term debt; the firm's equity value equals the firm's market capitalization by multiplying the quarter-end stock price by the common equity shares outstanding. For the equity volatility σ_E, we use daily equity returns within the quarter, requiring that the issuer has at least 10 trading days in the quarter. For the risk-free rate, we use the one-year bank deposit rate. With these inputs and the quarterly estimates for the asset value V and asset volatility σ_A from Equations (1), we compute the quarter-t distance to default by

$$DD_t = \frac{\ln(V_t/K) + (\mu - \sigma_A^2/2)\,T}{\sigma_A\sqrt{T}}\,. \tag{2}$$

The Merton model further translates the distance-to-default to default probability, under the assumption of normal distribution. The probability calculated from the normal distribution, however, is too low. More importantly, the transformation flatens out much of cross-issuer variation in the distance-to-default measure. An alternative approach adopted by Moody's KMV is to calibrate the mapping from distance-to-default to default probability, using the actual default experiences. The construction of this empirical distribution requires a large database of historical defaults, which is not feasible for the Chinese corporate bonds market. In this paper, we use the inverse of the distance-to-default, which we denote as DM (Default Measure), to measure the firm's default risk. Table 3 summarizes our sample at the issuer level. The key inputs of the models, including firm leverage K/V and asset volatility σ_A, are reported in Table 3. The average level of DM is 23% for the public SOE issuers and 21% for the public non-SOE issuers.

3 Empirical Results

3.1 Corporate Defaults in China

For much of its history, China's credit market was absent of default events, confirming the deep-rooted belief that debt investors will always be bailed out and default was merely a concept in theory. The first ever default in 2014 marks the beginning of an erosion to this rigid belief. The top panel of Figure 2 plots the quarterly default amount to the credit market, including both corporate bonds, commercial papers, private placement notes and bonds, and convertible bonds. The first wave of defaults occurred mostly to privately held issuers, with quarterly default amount ranging from less than RMB 1 billion to 12.7 billion in 2016Q1. Compared with the total size of the credit market, RMB 17.6 trillion in 2016, this amount of default is tiny. At the same time, the corporate bond market was expanding aggressively with RMB 608 billion new issuance in 2016Q1, as shown in the bottom panel of Figure 2. From 2015Q2 to 2016Q3, the private SOEs were affected more severely than private non-SOEs. It was especially true for the private SOEs in overcapacity industries. Starting from 2016Q4, the total amount of default in the credit market lessened, and the fraction of private SOE defaults reduced rather dramatically, from 78.9% in 2016Q3 to 10.8% a quarter later in 2016Q4. From that point on, non-SOEs took most of the blunt.

Starting from 2018Q2, the public non-SOE issuers, who remained largely intact during the first wave, were severely hit and, at its peak in 2018Q4, accounted for 30% of the total default amount in the credit market. Meanwhile, the magnitude of the default amount has also increased rather dramatically. From RMB 14.5 billion in 2018Q2 to over 50 billion in 2018Q4. Still a small amount compared to the overall size of the credit market, the fact that over 90% of the default occurs to non-SOE issuers is a clear signal to the market that these are the more vulnerable issuers. Around this time, the expression of "faith-based" pricing became popular among credit-market investors. The faith is hierarchical, with Chengtou bonds, issued by local government financing vehicles, at the top and there has not been a real default occurring to this group of Chengtou bonds. To most investors, the public SOEs also seem quite safe. Throughout our sample period, there are only two default events for the public SOEs with a total default amount of 0.8 billion.

The overall macroeconomic condition and the government policies are very much related to this sequence of events. Prior to 2018Q2, the Chinese credit market condition was already tightening in 2017 due to the continued campaign on financial de-leveraging, but the April 2018 release of "New Regulations on Asset Management" was a discernible trigger for the rapidly worsening credit conditions. This sequence of tightening policies at the macro-economic level impacted the corporate bond market by severely weakening the demand for corporate bonds from the asset-management industry and shrinking the financing and re-financing channels for corporate issuers. Compared with their SOE counterparts, the non-SOE issuers appeared to be more vulnerable due to their lack of outside support from central and local governments. Indeed, this perceived vulnerability is the driving force behind the segmentation as investors seek safety in SOE bonds and shun non-SOE bonds. As our results show, this schism, while dormant during normal condition, has the tendency to break open rapidly during market turmoil, threatening the stability of the market.

3.2 Segmentation between SOE and Non-SOE

The differentiation between the state-owned enterprises (SOEs) and non-SOEs is among the most important frictions in China's economy. The inefficiency of China's SOEs, their preferential access to banks loans, and their outside government support have been widely documented in the academic literature and popular press. At the same time, the contribution of China's non-SOEs (i.e., the private sector) to the country's economy has also been widely reported: they contribute 60% of Chinas GDP, and are responsible for 70% of innovation, 80% of urban employment and provide 90% of new jobs. Our focus in this section is to document the extent to which this existing friction in China's economy harms the price discovery in the credit market, threatens the market stability, and hurts the growth of non-SOEs.

Difference in Credit Spreads

Table 4 reports the results of the quarterly panel regressions:

$$\text{CreditSpread}_{i,t} = a + b\,\text{NonSOE}_i + c\,\text{Rating}_{i,t} + \sum_k \text{Controls}^k_{i,t} + \epsilon_{i,t}\,,$$

where the credit spread of bond i in quarter t is regressed on the NonSOE dummy, which equals one if bond i is issued by a non-SOE. Controlling for credit rating and other bond characteristics, the regression coefficient associated with the NonSOE dummy effectively captures the difference in credit spread between a non-SOE bond and an SOE bond with the same credit rating and same bond characteristics such as maturity, issuance size, age, coupon rate, etc. The regression further includes quarter fixed effect and industry fixed effect to control for potential market-wide fluctuations and industry differences. The reported t-stat's use standard errors double clustered by quarter and bond to take into account of cross-sectional as well as time-series correlations in credit spreads.

Using data from 2010 to 2019, we perform our empirical tests over three time periods. Period I, from 2010 through 2013, is the pre-default period; Period II, from 2014 through 2018Q1, captures the first wave of defaults; and Period III, from 2018Q2 to 2019Q2, captures the second and much more severe wave of defaults. In an ideal world with no market segmentation, the segmentation coefficient b should be statistically insignificantly from zero. In practice, as shown in Table 4, for the public sample, the segmentation coefficient is statistically significant in all three periods: 16 bps in Period I, 20 bps in Period II, and explodes to 113 bps in Period III. The top panel of Figure 3 further reports the time-series variation of this segmentation coefficient, which remains rather stable around 20 bps until the end of 2017. During the first two quarters of 2018, it doubles from 20 bps to 40 bps, and then explodes quickly to 90 bps in 2018Q3, 140 bps in 2018Q4, and 167 bps in 2019Q1. Also plotted in Figure 3 are the total quarterly default amounts in the credit market. As we can see, the most dramatic explosion in segmentation coincides with the record level of default amounts in the credit market. As the default amounts somewhat stabilize in the first two quarters of 2019, the segmentation further increases, although the speed of explosion slows down. To assess the economic significance of a 100 bps difference in credit spread, it is instructive to look at the difference in credit spread across credit ratings. For the full sample period, the average credit spreads are 139, 216, and 229 basis points, respectively, for AAA, AA+, and AA rated non-SOE bonds. In other words, the severity of the segmentation during Period III is equivalent of the difference in pricing of two bonds that two letter grades apart.

