The SOE Premium and Government Support in China's Credit Market

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Abstract

Studying China's credit market using a structural default model that integrates credit risk, liquidity, and bailout, we document improved price discovery and deepening divide between state-owned enterprises (SOEs) and non-SOEs. Amidst liquidity deterioration, the presence of government bailout helps alleviate the heightened liquidity-driven default, making SOE bonds more valuable and widening the SOE premium. Meanwhile, the increased importance of government support makes SOEs more sensitive to bailout, while the heightened default risk increases non-SOEs' sensitivity to credit quality. Examining the real impact, we find severe performance deteriorations of non-SOEs relative to SOEs, reversing the long-standing trend of non-SOEs outperforming SOEs.

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1 Introduction

The coexistence of the state-owned enterprises (SOE) with firms that are not state-owned (non-SOE) creates the single most important divide in China's economy, with non-SOE firms competing with the less efficient but more privileged SOEs for resources – economic, social, and political. On credit allocation, SOEs in China are known to have preferential access, although the actual magnitudes have not been well documented in the literature owing to the opacity of bank loans, the dominant credit channel in China.[1] Lacking this critical information, further discussions on the real impact of the credit misallocation and the ensuing welfare losses are incomplete. Moreover, changing government policies can influence, either intentionally or inadvertently, the relative credit allocation between SOEs and non-SOEs, adding complications to this enormously important topic.[2]

This paper studies the credit allocation between SOEs and non-SOEs using the pricing information from China's credit market and provides the first comprehensive evidence in the literature on this important topic. Bypassing bank loans and shadow banking, we focus our attention on the credit market, which, totaling $4.5 trillion by 2020, is second only to the United States. Unlike bank loans, the market prices of corporate bonds are driven exclusively by investors' concerns over the risk-and-return tradeoff, and can therefore best reflect the firm-level credit conditions. We quantify the extent of SOEs' advantage in credit allocation using the SOE premium, measured as the difference in credit spreads between non-SOE and SOE bonds, controlling for credit ratings and other bond and issuer characteristics. Because of the fluidity of credit dispensation, the information captured by the SOE premium from the credit market is a reflection of the relative credit allocation not only in the credit market but also across all other credit channels in China.

Our measure of the SOE premium reflects a deepening divide between SOEs and non-SOEs. Prior to 2018, the SOE premium for publicly-listed firms in China fluctuates around a stable level of 20 bps, indicating a moderate but non-trivial premium enjoyed by SOEs due to their perceived government support. After the release of the April 2018 New Regulations, we find a rapidly worsening credit condition faced by non-SOEs relative to their SOE counterparts. Over just one quarter, the SOE premium exploded from 28 bps to an unprecedented 98 bps in 2018Q2. Since November 2018, recognizing the adverse effects on the

[1] Among others, studies on China's credit allocations to SOEs and non-SOEs include Dollar and Wei (2007) using survey data, Lardy (2019) using aggregate loan volume data from China Banking Society, and Cong et al. (2019) using proprietary loan-level volume data during the 2009-2010 stimulus. To our knowledge, there have not been any comprehensive studies on the SOE misallocation using loan pricing data.

[2] Building on the observation that misallocation can lower aggregate total factor productivity, the seminal paper by Hsieh and Klenow (2009) quantifies the potential extent of resource misallocation in China and India versus the U.S. using microdata on manufacturing establishments.

private sector, the Chinese government offered reassurances and devised policies to support the private sector, but the SOE premium, or the non-SOE discount, deteriorates further, peaking at 154 bps in 2019Q3. It has since come down to 93 bps as of 2020Q2.

To understand this time-varying nature of the SOE premium, we build a structural default model that integrates credit risk, liquidity, and bailout. Throughout the model, the strength of the government support remains stable, and yet, its importance and value can increase sharply, resulting in an explosive SOE premium. Central to this result is the interaction between bailout probability and the liquidity-driven default. In He and Xiong (2012), liquidity-driven default emerges from the interaction between liquidity and credit risk – increased debt-market illiquidity forces firms to incur higher losses in rolling over their maturing debt, leading the equity holders to default at a higher fundamental threshold V_B. Just as in He and Xiong (2012), where the interaction between liquidity and credit risk highlights the role of short-term debt in exacerbating the rollover risk, in our model, the interaction between the rollover risk and the potential of government bailout highlights the role of SOE bonds in alleviating the liquidity-driven default. Conceptually, our model offers the important insight that, during market-wide liquidity deterioration, the presence of government bailout helps alleviate the heightened liquidity-driven default for SOEs, while the lack of government support leaves non-SOEs exposed, driving a wedge between the two.

Applying this important insight of our model to the liquidity crisis triggered by the April 2018 New Regulations, our model's implication for the explosive SOE premium is immediate. The primary purpose of the 2018 New Regulations is to contain the rapid increase of shadow banking and reduce the systematic risk in the asset-management industry. Over the short run, however, the unprecedented scope of the regulations severely shrinks the financing and re-financing channels of corporate issuers and weakens the demand for corporate bonds from asset managers, triggering a liquidity crisis in China's credit market. Consistent with the conditions laid out in He and Xiong (2012), we observe liquidity deteriorations, reduced access to the bond market, and increasing defaults. Important for our paper, these effects occur much more severely for non-SOEs than SOEs, reflecting the increased value of government support during the liquidity crisis. In essence, this classic episode of flight-to-safety has a Chinese characteristic – amid the heightened concern over default risk, investors seek safety in SOE bonds and shun non-SOE bonds, amplifying the SOE premium.

Empirical Tests on Credit Pricing – We test the credit-pricing implications of our model using the model-implied default measure, which integrates the empirical information on credit quality, liquidity condition, and the extent of government support into one unified measure. Under our model, $\ln(V_t/V_B)$ is the distance between a firm's current asset value V_t and its default boundary V_B, and, further divided by the firm's asset volatility σ_A, it becomes the standardized distance-to-default, a concept proposed by Merton (1974) and popularized by Moody's KMV. In our empirical test, we use the default measure (DM), defined as the inverse of the distance-to-default. Following the approach of Moody's KMV, we first estimate the issuer-level equity value and volatility, and then use them to back out, through our model's pricing relations, the firm's asset value and volatility. The final output is the quarterly firm-level DM. Intuitively, firms with higher DM's are closer to their default boundary V_B and more likely to default, and, within our model, the underlying driver can be multifaceted. While Merton's model-implied DM is driven purely by the firm's fundamental credit quality, our DM unifies credit quality, government support, and liquidity.[3] Moreover, our DM highlights the interactions of these three components in explaining credit pricing, contrary to the commonly used linear combinations of these components. Empirically, we find that while Merton's DM indicates that non-SOEs are on average healthier than SOEs, our DM concludes otherwise. Behind the opposing predictions is the presence of bailout probability in our model, which lowers the default boundary for SOEs and makes them safer than non-SOEs. Interacting bailout with illiquidity, this relative safety between SOEs and non-SOEs would further increase, and consistently, the quarterly difference in DM between non-SOEs and SOEs widens considerably after 2018Q2.

Equipped with our model-implied DM, we first study the extent to which our model can explain the time-varying SOE premium. From 2014Q1 to 2018Q1, the SOE premium is on average 27 bps (t-stat=4.28) and then elevates rapidly to an average level of 113 bps (t-stat=7.76) from 2018Q2 to 2020Q2. Focusing first on the period when the SOE premium is the most severe, we find that adding our DM as an explanatory variable reduces the SOE premium from the staggering 113 bps to 6 bps (t-stat=0.38), while adding Merton's DM further exacerbates the divide and increases the SOE premium from 113 bps to 116 bps.[4] Moreover, our DM also works during the relatively calm period from 2014Q1 to 2018Q1. Adding the DM reduces the SOE premium from the original 27 bps to 6 bps (t-stat=0.82), while adding Merton's DM increases the SOE premium from 27 bps to 32 bps (t-stat=5.05).

Equipped with our model-implied DM, we also study the evolving nature of price dis-

[3] To capture the extent of government support, we use the issuer-level government holdings data, which we construct from the ground up using the equity holdings of all government-owned entities within the top ten shareholders for each publicly listed firm. To capture the time-varying economy-wide liquidity condition, we set the liquidity shock intensity parameter $\xi = 1$ before 2018Q2 and $\xi = 2$ after 2018Q2 for all issuers.

[4] The fact that our DM can explain the SOE premium while Merton's DM cannot indicates the role of government support in deepening the divide between SOEs and non-SOEs, particularly during liquidity crises. The failure of Merton's DM in explaining the SOE premium also speaks to the competing explanation that due to their over-borrowing and over-expanding during the credit boom of 2014-2016, non-SOEs are weaker than SOEs in credit quality and are therefore ill-prepared for the severe credit contraction in 2018. Our results indicate that the credit deterioration of non-SOEs relative to SOEs is driven by the differential in the extent of government support, not that in fundamental credit quality.

covery in China's credit market. While the information content of credit spreads has been extensively studied for the U.S. market, our paper offers the first comprehensive study of the Chinese market. From 2010 to 2020, this market is informed by two important shocks. The first ever default in 2014Q1 changes investors' perception of credit risk and the 2018Q2 liquidity crisis underscores the increasing importance of government support. Using our model-implied DM to study the price discovery in China's credit market, we find a market of improved price efficiency as investors price two emerging risk factors – default risk after 2014Q1 and the extent of government support after 2018Q2, into the credit market.

Prior to 2014, as default had never occurred in China's credit market, the prevalent belief is that bonds are meant to be paid in full. Accordingly, prior to 2014Q1, default measures are unimportant in explaining credit spreads above and beyond credit ratings. Post 2014Q1, however, default measures emerge as an important pricing factor for both SOE and non-SOE bonds. From 2014Q1 to 2018Q1, one standard deviation increase in Merton's DM is associated with an increase in credit spread of 24 bps for non-SOE bonds and 23 bps for SOE bonds. Introducing our DM, the extent of the price discovery improves moderately, indicating that this post-default period is dominated by information with respect to "fundamental" credit quality, captured reasonably well by Merton's DM.

Post 2018Q2, SOEs and non-SOEs are divided not only in the level of credit pricing (i.e., the explosive SOE premium), but also in the content of price discovery. From 2018Q2 to 2020Q2, under the heightened concern over default risk, credit spreads of non-SOEs become significantly more sensitive to the fundamental credit quality as captured by Merton's DM. Specifically, the economic significance of Merton's DM increases from the previous 24 bps to 79 bps for the non-SOE sample, but decreases slightly from 23 bps to 20 bps for the SOE sample. Indeed, with government support to help alleviate the increased liquidity-driven default, the emerging concern within the SOE sample is not the firm's health but the extent of its government support. Accordingly, using our DM to explain the credit spreads of SOEs, the economic significance more than doubles from the previous 23 bps to 51 bps, which is to be contrasted with the lack of improvement of Merton's DM in explaining the SOE sample. Moreover, our unified DM also outperforms Merton's DM in explaining the credit spreads for the non-SOE sample and the economic significance improves from the previous 24 bps to 105 bps, reflecting the value of our model's unified approach.

Empirical Evidences on the Real Impact – The rapid widening of the SOE premium reflects the worsening credit condition faced by non-SOEs in the broader economy. Examining its real impact, we compared the relative performance between SOEs and non-SOEs before and after the 2018 credit tightening, and find a rapid performance deterioration of non-SOEs relative SOEs. Prior to 2018, consistent with the common perception that non-SOEs in China are more efficient than SOEs, the performance gap in quarterly return on asset (ROA) between non-SOEs and SOEs oscillates around an average level of 0.55% and remains significantly positive. Post 2018, driven by the severe performance deterioration of non-SOEs, this performance gap collapses precipitously and becomes indistinguishable from zero.

We further explain the performance deterioration of non-SOEs using the firm-level credit deterioration, measured as the change in the default measure, ΔDM, realized at the event quarter of 2018Q2. Measuring the post-event change in performance, ΔROA, by the difference between the post-event quarterly ROA and its pre-event average, we use ΔDM to predict ΔROA and find that, within the non-SOE sample, credit deterioration in 2018Q2 indeed leads to subsequent performance deterioration. Associated with one standard deviation increase of ΔDM at 2018Q2, the subsequent performance deterioration averaged over the first two quarters after 2018Q2 is 0.35%. Importantly, this credit channel is present only for the non-SOE sample, as we do not find strong evidence of predictability for the SOE sample. Moreover, using Merton's DM instead of our unified DM, the predictability for the non-SOE sample also goes away, underscoring the importance of our model's mechanism in capturing the true extent of the cross-sectional credit deterioration.

Taking advantage of the informativeness of ΔDM, we further sort all firms, SOEs and non-SOEs, by their ΔDM at 2018Q2 into two groups. Firms in the high group are faced with worsening credit conditions in 2018Q2, while those in the low group are less affected. Interestingly, we find significant performance deterioration of non-SOEs relative to SOEs in both groups, with 0.77% for the high group and 0.40% for the low group. The fact that the less-affected group, as measured by our DM, exhibits a significantly lower relative performance deterioration of 0.40% is consistent with our hypothesis that credit deterioration of non-SOEs contributes to their performance deterioration. But the fact that even the less-affected non-SOEs also underperform relative to their SOE counterparts indicates that the disadvantage faced by non-SOEs goes beyond the credit channel.

Relative to our main hypothesis, we consider two alternative explanations, which attribute the underperformance of non-SOEs to their own vulnerability that is unrelated to the lack of government support. First, the US-China trade war, which begins in March 2018, affects the non-SOEs more severely than SOEs, causing the performance deterioration of non-SOEs relative to SOEs. Second, SOEs can better withstand the 2018 credit tightening because the government-mandated SOE deleveraging in 2016-17 helps strengthen their balance sheet relative to non-SOEs. Using sorting variables motivated by these two alternative hypotheses, we do not find strong evidence that the cross-sectional variation along these dimensions can explain the post-event performance deterioration of non-SOEs relative to SOEs, contrary to the predictive results obtained using our model-implied DM.

Related Literature – Our paper is motivated by the literature on the SOE-related credit misallocation and its impact on China's growth (Dollar and Wei (2007), Hsieh and Klenow (2009), Brandt and Zhu (2000), Song, Storesletten, and Zilibotti (2011), and Lardy (2019)).[5] Relative to this literature, which has so far been focused on the SOEs' preferential access to bank loans, our paper is the first to approach the problem using pricing information from the credit market. Unencumbered by the opaqueness associated with the distributions of bank loans, we are able to uncover with precision and speed the relative credit allocation between SOEs and non-SOEs in China. For policymakers in China, our empirical findings should be informative and alarming, as the explosive SOE premium documented in our paper could have a destabilizing effect on China's credit market and the rapid performance deterioration of non-SOEs relative to SOEs calls for a better balance between the two indispensable segments of the economy.[6]

Our paper contributes to the asset-pricing literature as the first comprehensive study on the information content of credit spreads in China. For the U.S. market, the link between credit spreads and credit quality has been well established (Collin-Dufresne, Goldstein, and Martin (2001), Campbell and Taksler (2003), Bao (2009), and Bao, Pan, and Wang (2011)). For the Chinese market, however, this topic has not yet been systematically studied, and our paper fills the gap. By incorporating bailout probability into the structural default model of He and Xiong (2012) and taking the unified model to the data, our paper is also the first comprehensive empirical study on a structural model that unifies credit risk, liquidity, and bailout.[7] Unlike the commonly practiced reduced-form approach, which introduces liquidity or bailout as additional explanatory variables, outside of the credit risk, we take a unified approach by capturing the interactions of these components using our model-implied DM.

Our paper is also related to the literature studying the asset-pricing implications of the

[5]Bai, Hsieh, and Song (2020) examine how "special deals" for favored private firms in resource allocation can contribute to China's growth. Bai et al. (2020) show how the "connected" investors may increase the aggregate output of the private sector. Cong et al. (2019) show that the stimulus-driven credit expansion of 2009-2010 disproportionately favors SOEs. Huang, Pagano, and Panizza (2020) study how local public debt can crowd out the investment of private firms while leaving SOEs unaffected. Li, Wang, and Zhou (2021) find that China's recent anti-corruption campaign helps credit reallocation from SOEs to non-SOEs. Chen et al. (2023) study the impact of the 2009 stimulus and its interaction with infrastructure spending on credit allocation. Whited and Zhao (2021) estimate the real losses arising from the cross-sectional misallocation of financial liabilities. Other related studies include Chen et al. (2015) and Belo et al. (2022).