Behind this dramatic explosion in segmentation is the fast deteriorating credit-market conditions for the public non-SOE issuers. As shown in Table 1, without controlling for bond characteristics, the average credit spread for non-SOE issuers is 192 bps in Period I and 189 bps in Period II, and then almost doubles to 362 bps in Period III. By contrast, the average credit spread for SOE issuers barely moves: 120 bps in Period I, 119 bps in Period II, and 128 bps in Period III. At the same time, as shown in Figure 2, default by public non-SOE issuers increases dramatically in Period III, peaking to 30% by the end of 2018; new issuance by public non-SOEs as a percentage of the total new issuance in the corporate bond market (excluding Chengtou bonds) has decreased from its peak level of 21% to a mere 4% in 2019Q3.

Difference in Credit Quality

To test whether or not the segmentation is driven by the fundamentals of the firms, Table 4 also reports the results of the quarterly panel regressions:

$$\text{DM}_{i,t} = a + b\,\text{NonSOE}_i + c\,\text{Rating}_{i,t} + \sum_k \text{Controls}^k_{i,t} + \epsilon_{i,t}\,,$$

where $\text{DM}_{i,t}$ is the default measure for firm i in quarter t, which is the inverse of the distance-to-default measure in Merton's model of default. In this panel regression, parallel to the segmentation regression (at the issuer level), the coefficient b associated with the NonSOE dummy captures the difference in default measure between non-SOE and SOE issuers. As shown in Table 4, the difference in default measure is negative for all three time periods, with -0.93% in Period I with marginal statistic significance, -3.73% in Period II and -1.91% in Period III, both with strong statistical significance. In other words, these results indicate that the non-SOEs are in fact healthier than the SOEs. Nevertheless, the credit spreads of non-SOEs are on average higher than their SOE counterparts of the same rating categories.

The bottom panel of Figure 3 further reports the time-series variation of the difference in DM. It is interesting to see that the difference in DM reaches a record level of -12.77% in 2015Q3, after 2015 stock market crash in China. Given the standard deviation of DM is 13% for the full sample period, this difference in DM is economically large. It indicates that during the depth of the Chinese stock market crash, the SOEs are viewed by the equity market investors as more risky and of lower credit quality. Nevertheless, as shown in the top panel of Figure 3, the segmentation coefficient remains rather stable in 2015. In other words, with the perceived outside government support, the credit pricing of SOE bonds is de-coupled not only from their non-SOE counterparts, but also from their own balance sheet information and equity-market pricing. Effectively, this segmentation hurts the price discovery for the SOE bonds.

The impact of this segmentation on the non-SOE issuers is more profound. Throughout Period II, the non-SOE issuers remain significantly healthier than their SOE counterparts, while during Period I, the credit qualities of the two samples are statistically indistinguishable. One possible explanation is that, as investors become more aware of credit risk after 2014Q1, the non-SOE issuers are compensating for their lack of outside government support by providing healthier balance sheets and better performing stocks. In other words, moving from Period I to Period II, the non-SOE premium (i.e., the segmentation coefficient) remains stable because of the non-SOE issuers' improved credit quality. Moving into Period III, however, the overall credit market condition is such that keeping a healthy balance sheet is unattainable for the non-SOEs. As shown in the bottom panel of Figure 3, the difference in credit quality between these two samples starts to shrink steadily, pointing to the possibility that the credit-market stress begins to impact the balance sheet and equity performance of the non-SOEs. From this perspective, this segmentation hurts not only price discovery, but also harms the fundamentals of the non-SOEs.

Other Differences in Credit Pricing

Along with the alarming segmentation in the public sample, segmentation between non-SOE and SOE issuers also exists in the private sample. Table 4 also reports the segmentation coefficient between non-SOE and SOE for bonds issued by privately held firms: 14 bps in Period I, 63 bps in Period II, and 117 bps in Period III. Compared with our findings for the public sample, the most interesting difference is that the segmentation coefficient actually starts to increase during Period II, after the first default in 2014. Figure 4 plots the time-series of the segmentation coefficients for both the public and private samples. As we can see, the increase in segmentation for the private sample picks up speed in 2014Q1, consistent with the fact that the first wave of defaults occurs mostly for the privately held firms.

Figure 5 investigates other potential segmentation in our sample. The top panel plots the segmentation coefficients between private and public firms for both non-SOEs and SOEs. Prior to 2014, we do not find any evidence of such a segmentation. Post 2014 during Period II, the credit spreads for private firms become higher on average than their public counterparts of the same rating category, with the segmentation more severe for the non-SOEs. The bottom panel of Figure 5 plots the segmentation coefficients between local and central SOEs (LSOEs vs CSOEs), with the assumption of stronger government support for LSOEs. During the early sample period, the private CSOEs do pay a higher premium of around 30 bps relative to their CSOE counterparts of the same rating category. During the credit market stress in Period III, these differences are no longer important and the segmentation between non-SOEs and SOEs becomes the dominant force.

3.3 The Information Content of Credit Spreads in China

In this section, we examine the extent to which credit spreads in China contain information of the credit quality of the bond issuers. For this, we take advantage of our default measures, estimated using the Merton model with the firms' financial statements and equity valuation as the main inputs. Table 5 reports the results of the quarterly panel regressions:

$$\text{CreditSpread}_{i,t} = a + b\,\text{DM}_{i,t} + c\,\text{Rating}_{i,t} + \sum_k \text{Controls}^k_{i,t} + \epsilon_{i,t}\,,$$

where the credit spread of bond i in quarter t is regressed on the corresponding default measure (DM), controlling for credit rating and other bond and firm characteristics. The regression further includes quarter fixed effect and industry fixed effect to control for potential market-wide fluctuations and industry differences in credit spreads. The reported t-stat's use standard errors double clustered by quarter and bond to take into account of cross-sectional as well as time-series correlations in credit spreads.

The coefficient associated with the default measure, DM, captures the connection between credit spreads and credit quality, summarizing the information content of credit spreads. While this regression has been extensively studied for the US market, our paper is the first to apply it to the Chinese market. Given the known segmentation in this market, we perform this regression for our public non-SOE and public SOE samples separately. Moreover, recognizing that this is a market in transition, we perform the panel regressions over three time periods: Period I, from 2010 through 2013, is the pre-default period; Period II, from 2014 through 2018Q1, captures the first wave of defaults; and Period III, from 2018Q2 to 2019Q2, captures the second and much more severe wave of defaults.

Improved Information Content after the First Default

During Period I, there is no statistically significant relation between credit spreads and default measures. The point estimates are of rather small magnitude, with the wrong sign for the non-SOE sample. Given that investors had never experienced a default prior to the end of Period I, this lack of connection between credit spread and default measure makes intuitive sense. During this period, investors control for credit quality by focusing on credit rating. Once this variable is controlled, credit spreads do not contain any additional information about the credit quality of the issuer. For all practical purposes, there is very little incentive for the credit-market investors to move beyond credit rating since their belief is that default never happens.