[6]In examining the SOE and non-SOE tension, our paper is also related to Caballero, Hoshi, and Kashyap (2008), who documented how the bailout of zombie firms can cause congestion and hurt non-zombie firms. In our paper, the tension arises out of the perceived government support for SOEs during government-led credit tightening. Akin to the congestion story, the otherwise healthy non-SOEs are hurt because of the congestion in the credit market, while the SOEs with weaker "fundamental" credit quality remained intact.

[7]Huang, Nozawa, and Shi (2022) study the global credit spread puzzle using an extended structural model that incorporates endogenous liquidity.

presence of government support. Focusing on the impact of Lehman's default, Berndt, Duffie, and Zhu (2019) document large post-Lehman reductions in market-implied probabilities of government bailout and significant increases in U.S. banks' debt financing costs. Balasubramnian and Cyree (2011) examine the emergence of too-big-to-fail after the 1998 LTCM bailout. Kelly, Lustig, and Nieuwerburgh (2016) document the extent of too-big-to-fail during the 2008 crisis using the pricing difference between put options on the financial sector and those on individual banks. Related to this literature, we document the emerging importance of government support in driving the SOE premium and make the important observation that the value of government support increases during a liquidity crisis, deepening the SOE premium.[8]

Finally, our paper is part of the emerging literature on the Chinese credit market.[9] Studying the value of the implicit government guarantee, Jin, Wang, and Zhang (2023) focus on the first large SOE default in 2015, and Ang, Bai, and Zhou (2023) and Liu, Lyu, and Yu (2021) on China's Chengtou bonds. Chen, He, and Liu (2020) study the link between the growth of Chengtou bonds and the 2009 stimulus package in China.

The rest of our paper is organized as follows. Section 2 provides background information on China's credit market and documents the SOE premium. Section 3 presents a unified theoretical framework by incorporating government bailout into the structural model of He and Xiong (2012). Section 4 constructs our model-implied default measure and uses it to study our model's implication on credit pricing. Section 5 examines the real impact. Section 6 concludes. Further details are provided in an Internet Appendix.

2 China's Credit Market and the SOE Premium

2.1 China's Credit Market and Our Data Sample

The emergence of China's credit market is a recent phenomenon. From 2008 through 2020, domestic debt securities issued by China's non-financial companies increased by $4.3 trillion,

[8]Associated with the presence of government support is the moral hazard issue for the SOEs in China. Within the U.S. context, Kacperczyk and Schnabl (2013) document that money market funds supported by their sponsors took on more risk. In our sample, we find that the leverage and fundamental risk (Merton's DM) of SOEs remain stable two years before and after the 2018 New Regulations.

[9]For overviews on the Chinese credit market, see Hu, Pan, and Wang (2021) and Amstad and He (2019). Recent empirical studies include Mo and Subrahmanyam (2020) on credit bond liquidity, Chen et al. (2023) on the value of pledgeability in Chinese corporate bonds, Liu et al. (2019) on the pricing implications of yield-chasing retail investors, Ding, Xiong, and Zhang (2022) on the issuance overpricing of Chinese corporate bonds, Gao et al. (2015) on the determinants of loan defaults, Huang, Liu, and Shi (2022) on the determinants of short-term credit spreads, Gao, Huang, and Mo (2022) on the effect of credit enhancement on bond pricing.

from a negligible level in 2008 to \$4.5 trillion in 2020, second only to the U.S. For the bank-dominated financial system in China, the presence of this market-based credit channel has opened a new channel of debt financing that is cheaper and more efficient than traditional bank loans. Indeed, for non-financial firms in China, the emergence of this onshore market has increased their average ratio of market-based debt to bank debt from 3.8% in 2008 to 21.6% in 2020. 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.

In this paper, we focus our analysis on corporate bonds in China. Similar in structure to their counterparts in the U.S., corporate bonds in China are of three types: the medium-term notes account for the largest fraction and are traded in the inter-bank market, the corporate bonds are the second largest and are exchange traded, and the enterprise bonds, traded in both markets, account for only a very small portion of our listed sample. Focusing on the divide between SOEs and non-SOEs, we further identify the bond issuer via the NSOE dummy, which equals one for non-SOEs and zero otherwise. Though our sample includes bonds issued by listed and unlisted firms, our empirical analyses focus mostly on the publicly listed SOE and non-SOE firms, which are larger and more important to the economy and whose financial statements and equity market information help us measure their credit quality and the potential government support. Because of space limitations, we provide a brief summary of our data as follows. Further details of our data can be found in an Internet Appendix.

We obtain our data on bond and equity pricing and collect the issuer-level balance-sheet information from Wind, a Shanghai-based data service. For the purpose of studying credit pricing, we construct a sample of bonds issued by SOE and non-SOE firms with actively traded stocks and corporate bonds as follows. We include fixed-rate bonds issued by non-financial firms and exclude bonds with maturity less than one year, bonds whose issuer has less than 10 trading days in the equity market during a quarter or has missing financial statements during a quarter, sinkable bonds and defaulted bonds.[10] To prevent potential data errors or outliers from driving our results, we also take the conservative treatment by

[10]We exclude defaulted bonds and other bonds issued by the same defaulting firms starting from the quarter before the actual default date. Our results would otherwise be stronger, as this conservative treatment effectively takes out a few extremely high yields that occur before the actual default dates. Given the limited number of defaulted issuers in our sample, 28 listed non-SOE and 2 listed SOE issuers, the actual effect of this treatment on our results is mostly negligible.

winsorizing the credit spreads at lower 0.5% and upper 99.5% of the sample.

We choose our sample period to start from January 1, 2010 through June 30, 2020. Prior to 2010, the credit market in China is not developed enough to have adequate numbers of non-SOE issuers for our empirical analysis. We further separate our time period into three phases by two landmark events in China's credit market: the first ever default happened on March 4, 2014 and the "New Regulations on Asset Management" released on April 27, 2018. Accordingly, Phase I, from 2010Q1 to 2013Q4, covers the pre-default period; Phase II, from 2014Q1 to 2018Q1, captures the first wave of defaults, which occurred mostly to unlisted firms in industries suffering from overcapacity; and Phase III, from 2018Q2 to 2020Q2, covers post-regulations period, when the second and much more severe wave of defaults occurred, mostly to non-SOE issuers.

Our bond-level data are summarized in the top panel of Table 1, consisting of quarterly bond prices, bond characteristics, and bond trading information. For pricing data, we compute quarterly yield to maturity for each bond using its last transaction price of the quarter. Following the convention in the market, we use the Chinese Development Bank (CDB) bonds as the reference curve and calculate the credit spread as the difference between the corporate bond yield and CDB yield of the same maturity. For credit ratings, we merge our sample with the rating dataset of Wind, which updates changes in rating by the major rating agencies in China. We convert letter grades into numerical numbers 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-. Compared with the non-SOE bonds, the SOE bonds in general have higher ratings, larger issuance size, and are of longer maturity, older in age, and lower in coupon rate.

A non-trivial amount of corporate bonds in China are issued with embedded optionality, with call and put provisions being the two most common features. Puttable bonds give investors the option to sell back the bond at its face value at specified dates before maturity, making the bond more expensive and lowering its yield, while callable bonds give the issuer the option. Upon exercising the puttable or callable option, the issuer usually can further modify the coupon rate within a pre-set range to make the bonds less or more attractive. As non-SOEs are more prone to issuing puttable bonds, the presence of this optionality would in theory decrease the credit spreads for non-SOEs, lowering the estimated SOE premium and biasing against our findings. Our empirical estimation adjusts for this optionality by assigning Puttable and Callable dummies to the respective bonds.[11]

[11]Within our sample, we find 14.6% of medium-term notes (MTNs) are callable and 9.3% puttable, and SOEs bonds account for 84.2% of the callable MTNs and 54.2% puttable MTNs. For the exchange-traded corporate bonds, we find 2.4% callable and 62.0% puttable, and non-SOE bonds account for 58.3% of the

Another unique feature in China's bond market is the equal importance of the inter-bank market and exchanges as trading venues, with the former populated by large institutional investors and the latter by small and medium-size investors. Unlike the US corporate bond market, which is dominated by over-the-counter trading, both the exchanges and inter-bank market claim significant market share in bond trading. We use the dummy variable Exch to indicate whether the observed bond price is from exchange trading to control for the potential differences in investor behavior and regulatory authorities between these two markets. Finally, we report the bond trading variables to reflect the overall liquidity condition of the market. For example, TradingDays counts the number of trading days per quarter. Similar to the US market, corporate bonds are on average infrequently traded. As shown in Table 1, the average number of trading days per quarter is 15 for listed non-SOE and 10 for listed SOE. Relative to non-SOEs, SOE bonds are less frequently traded but with higher turnover.

The issuer-level equity information is summarized in the bottom panel of Table 1. For each of the 365 non-SOE and 401 SOE firms in our sample, we report the total market value of its equity in logarithm under EquitySize. We further report there important inputs used to measure the credit quality of a firm. We use daily stock returns within each quarter to measure quarterly equity volatility. To calculate firm leverage, we collect information on the firm's short- and long-term liabilities and its book value of asset from the quarterly financial statements. Leverage is calculated as the ratio of the total current liabilities plus the total non-current liabilities to the total asset value. The quarterly asset growth is computed as the growth rate of the asset value averaged over the past three years. Compared with non-SOE firms, SOEs on average have larger equity size, lower equity volatility, higher leverage and smaller asset growth than non-SOEs.

2.2 The SOE Premium in China's Credit Market

We measure the SOE premium by estimating the difference in credit spreads between a non-SOE and SOE bond after controlling for their credit ratings and other bond and equity characteristics. Using the credit spread of bond i in quarter t, we perform the quarterly panel regression:

$$\text{CreditSpread}_{i,t} = a + b^{\text{NSOE}}\,\text{NSOE}_{i,t} + c\,\text{Rating}_{i,t} + \sum\nolimits_k \text{Controls}^k_{i,t} + \epsilon_{i,t}\,, \tag{1}$$

where the quarterly updated NSOE dummy equals one for non-SOE issuers and zero for

puttable. As SOEs issue more callable bonds with negative option values for investors, while non-SOEs issue more puttable bonds with positive option values for investors, adjusting for this optionality would on average decrease the credit spreads for SOEs and increase those for non-SOEs, further widening the SOE premium.

SOEs, and the corresponding regression coefficient b^{NSOE} measures the SOE premium. Besides credit ratings, the additional control variables include bond maturity, issuance size, age, exchange market dummy, optionality, liquidity, and log of equity sizes for listed firms. We further include quarter fixed effect and industry fixed effect to control for potential market-wide fluctuations and industry differences in credit spreads.

The regression results are summarized in Table 2, with t-stat's reported in squared brackets, using standard errors double clustered by quarter and bond to take into account of cross-sectional as well as time-series correlations in credit spreads. Before 2018Q2, the SOE premium for the listed sample is estimated at 20 bps (t-stat=2.97) and 27 bps (t-stat=4.28) in Phase I and II, respectively. Controlling for credit rating and other bond characteristics and firm size, the SOE issuers on average enjoy a premium of about 20 bps over their non-SOE counterparts. As one notch improvement in credit rating is associated with a reduction in credit spread of around 50 bps during this time period, this difference in financing cost between non-SOEs and SOEs is economically significant. The top panel of Figure 1 further reports the time-series of the SOE premium at the quarterly frequency. Prior to 2018Q2, the SOE premium fluctuates around 20 bps and stays mostly below 50 bps, and the first default in 2014Q1 does not seem to have any significant adverse effect on the SOE premium. Table 2 also reports the SOE premium for bonds issued by unlisted firms: 25 bps in Phase I, 91 bps in Phase II, and 181 bps in Phase III. Compared with the listed sample, the SOE premium for the unlisted firms starts to increase during Phase II, after the first default in 2014, consistent with the fact that the first wave of defaults occurs mostly for unlisted firms.

Post 2018Q2, the SOE premium explodes rather suddenly and the average SOE premium increases to 113 bps (t-stat=7.76) in Phase III, equivalent to the full-sample difference in credit spread between a top-notch AAA-rated bond and a speculative-grade AA-rated bond. As shown in the top panel of Figure 1, over just one quarter, the SOE premium rises sharply from 28 bps in 2018Q1 to an unprecedented 98 bps in 2018Q2. Behind this dramatic explosion in SOE premium is the fast deteriorating credit-market conditions for non-SOE issuers. As shown in Table 1, without any controls, the average credit spread for non-SOE issuers is 203 bps and 204 bps in Phases I and II, respectively. It then jumps to 354 bps in Phase III. By contrast, the average credit spread for SOE issuers has relatively modest increases over the three phases: 121 bps, 132 bps, and 170 bps, respectively. Since November 2018, recognizing the adverse effects on the private sector, the Chinese government at various levels offer reassurances and devise policies to support the private sector, but the SOE premium, or the non-SOE discount, deteriorates further, peaking at 154 bps in 2019Q3. It has since come down to below 100 bps and is at 93 bps in 2020Q2.

Also plotted in the background of the top panel of Figure 1 are the total quarterly default amounts in the credit market. Prior to 2014Q1, China's credit market is free of default events, confirming the deep-rooted belief that debt investors will always be bailed out. The first ever default in 2014 marks the beginning of an erosion to this strongly held belief.[12] The first wave of defaults occurs around 2016Q1 and mostly to unlisted issuers, with quarterly default amounts ranging from less than RMB 1 billion to 12.2 billion, small compared with the total amount of RMB 16.1 trillion of the credit market in 2016. From 2015Q2 to 2016Q3, the unlisted SOEs are affected more severely than unlisted non-SOEs, particularly for the unlisted SOEs in overcapacity industries. Starting from 2016Q4, the total amount of default in the credit market lessens, and the fraction of unlisted SOE defaults reduced rather dramatically, from 83% in 2016Q3 to 10% one quarter later in 2016Q4. From that point on, the non-SOEs take most of the blunt.

2.3 Credit Tightening and Liquidity Deterioration

In China, non-financial firms have access to three interconnected debt-financing channels: bank loans, credit market, and shadow banking. Relative to the opaque bank loans that dominate the financial system in China, the emergence of the credit market has opened a new channel of debt financing that is cheaper, more transparent, and more efficiently allocated. For the asset-management industry in China, the growth of the credit market has also 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.

The 2018 New Regulations on Asset Management

The government-led credit tightening starts around 2017, driven by concerns over unsustainable debt burdens fueled by the rapid expansion of the shadow banking sector. Estimated by Moody's Quarterly China Shadow Banking Monitor, the size of the shadow banking stood at 64.5 trillion RMB by end-2016, of which 30.1 trillion are assets funded by the Wealth Management Product (WMP) and 19.5 trillion by entrusted and trusted loans. Such shadow banking players are also dominant in the corporate bond market, connecting the shadow

[12] The first ever default in China's credit market took place on March 4, 2014, when the privately-held publicly-listed solar equipment company, Shanghai Chaori Solar and Technology Co. Ltd (Chaori), was unable to meet the interest payment of 89.8 million RMB on its 1 billion exchange-traded bond. The Chaori default surprised the credit-market investors, who had previously believed that the government would step in to avert the default. Triggered by the Chaori default, the credit spreads of other low credit-quality bonds also increased significantly. Further details can be found in Amstad and He (2019).

banking sector to the credit market.

The "New Regulations on Asset Management" was announced in April 2018 with the primary purpose of restricting the sharp increase in the shadow banking sector and reducing systematic risk in the long run. The new rules force asset managers to adopt net-asset valuation and abandon amortized accounting, ban the practice of principal and return guarantees to fund investors, limit the scope of maturity mismatch of their assets and liabilities, forbid multi-tier nesting, fund pooling and channel business, and narrow the scope of qualified products and qualified investors. Although the target of the 2018 New Regulations was the asset-management industry in the shadow banking sector, the dominance of such players in the credit market means that the liquidity shock in the shadow banking sector gets transmitted to the credit market almost instantly.

The 2018 New Regulations affect bond market liquidity through both direct and indirect channels. In particular, by banning asset management products from investing in nonstandard assets, the new regulations can impact the firms (particularly non-SOEs) indirectly through their inability to roll over their debt in the shadow banking sector. Moreover, the new rules significantly reduce the attractiveness of the asset management products, limit the regulation-affected asset managers' capacity to delay the realization of market risk, and force them to value safety over yield. As a result, the fraction of holdings by regulation-affected asset managers in both the medium-term notes market and corporate bonds market decreases.[13] Given the transparency over the opaqueness of bank loans and shadow banking, the immediate liquidity impact of the 2018 government-led credit tightening is felt and observed most visibly in the credit market. In other words, although our empirical evidences are focused on the credit market, the inter-connectedness of the three credit channels means that the government-led tightening brought on by the 2018 New Regulations affects the credit and liquidity conditions of the entire economy.