This situation is improved during Period II, after the first default in the Spring of 2014. For both the non-SOE and SOE samples, the coefficients for DM are positive and statistically significant: 0.84 for non-SOE and 0.92 for SOE. This indicates that, as credit-market investors become aware of the potential default risk, credit spreads start to incorporate default related information above and beyond credit rating. In particular, information related to the issuer's financial statements and equity market valuation starts to get incorporated into credit spreads. Qualitatively, this is a welcoming improvement for a young market in transition. Quantitatively, however, the economic significance of the information content is rather limited. As reported in Table 3, the standard deviation of DM during Period II is 0.15 and 0.19, respectively, for the non-SOE and SOE samples. This implies that one standard deviation increase in DM is associated with 12.6 bps and 17.5 bps increases in credit spreads for non-SOE and SOE, respectively. Inferring from the regression coefficients for credit rating during Period II, associated with an improvement of one letter grade in credit rating is an average reduction of 60 bps in credit spread. From this perspective, the economic significance of the coefficients for DM are rather moderate.

Moreover, as shown in Table 5, during Period II, the adjusted R-squared of the panel regression barely moves after the inclusion of the default measure. This is in stark contrast with the findings for the US credit market, where, as documented by Collin-Dufresne et al. (2001), a significant portion of the variation in credit spreads can be explained by issuer-level variables known to affect the credit quality of a firm. At the same quarterly frequency, Bao (2009) reports that default measures constructed using models of Merton (1974) and Black and Cox (1976) can explain as much as 45% of the cross-sectional variation in credit spreads for the US sample.

Price Discovery under Market Segmentation

Moving from Period II to Period III gives us a unique opportunity to study price discovery under a segmented market. As shown in the previous section, during Period III, the public non-SOE issuers suffer from explosive credit spreads, unprecedented defaults, and shrinking new issuance, while the SOE issuers remain largely intact. It is therefore interesting to examine the extent to which this market segmentation affects the information content of credit spreads.

For the non-SOE sample, we find a marked improvement in the information content of credit spreads. As shown in Table 5, during Period III, the regression coefficient associated with DM increases for the non-SOE sample to 18.26, with very strong statistical significance. During this period, the standard deviation of DM for public non-SOE issuers is 0.09. This implies that, associated with one standard deviation increase in DM, credit spreads increase on average by 164 basis points. During this stressful time period for non-SOE issuers, associated with an improvement of one letter grade in credit rating is an average reduction of 200 bps in credit spread. From this perspective, the default measure has an economically significant impact on the credit spread, above and beyond credit rating. Moreover, the adjusted R-squared of the panel regression improves by 6.1% with the inclusion of the default measure. Compared to the US market, the explanatory power of the default measure is rather small, but it is by far the best performance of the default measure.

For the SOE sample, however, the coefficient associated with DM has a tstat of 1.65, no longer significant at the 5% confidence interval. The coefficient estimate is 2.87. For the SOE sample, the standard deviation of DM is 0.08 during Period III. This implies an increase of 23 bps in credit spread associated with one standard deviation increase in DM. Overall, unlike for the non-SOE sample, there is no important in the information content of credit spreads for the SOE sample. Given that most investors seek safety in SOE bonds while abandoning the non-SOE bonds amidst the credit turmoil, the price discovery for non-SOE bonds is forced to be more informative, while SOE bonds with their outside government support are under no such pressure.

The Control Variables

It is instructive for us to go over the control variables and study their relation with credit spreads. First of all, the regression coefficients associated with credit rating, the widely adopted measure of credit quality, are as expected. During Period I and Period II, the magnitudes are comparable for the SOE and non-SOE samples. A letter-grade improvement in credit rating is associated with a reduction of around 50 bps in credit spread. During Period III, however, there is a divergence in the sensitivity, with the non-SOE sample increasing to around 200 bps and the SOE sample increasing to around 100 bps.

There is in general a positive relation between bond maturity and credit spread, although the connection is unstable and becomes rather weak in Period III. The relation with bond age is mixed. It is interesting to observe that during, Period III, older bonds have higher credit spreads. In the US, there is a rather robust relation between credit spreads and age, driven by the liquidity premium associated with the older and less liquid bonds. In China, however, this connection has not be explored extensively. When it comes to the bond issuance size, however, the result is pretty stable: bonds with larger issuance command a lower yield.

The variable ZeroDays counts the percentage of days in a quarter when the bond has zero trading. As shown in Table 2, this variable increases rather dramatically, from 62% in Period I, 77% in Period II, to 88% in Period III for the non-SOE sample. A higher value indicates a less liquid market. The lack of liquidity is even more severe for the SOE sample. Interestingly, the regression coefficients on this variable are consistently negative, indicating that the bond with less frequent trading enjoys a lower yield. This result, counter to our usual understanding of liquidity premium, could be explained by the fact that higher yielding bonds are actually traded more frequently by investors who are reaching for yield.

We also include the dummy variable, Embed, to take into account that some bonds have embedded optionality; and the dummy variable, Exch, to differentiate the exchange-traded bonds, which attract more retail investors, from the interbank market, which are populated largely by institutional investors. The most significant result is that among the exchange-traded bonds, the ones with embedded option enjoys lower yields. We further separate the SOE bonds into local and central government SOEs. As shown in Table 5, there is a central government SOE premium during Period II of about 13 bps.

4 Conclusions

In this paper, we study the price efficiency of the onshore Chinese corporate bond market, focusing in particular on the link between the market-observed credit spreads and the underlying credit quality of the issuers. Unlike the US market, where a significant portion of the cross-sectional variation in credit spreads can be explained by issuer-level information, the link between credit spreads and credit quality is generally weak in China. Prior to the first default in 2014, credit spreads in China are uninformative. Growing out of the pre-default era, credit spreads become more informative, but with rather moderate magnitude. More alarming is the severe segmentation that has developed between state-owned enterprise (SOE) and non-SOE issuers since the credit tightening of 2017-18. Our results show that this segmentation is driven not by the fundamentals of the firms, but by the perceived vulnerability of non-SOE issuers due to their lack of outside government support. This schism, while dormant during normal condition, has the tendency to break open at a rapid speed during stressful market condition, undermining the stability of the market. On the bright side, the unprecedented credit risk forces investors to price non-SOE bonds with more differentiation, making the non-SOE credit spreads markedly more informative. Controlling for credit rating, a one standard deviation in default measure is associated with 100 bps widening in credit spread. But this comes at a huge cost, with non-SOEs suffering from exploding credit spreads, unprecedented defaults, and shrinking new issuance. At the same time, as investors seek for safety in the SOE bonds, their information content remains rather limited.