Bond Liquidity, Issuance, and Defaults after the 2018 New Regulations

To better understand the link between the liquidity shock triggered by the 2018 New Regulations and the post-2018Q2 explosion of the SOE premium, we work under the framework of He and Xiong (2012). A formal development of the model is to be presented in Section 3. Here in this section we map the key insight of their model to our setting and provide empirical evidences on corporate bond liquidity, issuance, and defaults surrounding the 2018 New

[13]By our estimation from Shanghai Clearing House and Shanghai Stock Exchange, the fraction of holdings by regulation-affected asset managers in medium-term notes increases from 22.7% in 2014 to the peak of 62.9% in 2017 and then decreases to 60.1% in 2018. The reduction is more severe in corporate bonds, decreasing from 47.0% in 2017 to 39.2% in 2018.

Regulations. As laid out in He and Xiong (2012), liquidity deterioration, increased rollover risk, and higher default rates are important mechanisms and implications of their model. We now provide related empirical evidence surrounding the 2018 New Regulations.

First, on liquidity, we use the price-based illiquidity measure proposed by Bao, Pan, and Wang (2011) and compute the monthly bond-level Gamma, which equals the negative of $\text{cov}(\Delta p_t, \Delta p_{t-1})$ with Δp_t being the day-t change of the log of end-of-day transaction prices. To estimate the monthly Gamma, we require the bond to have at least 10 pairs of Δp_t and Δp_{t-1} during a month and this filters out a large fraction of the bonds. As such, our estimated Gamma's are for the most liquid bonds in our sample. To further compare between SOEs and non-SOEs of similar ratings and maturity, we apply our calculations to a sub-sample with bond ratings between AA and AAA and maturity between 2 years to 5 years. For this sample of bonds, we find that, during Phase II, SOE and non-SOE bonds are of similar magnitude in Gamma with SOEs slightly less liquid than non-SOEs. Post 2018Q2, however, we observe a sharp increase in the illiquidity measure for both SOEs and non-SOEs, indicating an overall deterioration of the liquidity condition after the 2018 New Regulations. Moreover, the increase in Gamma is more prominent for non-SOEs relative to SOEs. As shown in panel (a) of Figure A.1, from Phase II to III, the average Gamma increases from 0.07 to 0.27 for non-SOEs, compared with an increase from 0.09 to 0.17 for non-SOEs, indicating that the post-2018Q2 liquidity worsens by a factor of 3.8 for non-SOEs and 1.9 for SOEs. Given that we are able to estimate the Gamma for the most liquid bonds in our sample, the situation for the other less liquid bonds would be even more severe.

As a less direct measure of liquidity, the trading activities summarized in Table 1 also offer consistent evidences. For example, the quarterly turnovers for both non-SOEs and SOEs drop from Phase II to III, but the reduced trading activity is more severe for the non-SOE bonds. Specifically, the average quarterly turnover is around 31% for both non-SOEs and SOEs in Phase II, and drops to 20% for non-SOEs and 27% for SOEs. Overall, our evidence suggests that the liquidity condition indeed deteriorates after the 2018 New Regulations and that deterioration is more severe for non-SOEs than SOEs.

Second, on rollover risk, we compare the amount of new issuance by SOEs and non-SOEs in the credit market. We find that the fraction of new issuance by non-SOEs drops significantly after the 2018 New Regulations, reflecting the increased difficulty for non-SOEs to issue new bonds to rollover over their existing debt. Focusing on the sub-sample of corporate bonds rated between AA and AAA, the fraction of new issuance by non-SOEs drops from 39.1% to 19.4%, when averaged over two years before and after 2018Q2. Panel (b) of Figure A.1 further shows the average difference in bond issuance size between non-SOEs and SOEs, which is estimated from the quarterly firm-level regression after controlling for size and industry. We can see a strong decreasing trend since the 2018 New Regulations. Meanwhile, the requirement on credit rating has also increased for new issuance. From Phase II to III, the average numerical rating at issuance decreases from 2.4 to 1.6 for non-SOEs and from 1.7 to 1.3 for SOEs. As lower numerical ratings translate to higher credit ratings, these changes indicate that some issuers have lost access to the corporate bond market in Phase III and this situation is more severe for non-SOEs. Overall, we see a pattern of reduced access to credit by non-SOEs in the corporate bond market after the 2018 New Regulations.

Third, on default amounts and default rate, we observed unprecedented defaults by non-SOEs starting from 2018Q3. The listed non-SOE issuers, who remain largely intact during the first wave around 2016Q1, are severely hit and account for 37% of the total default amount in the credit market in 2019Q4. Meanwhile, the magnitude of the default amount has also increased dramatically from RMB 14.4 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. We also compute the one-year default rates for our sample of bonds constructed for credit pricing. The default rate for listed non-SOE increased rapidly from less than 5 bps before 2018 to 35 bps in 2018Q2, while the average default rate for listed SOEs remains close to zero at around 2 bps.

Overall, the 2018 New Regulation had a profound effect on the corporate bond market. Consistent with the mechanism laid out in He and Xiong (2012), we observe worsening liquidity conditions, reduced access to the bond market, and increasing defaults. Important for our paper, these effects occur much more severely for non-SOEs than SOEs, reflecting the increased value of government support during a liquidity crisis. Just as in He and Xiong (2012), where the interaction between liquidity and credit risk highlights the role of short-term debt in exacerbating the rollover risk, in our paper, the interaction between the rollover risk and the potential of government bailout highlights the role of SOE bonds in alleviating liquidity-driven default.

3 The Model

3.1 A Model of Rollover Risk with Bailout

We work with a unified framework by incorporating government bailout into the structural model of He and Xiong (2012). Our setting follows directly that of He and Xiong (2012). For completeness, we provide a brief exposition of the model.

Firm Asset Process and Debt Structure

As in He and Xiong (2012), the firm's asset value V_t follows a geometric Brownian motion under the risk-neutral measure,

$$\frac{dV_t}{V_t} = (r - \delta)dt + \sigma dZ_t \tag{2}$$

where r is the risk-free rate, δ is the cash payout rate, σ is the asset volatility and Z_t is a standard Brownian motion. Following Leland and Toft (1996), the firm commits to a stationary debt structure (C, P, m), where m is the maturity of new debt continuously issued by the firm, P is the total principal of this continuum of bonds, and C is the total annual coupon. At any time t, the time-to-maturities of the bonds are uniformly distributed, as the firm issues new bonds to roll over the matured bond with a principal of $p = P/m$ and coupon payment of $c = C/m$ per year.

Liquidity Shock and Debt Rollover

Let $d(V_t, m)$ be the market price of a newly issued bond, which is used to replace the maturing bond with principal p. Depending on the liquidity condition in the secondary market, $d(V_t, m)$ can be different from p, and when $d(V_t, m) < p$, the firm incurs a rollover loss. He and Xiong (2012) model the secondary bond market liquidity condition via liquidity-shocked bond investors, each experiencing an idiosyncratic liquidity shock, whose arrival time is governed by a Poisson process with intensity ξ. Upon the arrival of the liquidity shock, the investor pays k fraction of the bond value as a cost.

The valuation of one unit of a bond with a time-to-maturity of $\tau < m$ follows the standard partial differential equation,

$$rd\left(V_t, \tau\right) = c - \xi k d\left(V_t, \tau\right) - \frac{\partial d\left(V_t, \tau\right)}{\partial \tau} + (r - \delta)V_t \frac{\partial d\left(V_t, \tau\right)}{\partial V} + \frac{1}{2}\sigma^2 V_t^2 \frac{\partial^2 d\left(V_t, \tau\right)}{\partial V^2}\,, \tag{3}$$

where $rd(V_t, \tau)$ is the required bond return, on the right-hand side, c is the coupon payment, $\xi k\, d(V_t, \tau)$ is the loss due to the liquidity shock. The last three terms are the usual infinitesimal generator for V.

Taking the firm's default boundary V_B as given, the bond price can be solved via the following two boundary conditions. Conditioning on survival,

$$d(V_t, 0; V_B) = p\,,\ \text{for all}\, V_t > V_B\,. \tag{4}$$

Conditioning on defaulting at time τ to maturity and assuming a recovery rate α,

$$d(V_B, \tau; V_B) = \frac{\alpha V_B}{m}\,. \tag{5}$$

Government Bailout

Relative to the original setup of He and Xiong (2012), we modify their boundary condition in equation (5) by

$$d\left(V_B, \tau, \pi_g; V_B\right) = \frac{\alpha V_B}{m}(1-\pi_g) + \frac{P}{m}\pi_g\,, \tag{6}$$

where we assume that, conditioning on default at $\tau \in [0, m]$, the government will step in with a risk-neutral probability π_g, and in the event of a bailout, the government helps the firm pay back the principal in full to the bondholders, avoiding any deadweight loss.[14] Our bailout specification is similar to that in Berndt, Duffie, and Zhu (2019) except that we do not consider future bailouts of the same firm.[15]

With the introduction of government bailout in equation (6), we can differentiate SOEs from non-SOEs by considering two firms with different bailout probability π_g. For non-SOEs, we assume that π_g is always zero, reducing them to the setting studied in He and Xiong (2012). For SOEs, the bailout probability π_g is always non-zero and the varying magnitude of π_g can be used to model SOEs with varying degrees of government support. Following He and Xiong (2012), for a given value of V_B, we can solve the bond value from equation (3) with boundary conditions (4) and (6).

Endogenous Default Boundary and the SOE Premium

To solve for the endogenous default boundary V_B, we need to calculate the value for the equity holders. Due to the liquidity shock in the secondary bond market, the newly issued bond can be traded at a price lower than p and the equity holders have to issue additional equity to bear the rollover loss. As a result, the rollover loss enters into the equity value, affecting the equity holders' decision on default. Default happens when the equity value

[14]The case of Qinghai Salt Lake Industry (QHSL) constitutes an illustrative example of government bailing out an SOE. Starting from September 30, 2019, QHSL, a listed SOE held by the State-owned Assets Supervision and Administration (SASAC) of Qinghai Province, defaulted on its RMB 6.174 billion medium-term notes and corporate bonds. With the help of the local government, the restructuring plan was quickly approved by the court on April 20, 2020. The recovery rate for the bondholders was 100% if choosing to roll over the debt over 5 years, which is much higher than the estimated recovery rate (38.51%) under liquidation. The stock price of QHSL increased from 7.66 at the default date to 35.90 after restructuring and resumption.

[15]Berndt, Duffie, and Zhu (2019) considers all the future potential bailouts after the first bailout. They show that one-half to two-thirds of the market value of future bailout subsidies is associated with the first potential bailout. The results would be qualitatively similar if we add future bailouts into the model. As the main purpose of our model is to illustrate the basic mechanism in generating the SOE premium, we do not consider the dynasty of the bailout for simplicity.

drops to 0 and the equity holders walk away from further servicing the debt. Letting $E(V_t)$ be the equity value, default happens when $E(V_B) = 0$. Following He and Xiong (2012), the partial differential equation for the equity valuation is given by

$$rE = (r-\delta)V_t E_V + \frac{1}{2}\sigma^2 V_t^2 E_{VV} + \delta V_t - (1-\pi)C + d(V_t, m, \pi_g) - p\,, \tag{7}$$

where rE is the required equity return, and on the right-hand side, the first two terms are the expected equity value change with respect to the dynamics of asset value, δV_t is the firm's cash flow, and $(1-\pi)C$ is the after-tax coupon payment. Lastly and most importantly, $d(V_t, m, \pi_g) - p$ is the rollover gain/loss borne by the equity holders.

As discussed in He and Xiong (2012), solving the equity value from equation (7) is challenging because it further involves the bond valuation function $d(V_t, m)$, to be solved from equation (3), given default boundary V_B. Luckily, our modification of He and Xiong (2012) does not alter their solution method and, following the derivations in their appendix, we solve the equity value from equation (7) with the boundary conditions. The endogenous default boundary V_B can be solved from the smooth pasting condition $E'(V_B) = 0$. Plug V_B into the bond-pricing equation (3), we obtain a closed-form solution for bond value $d(V_t, m, \pi_g)$. The corresponding yield $y(\pi_g)$ for a bond with π_g is given by

$$d(V_t, m, \pi_g) = \frac{c}{y(\pi_g)}\left(1 - e^{-y(\pi_g)m}\right) + p\,e^{-y(\pi_g)m}\,. \tag{8}$$

Consider two bonds with identical debt structure, except one is issued by an SOE with bailout probability $\pi_g > 0$ and the other issued by a non-SOE with $\pi_g = 0$. The SOE premium is defined as the difference between their yields.

Proposition 1. *The SOE premium (SOEP) is defined as*

$$SOEP = y(0) - y(\pi_g), \tag{9}$$

where $y(\pi_g)$ is solved based on equation (3), (4), (6) and (8) and the endogenous bankruptcy boundary $V_B(\pi_g)$ is given by

$$V_B(\pi_g) = \frac{\frac{(1-\pi)C + \left(1-e^{-(r+\xi k)m}\right)(p - \frac{c}{r+\xi k})}{\eta} + (p - \frac{c}{r+\xi k})[b(-a)+b(a)] + (\frac{c}{r+\xi k} - p\pi_g)[(B(-\widehat{z}) + B(\widehat{z})]}{\frac{\delta}{\eta-1} + \frac{\alpha}{m}[B(-\widehat{z}) + B(\widehat{z})](1-\pi_g)},$$

$$\text{where } a \equiv \frac{r-\delta-\sigma^2/2}{\sigma^2}, z \equiv \frac{\left(a^2\sigma^4 + 2r\sigma^2\right)^{1/2}}{\sigma^2}, \eta \equiv z - a > 1, \widehat{z} \equiv \frac{\left[a^2\sigma^4 + 2(r+\xi k)\sigma^2\right]^{1/2}}{\sigma^2},$$

$$b(x) = \frac{1}{z+x}e^{-(r+\xi k)m}\left[N(x\sigma\sqrt{m}) - e^{rm}N(-z\sigma\sqrt{m})\right],$$

$$B(x) = \frac{1}{z+x}\left[N(x\sigma\sqrt{m}) - e^{\frac{1}{2}\left[z^2-x^2\right]\sigma^2 m}N(-z\sigma\sqrt{m})\right].$$

Central to the key determinants of the SOE premium is the interaction between government bailout and liquidity-driven credit risk (i.e., rollover risk). As shown in He and Xiong (2012), over time, rollover risk increases with deteriorating liquidity condition (i.e., higher ξ); across bonds, rollover risk heightens for those with shorter maturities (i.e., lower m). Adding bailout probability π_g to this setting, we introduce a new form of cross-issuer variation that is unique to China's credit market. Under our model, SOE issuers with positive bailout probability π_g are safer, with lower default probability, than non-SOE issuers with $\pi_g = 0$. And the value of that safety can be measured directly from the corporate bond market via the SOE premium. As the liquidity condition deteriorates with increasing ξ, government bailout becomes more valuable in alleviating the heightened rollover risk, and the SOE premium increases accordingly.

3.2 Model Calibration

To illustrate numerically how the interaction between bailout probability and liquidity shock affects bond pricing and the SOE premium, we calibrate our model by adopting the calibration parameters from He and Xiong (2012), with minor adjustments to match our sample. A more comprehensive estimation of our model will be carried out in Section 4.

For the general environment, we set the risk-free rate $r = 4\%$ and the tax rate $\tau = 25\%$. At the firm level, we set the bond recovery rate given default $\alpha = 50\%$, the payout rate $\delta = 1\%$, and the asset volatility $\sigma = 15\%$, estimated from Table 1. For bond market liquidity, we set the transaction cost parameter $k = 1.0\%$ and the liquidity shock intensity parameter $\xi = 1$. For debt structure, we set the bond maturity $m = 1$, the current firm fundamental value $V_0 = 100$, annual coupon payment $C = 2.68$, and the average bond principal $P = 51.30$. With this set of baseline parameters, the one-year newly issued par bonds have a credit spread of 150 bps under the He and Xiong (2012) model, equivalent to a non-SOE bond with bailout probability $\pi_g = 0$.