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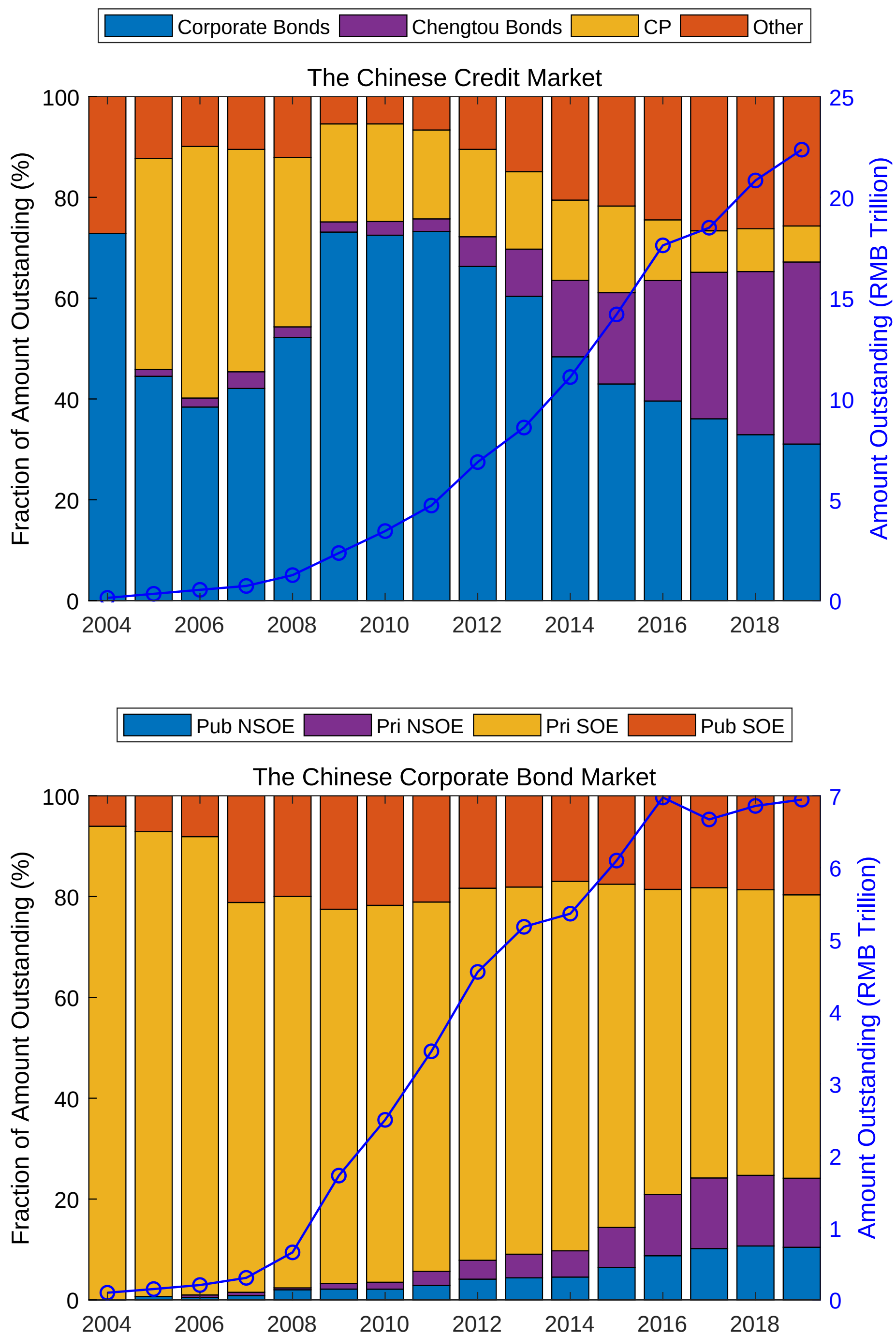

Figure 1: The top panel plots the total amount outstanding of the Chinese credit market (right axis) and the fraction by instrument type (left axis). The bottom panel plots the total amount outstanding of the corporate bond market (right axis) and the fraction by issuer type (left axis).

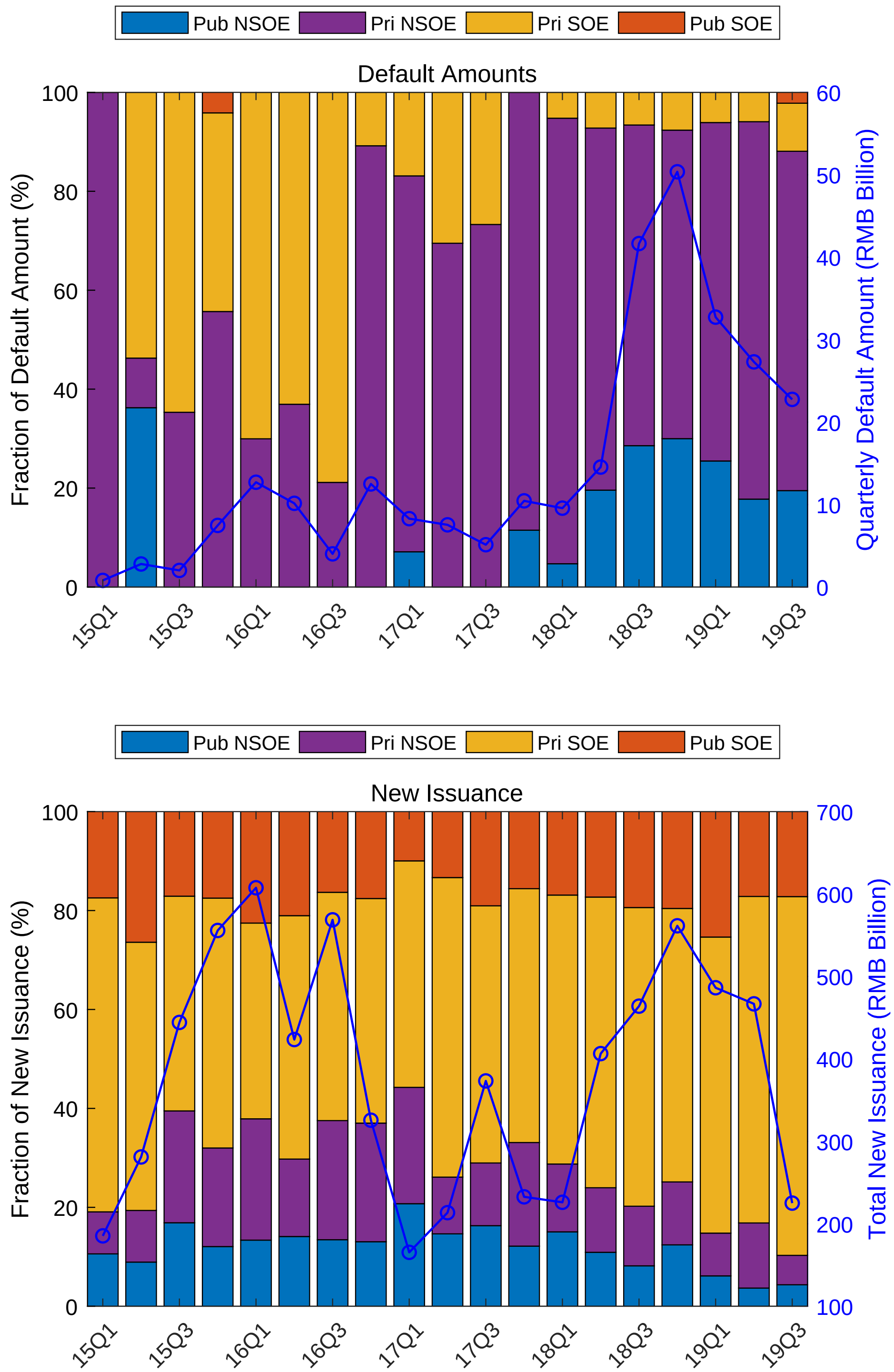

Figure 2: The top panel plots the quarterly default amount (right axis) and the fraction by issuer type (left axis). Defaults by all instruments in the credit market are included. The bottom panel plots quarterly new issuace of corporate bonds (right axis) and the fraction by issuer type (left axis). Corporate bonds issued by Chengtou are excluded.