While the effect of the liquidity-driven default has been well documented in He and Xiong (2012), what is new in our model is the interaction between bailout and the liquidity-driven default. Fixing the model at its baseline parameters, we vary the two key parameters of our model, bailout probability π_g and the liquidity shock intensity ξ, and report the credit spread in the top panel and the SOE premium in the bottom panel of Figure 2. Consistent with our intuition, credit spreads decrease in bailout probability π_g and increase in the liquidity shock intensity ξ. More importantly, the sensitivity of credit spread to bailout probability π_g is mild for small ξ, but increases rather dramatically with an increasing ξ. As shown in the top panel, with $\xi = 2$, the convex relation between credit spread and bailout is especially prominent near $\pi_g = 0$. Mapping this observation to our setting, non-SOEs with $\pi_g = 0$ and SOEs with positive π_g, we see that, as the overall liquidity condition deteriorates with ξ moving toward 2, the credit spread of non-SOE and SOE bonds both increases. But the non-linear interaction between ξ and π_g means that the credit spread of the non-SOE bond increases much more severely, giving rise to the explosive SOE premium.

The same observation can be made in Panel A of Table 3, where we report the credit spreads for bonds issued by firms with varying π_g. Focusing on the non-SOE bond with $\pi_g = 0$ and the SOE bond with $\pi_g = 0.6$, we see that, when $\xi = 1$, the credit spread is 150 bps for non-SOE and 100 bps for SOE. The corresponding SOE premium is 50 bps, as reported in Panel B of the same table. Increasing ξ from 1 to 2, the credit spread increases to 312 bps for non-SOE and 201 bps for SOE, resulting in an SOE premium of 111 bps at $\xi = 2$, which more than doubles the SOE premium at $\xi = 1$. It should be emphasized that, in our current model calibration, as well as in the later empirical estimation, we set the same liquidity parameter for the non-SOE and SOE bonds. As such, the impact of illiquidity does not enter directly into the SOE premium. Instead, the result of increasing SOE premium with increasing ξ is driven by the interaction between bailout probability and liquidity-driven default risk, demonstrating the key mechanism of our model. Hit by the same liquidity shock, non-SOEs differ from SOEs in that, without government bailout, they are more vulnerable to the increased liquidity-driven default. Conversely, government support helps alleviate the rollover risk for SOEs, making them safer. In the extreme case when $\pi_g = 1$, there will be no liquidity-driven default because the government will always bail out the firm no matter how much the ξ is. In this case, the sensitivity of credit spreads on ξ will only rely on the pure liquidity channel.

The impact of the bailout probability on the liquidity-drive default is further shown in Panel C of Table 3, which reports the model-implied one-year default probability for varying bailout probability π_g. In calculating the actual default rate, we set the asset growth under the actual probability measure to $\mu = 15\%$ following Table 1. Demonstrating the liquidity-driven default of He and Xiong (2012), increasing ξ heightens the one-year default rate for both SOEs and non-SOEs. Reflecting the interaction between bailout and the liquidity-driven default, we find that the one-year default rate of the non-SOE bond increases much more precipitously with increasing ξ than that of the SOE bond.

Panel D of Table 3 shows how the maturity m affects the SOE premium. For brevity, we fix the bailout probability to be 0.6 for the SOE bond and 0 for the non-SOE bond. When $\xi = 1$, we can see that the SOE premium decreases as maturity increases, implying that the SOE premium is more prominent when the rollover pressure is higher. More importantly, the difference in the SOE premium (or multiplier) between a high-ξ case ($\xi = 2$) and a low-ξ

one ($\xi = 1$) also becomes larger when the maturity m decreases (i.e., the rollover pressure increases). In other words, our results become more significant when the rollover risk is higher, consistent with the main intuition in He and Xiong (2012).

Moving away from the region of $\pi_g = 0$, which differentiates non-SOEs from SOEs, our model has implications for the credit pricing among the SOEs with $\pi_g > 0$. As illustrated by the bottom panel of Figure 2, under the same ξ, the sensitivity of the SOE premium to π_g eventually tapers off when π_g gets close to 1. For low ξ, that transition occurs close to $\pi_g = 0$, indicating that the value of government support can be proxied by a zero-one variable, akin to our non-SOE dummy. Effectively, when ξ is low, the deciding factor is whether or not the firm has government support. But as ξ increases, that transition point moves further away from $\pi_g = 0$. For example, fixing $\xi = 2$, the SOE premium increases rather rapidly within the range of $\pi_g \in [0, 0.4]$ and then tapers off. This implies that, as ξ increases, whether or not a firm has government support (i.e., the SOE dummy) is not sufficient information to determine the magnitude of its SOE premium. Instead, the extent of the government support (i.e., the actual magnitude of π_g) becomes important in determining the SOE premium. This observation turns out to be important as we apply our model empirically to study the price discovery for SOE bonds, before and after the 2018 New Regulations.

4 Empirical Tests on Credit Pricing

This section takes our model to the data by first constructing our model-implied default measure, which unifies the three components of our model, namely credit, liquidity, and government support, into one single measure. We then examine our model's implication on credit pricing, including explaining the SOE premium and studying the price discovery.

4.1 The Model-Implied Default Measures

Proposed by Merton (1974) and popularized by Moody's KMV, the concept of distance-to-default evaluates, in unit of standard deviation, the distance between a firm's current asset value and its default boundary. Guided by structural models of default, it is an effective and disciplined way to measure the issuer-level credit quality. In our empirical study, we use default measure (DM), which is the inverse of the distance-to-default (DD). A firm with a higher default measure is closer to its default boundary and more likely to default.[16]

[16] Distance-to-default can be further translated to default probability. Under most of the structural models of default, however, that transformation flattens out much of cross-issuer variation in distance-to-default. For this reason, we use the model-implied default measure instead of model-implied probability of default for our empirical tests.

At each quarter t and for each issuer i, the empirical construction of $\mathrm{DM}_{t,i}$ feeds the model firm-i's balance sheet and equity information in quarter t, and then brings back the model-implied default measure. We start our exposition with Merton's DM, and then move on to construct the DM implied by our model, incorporating the issuer-level government support (i.e., π_g) and the economy-wide liquidity condition (i.e., ξ). We refer to it as a unified default measure, as it combines information on credit, liquidity, and government support into one single measure.

Merton's Default Measure

Within the structural model of Merton (1974), the one-year distance-to-default under the actual probability measure is

$$\mathrm{DD}_t^{\mathrm{Merton}} = \frac{\ln(V_t/K) + (\mu - \sigma_A^2/2)}{\sigma_A}\,; \quad \mathrm{DM}_t^{\mathrm{Merton}} = \left(\mathrm{DD}_t^{\mathrm{Merton}}\right)^{-1}\,, \tag{10}$$

where V_t is the time-t asset value of the firm, μ is its asset growth, σ_A is its asset volatility, and K is its default boundary. Under Merton's model, default boundary is an exogenous concept, equaling to the face value of the firm's debt outstanding. Although it is the risk-neutral distance-to-default that matters for credit price (i.e., replace μ by r), we follow the convention by incorporating the issuer-level asset growth μ into the default measure. Empirically, we find the asset growth to be informative in cross-sectional credit pricing.

Following 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,

$$E_t = V_t\, N(d_1) - e^{rT}\, K N(d_2)\,; \quad \sigma_E = \frac{V}{E}\frac{\partial E}{\partial V}\sigma_A\,, \tag{11}$$

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, with T capturing the time-horizon of interest,

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

Throughout the paper, we fix $T = 1$ to focus on the default measure over a one-year horizon.

For each quarter, we use the average growth rate of the asset value in the past three years to estimate μ, the default boundary K equals the firm's current liabilities plus one half of its long-term liability, the firm's equity value equals the firm's market capitalization, calculated 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, we estimate the quarterly asset value V and asset volatility σ_A from equations (11) and compute the quarter-t default measure by equation (10).

Unified Default Measure

Under our model specified in Section 3.1, the one-year risk-neutral distance-to-default is

$$\mathrm{DD}_t^{\text{Unified}} = \frac{\ln(V_t/V_B)}{\sigma_A}; \quad \mathrm{DM}_t^{\text{Unified}} = \left(\mathrm{DD}_t^{\text{Unified}}\right)^{-1}, \tag{12}$$

where V_B is the endogenous default boundary derived in Proposition 1, V_t is the time-t asset value, and σ_A is the asset volatility.[17] To estimate asset value σ_A and asset volatility V_t, we follow the same approach as earlier for the Merton model, except that the computation involves more model parameters, including government support π_g and liquidity parameter ξ.