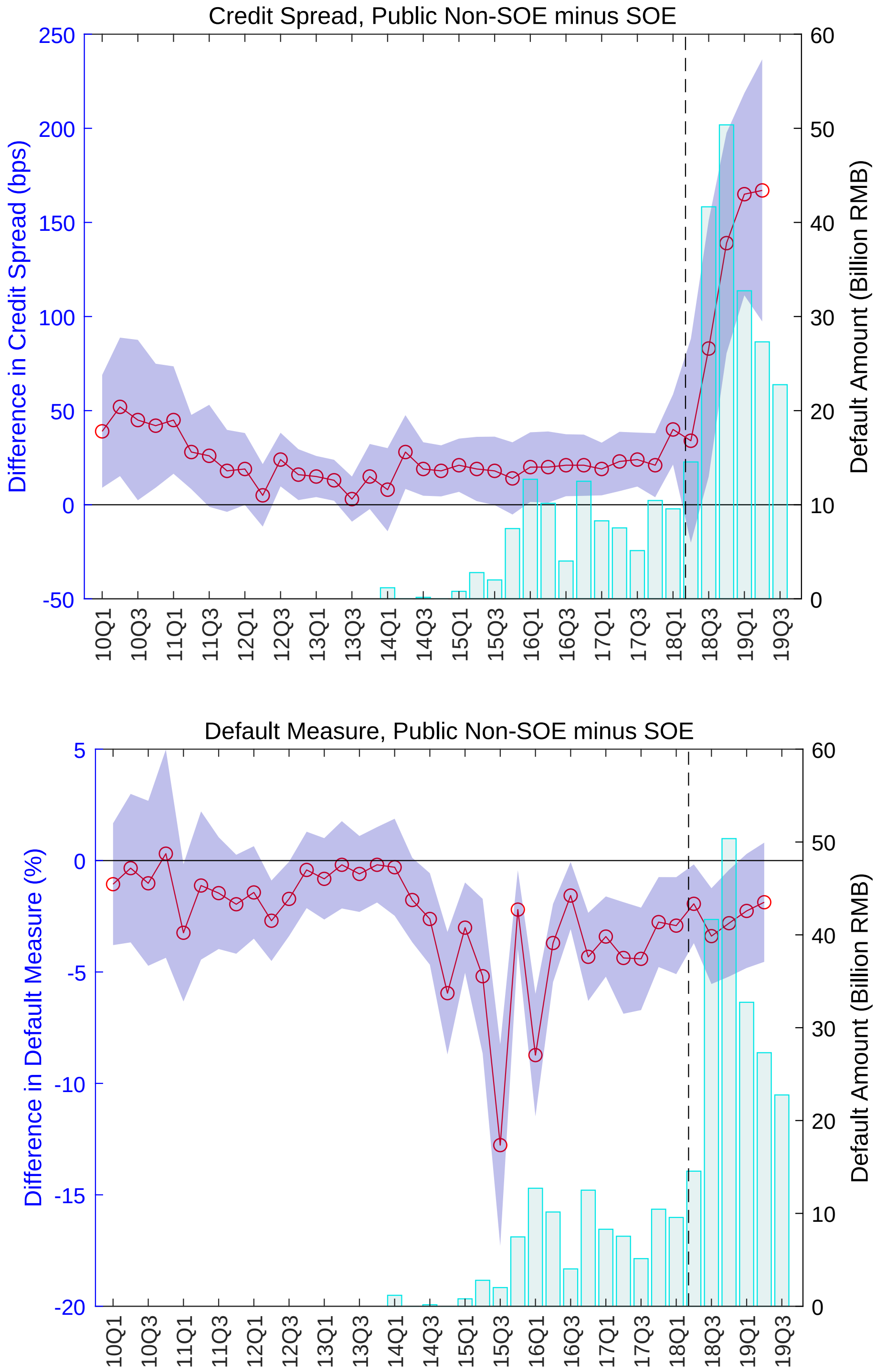

Figure 3: This figure plots the difference between public non-SOEs and public SOEs in credit spread (top panel, left axis) and in default measure (bottom panel, left axis), estimated using quarterly regressions, controlling for credit ratings and other bond and firm characteristics. The shaded area indicates the 95% confidence intervals. Also reported are the total quarterly default amounts in the credit market (right axis). The vertical dashed line marks the release of New Regulations on Asset Management.

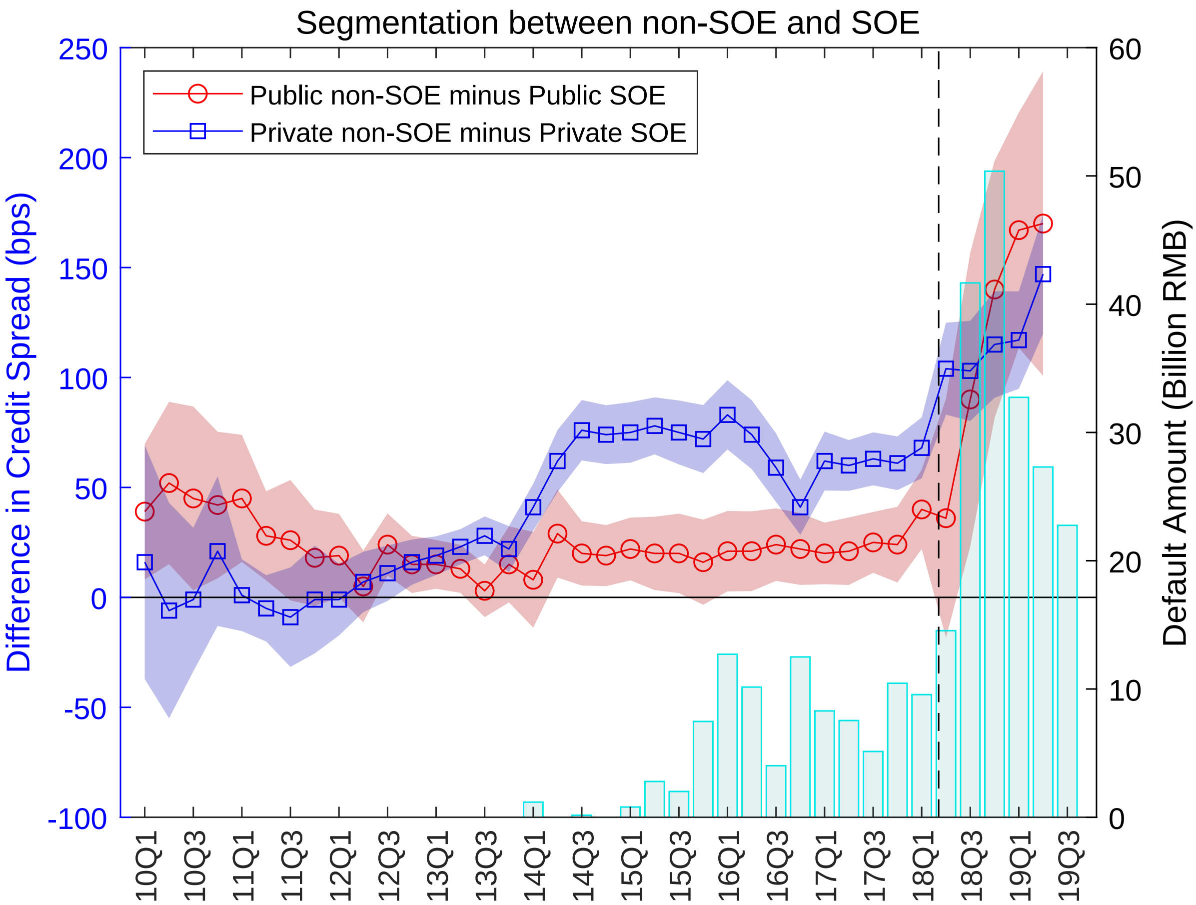

Figure 4: This figure plots the differences in credit spread of non-SOE and SOE bonds (left axis). The differences are estimated using quarterly pooled regressions, controlling for credit rating, and bond and firm characteristics. The shaded area indicates the 95% confidence intervals with robust standard errors. Also reported are the total quarterly default amounts in the credit market, including corporate bonds and commercial papers (right axis). The vertical dashed line marks the release of New Regulations on Asset Management.

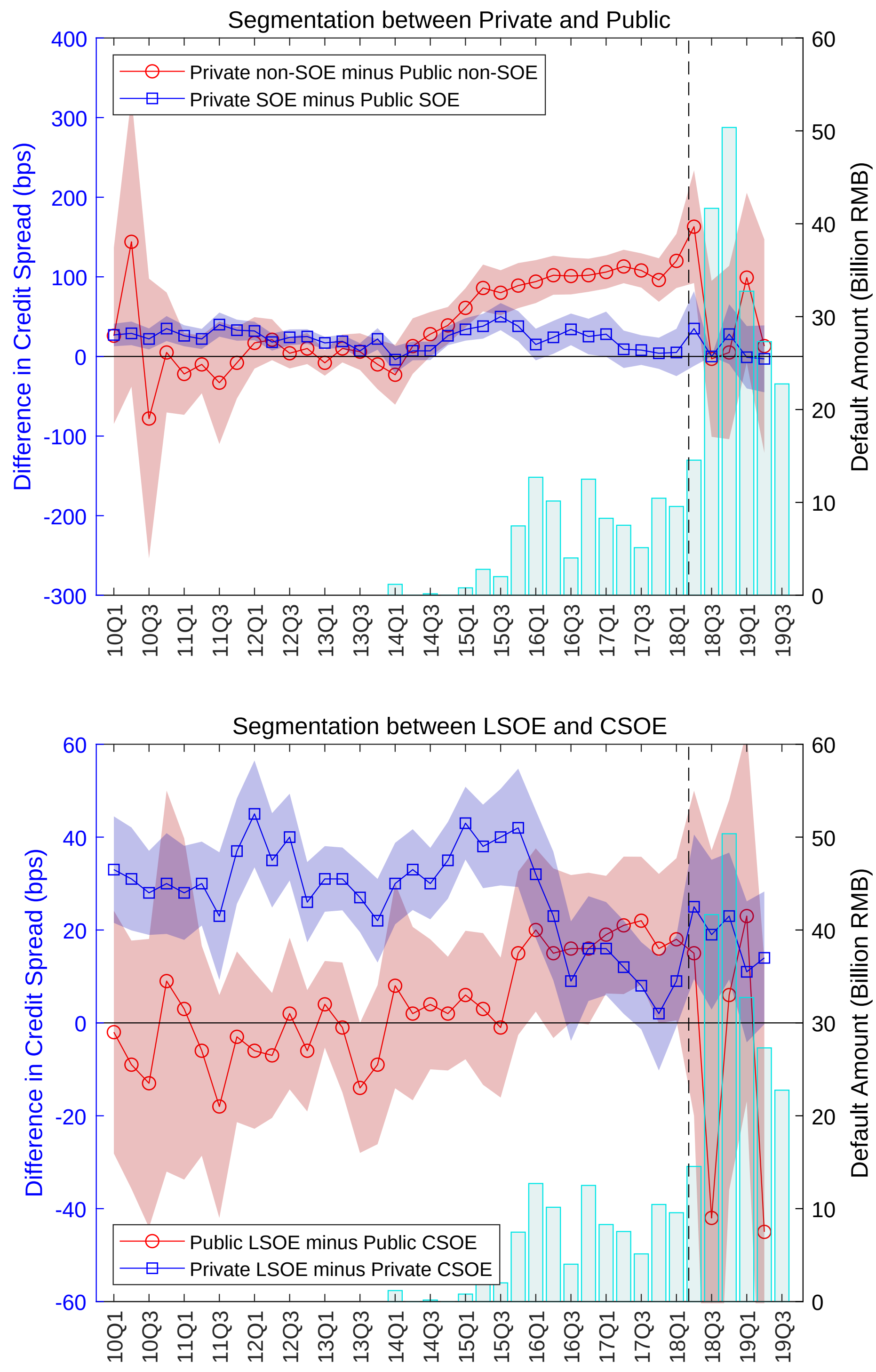

Figure 5: This figure plots the differences in credit spread of bonds issued by private and public firms (top panel, left axis) and by local and central SOEs (bottom panel, left axis). The differences are estimated using quarterly pooled regressions, controlling for credit rating, and bond and firm characteristics. The shaded area indicates the 95% confidence intervals with robust standard errors. Also reported are the total quarterly default amounts in the credit market, including corporate bonds and commercial papers (right axis). The vertical dashed line marks the release of New Regulations on Asset Management.

Table 1: **Summary Statistics: Bond-Level Data**

	Public Non-SOE			**Public SOE**		
	mean	med	std	mean	med	std
NumIssuers	326			369		
NumBonds	761			1,147		
CreditSpread (%)	2.24	1.78	2.68	1.21	0.98	1.16
Rating	2.45	3.00	0.83	1.76	1.00	0.88
Maturity (yr)	3.06	2.88	1.27	3.40	3.00	1.73
IssueSize (billion)	1.03	0.80	0.92	2.04	1.20	2.69
Age (yr)	1.75	1.52	1.28	2.05	1.67	1.67
Coupon (%)	5.90	5.89	1.21	5.23	5.20	1.09
Embed	0.62	1.00	0.49	0.39	0.00	0.49
Exch	0.70	1.00	0.46	0.55	1.00	0.50
ZeroDays (%)	76	88	27	85	93	19
Turnover (%)	31	13	60	34	10	75
TradingDays (day)	16	8	18	10	5	13
	Private Non-SOE			**Private SOE**		
	mean	med	std	mean	med	std
NumIssuers	387			1,511		
NumBonds	1,287			5,243		
CreditSpread (%)	2.48	2.23	1.69	1.54	1.29	1.15
Rating	2.38	2.00	0.76	1.89	2.00	0.87
Maturity (yr)	3.20	2.89	1.48	3.64	3.30	1.89
IssueSize (billion)	1.09	1.00	0.89	1.87	1.10	2.46
Age (yr)	1.60	1.34	1.27	2.20	1.79	1.84
Coupon (%)	6.09	6.20	1.29	5.70	5.60	1.25
Embed	0.55	1.00	0.50	0.29	0.00	0.45
Exch	0.46	0.00	0.50	0.19	0.00	0.39
ZeroDays (%)	58	78	57	61	78	52
Turnover (%)	46	16	102	71	22	159
TradingDays (day)	10	5	13	9	5	12

The sample extends from January 2010 through June 2019. CreditSpread is the difference in yield between corporate bond and CDB bond of the same maturity. Rating is a numerical number: 1=AAA, 2=AA+, 3=AA, 4=AA-, etc. Embed is 1 for bonds issued with emdedded option. Exch is 1 for exchange-traded bonds. ZeroDays is the percent of non-trading days per quarter. Turnover is the ratio of quarterly trading volume to issuance size. TradingDays is the number of trading days per quarter.

Table 2: **Summary Statistics: Bond-Level Data by Period**

	Public Non-SOE						Public SOE					
	Period I		Period II		Period III		Period I		Period II		Period III	
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
NumIssuers	166		292		196		248		332		209	
NumBonds	204		587		443		445		796		568	
CreditSpread (%)	1.92	0.92	1.89	1.19	3.62	5.34	1.20	0.78	1.19	1.07	1.28	1.83
Rating	2.68	0.76	2.55	0.78	1.94	0.88	1.83	0.87	1.82	0.91	1.39	0.65
Maturity (yr)	3.93	1.39	2.96	1.18	2.48	0.92	4.13	2.02	3.19	1.56	2.84	1.29
IssueSize (billion)	0.98	0.83	1.01	0.95	1.14	0.88	2.33	3.19	1.90	2.51	2.01	2.20
Age (yr)	1.31	1.08	1.83	1.33	1.95	1.22	1.53	1.36	2.26	1.69	2.23	1.86
Coupon (%)	6.40	0.95	5.88	1.22	5.44	1.21	5.44	0.99	5.27	1.10	4.70	1.04
Embed	0.51	0.50	0.65	0.48	0.65	0.48	0.28	0.45	0.43	0.49	0.46	0.50
Exch	0.78	0.41	0.70	0.46	0.63	0.48	0.56	0.50	0.56	0.50	0.48	0.50
ZeroDays (%)	62	30	77	26	88	15	79	21	85	19	92	10
Turnover (%)	46	103	30	44	18	29	53	119	28	48	22	34
TradingDays (day)	26	20	15	17	8	10	14	14	10	13	5	7

	Private Non-SOE						Private SOE					
	Period I		Period II		Period III		Period I		Period II		Period III	
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
NumIssuers	142		354		276		1,062		1,398		614	
NumBonds	280		1,014		775		2,579		3,913		2,064	
CreditSpread (%)	1.98	0.82	2.32	1.33	3.25	2.53	1.61	0.95	1.53	1.23	1.33	1.25
Rating	2.74	0.70	2.43	0.71	2.02	0.75	2.02	0.87	1.93	0.86	1.33	0.62
Maturity (yr)	3.97	1.80	3.22	1.42	2.64	1.10	4.51	1.90	3.21	1.73	2.89	1.53
IssueSize (billion)	1.03	0.71	1.08	0.89	1.16	0.99	1.90	2.60	1.81	2.41	2.05	2.23
Age (yr)	1.04	0.92	1.58	1.28	2.00	1.28	1.71	1.56	2.58	1.89	2.02	2.02
Coupon (%)	6.30	0.98	6.13	1.33	5.84	1.30	5.79	1.20	5.79	1.27	4.97	1.06
Embed	0.36	0.48	0.54	0.50	0.70	0.46	0.29	0.46	0.27	0.45	0.38	0.49
Exch	0.16	0.37	0.47	0.50	0.65	0.48	0.19	0.39	0.18	0.39	0.24	0.43
ZeroDays (%)	49	55	58	60	64	48	42	64	70	42	78	25
Turnover (%)	116	205	38	66	21	33	124	239	43	76	33	42
TradingDays (day)	12	13	10	14	8	10	13	15	7	10	5	6

The sample period is from January 2010 to June 2019. Period I, from 2010 through 2013, is the pre-default period; Period II, from 2014 through 2018Q1, captures the first wave of defaults; and Period III, from 2018Q2 to 2019Q2, captures the second and much more severe wave of defaults. See Table 1 for variable definitions.

Table 3: **Summary Statistics: Equity-Level Data**

	Public Non-SOE											
	All			Period I			Period II			Period III		
	mean	med	std	mean	med	std	mean	med	std	mean	med	std
NumFirms	326			166			292			196		
EquitySize (log)	23.24	23.20	1.00	22.59	22.49	0.95	23.31	23.26	0.88	23.69	23.64	1.03
EquityRet (%)	3.04	1.68	10.00	2.32	2.04	8.12	2.24	0.88	10.36	6.16	5.16	10.04
EquityVolatility (%)	40.75	36.85	17.89	37.34	35.92	9.73	42.23	36.74	21.27	39.87	38.40	11.89
Leverage (%)	47.95	48.00	14.47	46.03	46.68	13.09	47.19	47.20	14.54	52.19	51.38	14.80
AssetValue (log)	23.89	23.78	1.18	23.21	23.08	0.99	23.89	23.79	1.06	24.62	24.54	1.27
AssetVolatility (%)	23.89	20.75	15.45	21.88	21.18	9.92	26.36	21.85	17.49	18.61	16.18	11.62
DM	0.21	0.18	0.13	0.19	0.18	0.07	0.23	0.19	0.15	0.20	0.18	0.09
	Public SOE											
	All			Period I			Period II			Period III		
	mean	med	std	mean	med	std	mean	med	std	mean	med	std
NumFirms	369			248			332			209		
EquitySize (log)	23.66	23.51	1.35	23.33	23.06	1.41	23.73	23.55	1.28	24.06	23.98	1.32
EquityRet (%)	2.52	1.60	9.08	2.56	2.68	7.48	1.88	0.64	9.92	4.72	3.76	8.20
EquityVolatility (%)	37.92	33.41	18.68	32.37	31.24	10.47	41.89	36.14	22.33	33.72	32.94	10.79
Leverage (%)	49.75	50.33	14.10	48.94	49.91	13.69	49.85	50.22	14.53	50.90	51.78	13.13
AssetValue (log)	24.55	24.31	1.46	24.25	23.98	1.47	24.54	24.31	1.41	25.15	25.01	1.44
AssetVolatility (%)	18.40	14.44	14.07	15.01	12.88	9.33	21.61	16.87	16.29	13.03	10.90	8.43
DM	0.23	0.19	0.16	0.18	0.18	0.07	0.27	0.21	0.19	0.20	0.19	0.08

DM is the default measure, the inverse of Merton's distance-to-default. EquitySize and AssetValue are the log of the firm's equity size and asset value, respectively. EquityVolatility and AssetVolatility are the annualized equity and asset volatility, respectively. Leverage is the ratio of total current liabilities plus half of the total non-current liabilities to the total asset value. EquityRet is the annualized stock return. The sample period is from January 2010 to June 2019.

Table 4: **Market Segmentation between SOE and Non-SOE**

	Public Sample						**Private Sample**		
	CreditSpread (%)			**DM (%)**			**CreditSpread (%)**		
	Period I	Period II	Period III	Period I	Period II	Period III	Period I	Period II	Period III
NonSOE	0.16***	0.20***	1.13***	-0.93*	-3.73***	-1.91***	0.14***	0.63***	1.17***
	[3.33]	[4.11]	[3.77]	[-1.91]	[-4.72]	[-3.24]	[2.91]	[13.57]	[10.88]
Rating	0.49***	0.63***	1.83***	0.68*	0.87**	1.96***	0.55***	0.60***	1.04***
	[13.17]	[17.38]	[3.97]	[1.70]	[2.41]	[2.93]	[16.01]	[25.39]	[14.44]
Maturity	0.04***	0.04**	0.08	-0.13	0.09	-0.01	0.09***	0.03**	-0.07***
	[2.75]	[2.26]	[0.94]	[-0.95]	[0.41]	[-0.06]	[8.76]	[2.10]	[-4.50]
Age	-0.01	0.03	0.22***	-0.20	0.58***	0.28*	-0.01	0.05***	0.03
	[-0.84]	[1.63]	[2.90]	[-1.01]	[2.77]	[1.87]	[-1.18]	[3.74]	[1.48]
IssueSize	-0.05***	-0.11***	-0.13	-0.60***	-0.19	-0.62***	-4.70***	-11.79***	-11.79***
	[-4.05]	[-7.55]	[-1.61]	[-5.07]	[-0.85]	[-2.59]	[-9.70]	[-9.33]	[-10.10]
ZeroDays	-0.88***	-1.77***	-5.63***	0.13	-4.92***	-1.65	-0.00***	-0.00***	-0.01***
	[-4.51]	[-9.44]	[-5.40]	[0.17]	[-3.32]	[-1.52]	[-4.13]	[-8.12]	[-7.32]
Embed	-0.15	0.54***	0.53**	-2.59**	1.59	-0.64	-0.02	0.08	0.90***
	[-1.11]	[5.93]	[2.10]	[-2.33]	[1.44]	[-0.68]	[-0.42]	[1.19]	[14.82]
Exch	0.01	-0.24***	-0.33	-0.50	-0.65	-0.78	0.07	0.26**	0.10
	[0.18]	[-4.16]	[-1.24]	[-0.87]	[-0.96]	[-1.27]	[1.21]	[2.34]	[1.46]
Embed×Exch	0.08	-0.75***	-1.43***	2.87**	-1.61	1.43	-0.24***	-0.71***	-0.92***
	[0.49]	[-7.48]	[-4.27]	[2.23]	[-1.21]	[1.53]	[-3.60]	[-6.35]	[-5.22]
Constant	1.19***	1.97***	3.21***	16.37***	22.04***	18.63***	0.15	0.84***	1.08***
	[5.15]	[9.77]	[2.75]	[9.47]	[10.15]	[8.22]	[1.42]	[5.77]	[6.06]
Observations	4,225	9,560	2,878	4,225	9,560	2,878	20,222	33,761	8,202
Adjusted R^2	0.606	0.544	0.294	0.162	0.660	0.189	0.558	0.384	0.445

Quarterly panel regressions with credit spreads and default measures (DM) as the dependent variables, respectively, with quarter and industry fixed effects. NonSOE is one for bonds issued by non-SOEs and zero for SOEs. Reported in square brackets are tstat's using standard errors clustered by bond and quarter. See Table 1 for bond-level variable definitions. The sample extends from January 2010 to June 2019. Period I, from 2010 through 2013, is the pre-default period; Period II, from 2014 through 2018Q1, captures the first wave of defaults; and Period III, from 2018Q2 to 2019Q2, captures the second and much more severe wave of defaults.

Table 5: **Panel Regressions of Credit Spreads on Default Measures**

	Public Non-SOE						Public SOE					
	Period I		Period II		Period III		Period I		Period II		Period III	
DM		-0.28		0.84***		18.26***		0.17		0.92***		2.87*
		[-0.69]		[2.59]		[5.34]		[1.08]		[4.01]		[1.65]
Rating	0.54***	0.54***	0.62***	0.62***	2.39***	1.98***	0.47***	0.46***	0.61***	0.60***	1.14***	1.08***
	[8.35]	[8.26]	[7.96]	[8.05]	[3.08]	[3.31]	[10.85]	[10.72]	[17.22]	[17.49]	[4.98]	[5.60]
Maturity	0.11***	0.11***	0.03	0.03	0.40	0.29	0.03**	0.03**	0.05***	0.05***	-0.01	0.00
	[3.05]	[3.08]	[0.77]	[0.76]	[1.40]	[1.40]	[2.25]	[2.26]	[2.84]	[2.82]	[-0.23]	[0.01]
Age	-0.12***	-0.12***	0.01	-0.00	0.61**	0.59*	0.01	0.01	0.04**	0.04**	0.08***	0.07**
	[-3.22]	[-3.30]	[0.12]	[-0.00]	[2.07]	[1.93]	[0.46]	[0.48]	[2.37]	[2.12]	[3.50]	[2.51]
IssueSize	-0.13***	-0.13***	-0.16**	-0.17**	-0.02	-0.08	-0.04***	-0.04***	-0.10***	-0.09***	-0.13***	-0.11***
	[-3.98]	[-3.98]	[-2.46]	[-2.49]	[-0.08]	[-0.32]	[-3.52]	[-3.46]	[-6.51]	[-6.60]	[-4.09]	[-3.12]
ZeroDays	-1.28***	-1.28***	-1.95***	-1.91***	-6.50***	-5.88***	-0.58***	-0.58***	-1.57***	-1.53***	-3.71***	-3.70***
	[-5.46]	[-5.46]	[-9.14]	[-8.96]	[-4.34]	[-4.04]	[-2.76]	[-2.78]	[-7.24]	[-7.36]	[-3.05]	[-3.07]
Embed	-0.16	-0.17	0.53***	0.53***	-0.76	-0.64	-0.16	-0.15	0.53***	0.51***	1.09***	1.10***
	[-1.13]	[-1.17]	[3.65]	[3.67]	[-1.00]	[-0.93]	[-1.24]	[-1.21]	[5.53]	[5.54]	[6.34]	[6.51]
Exch	0.00	0.01	-0.40***	-0.39***	-0.68	-0.66	0.04	0.04	-0.20***	-0.20***	0.08	0.10
	[0.01]	[0.04]	[-3.90]	[-3.86]	[-1.02]	[-1.02]	[0.59]	[0.61]	[-3.07]	[-3.00]	[0.80]	[1.09]
Embed×Exch			-0.65***	-0.64***	-1.37**	-1.28*	0.10	0.10	-0.73***	-0.72***	-1.46***	-1.52***
			[-3.55]	[-3.55]	[-2.03]	[-1.72]	[0.66]	[0.63]	[-6.90]	[-6.92]	[-7.51]	[-7.45]
CSOE							-0.01	-0.01	-0.12***	-0.13***	-0.16	-0.17
							[-0.34]	[-0.33]	[-2.69]	[-3.08]	[-0.96]	[-1.31]
Constant	1.20***	1.24***	2.59***	2.40***	3.08*	-0.10	0.97***	0.94***	1.70***	1.51***	3.11**	2.62*
	[2.69]	[2.65]	[7.24]	[6.79]	[1.96]	[-0.06]	[4.37]	[4.29]	[7.20]	[7.11]	[2.38]	[1.85]
Observations	1,351	1,351	3,871	3,871	1,300	1,300	2,874	2,874	5,689	5,689	1,578	1,578
Adjusted R^2	0.587	0.587	0.471	0.474	0.269	0.330	0.553	0.553	0.551	0.560	0.303	0.317

Quarterly panel regressions of credit spreads on default measures (DM) with quarter and industry fixed effects. Reported in square brackets are tstat's using standard errors clustered by bond and quarter. Embed×Exch is the interation between the Embed and Exch dummies. CSOE is one for central government SOEs. See Table 1 for bond-level variable definitions. The sample extends from January 2010 to June 2019. Period I, from 2010 through 2013, is the pre-default period; Period II, from 2014 through 2018Q1, captures the first wave of defaults; and Period III, from 2018Q2 to 2019Q2, captures the second and much more severe wave of defaults.