We first estimate, at the quarterly frequency, the issuer-level equity value E_t and equity volatility σ_E and then use them to back out the asset value V_t and asset volatility σ_V from

$$E_t = f(V_t); \quad \sigma_E = \frac{V}{E}\frac{\partial f(V)}{\partial V}\sigma_A\,, \tag{13}$$

where the closed-form formula $f(\cdot)$ linking the firm value V_t to its equity value E_t can be found in equation (21) in Appendix A.1. Using the estimated asset value and asset volatility, we then compute the default boundary V_B and obtain the unified default measure via equation (12).

Our default measure is unified in that it combines information on credit, liquidity, and bailout into one single measure. The focal point of the measure is the endogenous default boundary V_B, driven by the interaction of these three components. Relative to Merton's measure, the construction of the unified default measure requires two additional pieces of information: bailout and liquidity. To capture the deteriorating liquidity condition triggered by the government-led credit tightening, we set the liquidity parameter $\xi = 1$ before 2018Q2 and $\xi = 2$ after 2018Q2. As illustrated in equation (3), $\xi\, k$ exerts a liquidity cost on the pricing of the bond, and setting $k = 1.0\%$ and $\xi = 1$ translates to a liquidity cost of 100 bps per unit value of the bond, which is also consistent with the average bid-ask spread in the data estimated from the exchange-traded bonds. In our base-case estimations, we set the cross-issuer ξ and k to be the same for both non-SOEs and SOEs, although we also consider an alternative version allowing for heterogeneous liquidity parameters.

To calibrate the issuer-level bailout probability π_g, the simplest approach is to set $\pi_g = 0$ for non-SOEs and a positive π_g, say 80%, for SOEs. But as discussed in Section 3.2, with

[17]This approach is similar to that of Berndt, Duffie, and Zhu (2019), who add bailout probability to the Leland model and use the model-implied endogenous default boundary to compute distance-to-default.

increasing ξ, a simple yes-or-no dummy is not sufficient to capture the sensitivity of the model-implied SOE premium to π_g. To take into account the extent of government support above and beyond the non-SOE dummy, we use the issuer-level government holdings data. Constructed from the ground up, our government-holdings variable measures the sum of equity holdings by all government-related entities within the top ten shareholders for each publicly listed firm.[18] The exact mapping from government holdings to bailout probability is influenced by the observation that while more government holdings is associated with higher bailout probability, the relation is not necessarily linear. Small increases in government holdings can be translated to large increases in bailout probability when government holdings is low, but, above a certain threshold, this effect tapers off. In our study, we use a polynomial function to capture this form of non-linearity and keep the mapping fixed across time.[19]

For other parameters in the model, we use the same value as in the model calibration detailed in Section 3.2, with the exception of debt principal P and coupon C. We calibrate the total debt principle P as the sum of long- and short-term liability for firm i in quarter t. For the coupon rate of c per unit of principal, we set it to be the average coupon rate for firm i in quarter t.

4.2 Further Discussions on the Estimated Default Measures

The summary statistics of the model-implied default measures (DM) are reported in Table 1, along with the respective estimates of asset value and volatility backed out from the equity value and volatility via equation (13). Over the full sample, the Merton's DM is on average 22.56% for SOEs and 21.19% for non-SOEs, indicating that non-SOEs are in general healthier than SOEs according to the Merton model. By contrast, as illustrated in panels (c) and (d) of Figure 3, our unified DM paints a different picture and assigns the non-SOEs as the more risky group by a wide margin. Behind this differing message, is the fact that our unified DM evaluates the credit quality of a firm by integrating the "fundamental" credit quality as captured by Merton's DM together with bailout probability π_g and the liquidity parameter ξ. A clean decomposition is difficult as it is the interaction of these three forces that matters

[18] While the non-SOE dummy has been used widely as a measure of government support, our government-holdings variable, to our knowledge, has not been comprehensively explored in the literature for credit pricing. Our robust measure of government holdings, compiled from several data sources, can be valuable for future studies in this area.

[19] Let y be bailout probability and x be government holdings. We use the mapping $y = 1 - (x - 1)^4$ so that the sensitivity of bailout probability to government holdings is high when government holdings is low and flattens out when government holdings approach 1. We collect recovery rate information on all the defaulted SOEs and find an increasing and convex relationship between government holdings and recovery rates. Results using alternative mappings, including the binary mapping via the non-SOE dummy and $y = x$, are reported in the Internet Appendix A.4.

for the evaluation of credit risk. Nevertheless, it is instructive to discuss how the two key parameters (π_g and ξ) influence our unified DM.

The Role of Government Support π_g

Government holdings, a key input to the empirical construction of our unified default measure, is on average 52.0% for the SOE sample and exhibits a quite large cross-issuer variation, as shown in panel (a) of Figure 3. For the non-SOE sample, government holdings is markedly lower – an average of 2.8% for the privately-owned enterprises (POE) and 12.5% for a mixture of other non-SOE firms, and the cross-issuer variation is fairly narrow. Moreover, as shown in panel (b) of Figure 3, the time-series variation of government holdings is stable during our sample period. In particular, the government holdings for SOEs, which are mapped into the issuer-level bailout probability π_g, does not exhibit any large increase during Phase III. At the same time, however, the unified DM increases significantly for non-SOEs relative to SOEs during Phase III, as shown in panel (d) of Figure 3. In other words, the strength of the bailout remains the same, while the value of that bailout increases during Phase III, consistent with our model's mechanism.

The presence of the positive bailout probability π_g for SOEs lowers the default boundary and reduces the default measures for SOEs relative to non-SOEs. This message is loud and clear in the empirically estimated default measures. Contrary to Merton's DM, our unified DM indicates that SOEs are significantly healthier than non-SOEs. As shown in Table 1, the unified DM is on average 21.94% for SOEs and 33.43% for non-SOEs. As plotted in panel (d) of Figure 3, the difference in the unified DM between non-SOEs and SOEs is consistently positive. Moreover, interacting bailout probability π_g with the liquidity parameter ξ, our model further indicates an increased value of bailout probability during liquidity deterioration. Consistently, we see in panel (d) of Figure 3 that the difference in the unified DM between non-SOEs and SOEs oscillates around an average level of 8.42% in Phase II and widens to 12.20% in Phase III, reflecting this interaction effect.

The Role of Liquidity Parameter ξ

To illustrate the role of ξ in generating the difference in the unified DM between non-SOEs and SOEs, we can perform a hypothetical calculation by turning off the liquidity component. Keeping other parameters exactly the same, particularly the asset values and volatilities that have already been backed out under our specification of ξ (i.e., $\xi = 1$ before 2018Q2 and $\xi = 2$ afterwards), we compute the unified DM with $\xi = 0.001$. The difference in DM between non-SOEs and SOEs reduces to an average level of 5.30% in Phase II and remains at an average level of 5.53% in Phase III. Compared to 8.42% in Phase II and 12.20% in Phase III, this reduction in the unified DM follows directly from our model's key mechanism. Keeping all parameters fixed, including the asset values and volatilities, a higher ξ intensifies the liquidity-driven default. Under such a situation, the role of government support in alleviating liquidity-driven default becomes more important. Hence we see a higher difference in the unified DM between non-SOEs and SOEs.

Unlike the above illustration, where the amount of liquidity-driven default can be dialed up and down using the liquidity parameter ξ while keeping the firm fundamentals fixed, the actual empirical construction of the unified DM is constrained by the data, particularly the equity market information via equation (13). It is important to point out that, moving from Phase II to III, the further divergence in unified DM between non-SOEs and SOEs is not created mechanically by the increase in ξ. Rather, it is driven by the equity market information. Specifically, in constructing the unified DM, we use the market-observed equity value and volatility to first back out the unlevered asset value and volatility, and then use them to compute the empirical DM. In both processes, the liquidity parameter ξ is involved, but with opposing effects. In the first step, a higher ξ would lower the asset volatility and increase the asset value, making the firm safer to match observed equity value and volatility, while in the second step, this higher ξ would move up the default boundary and increase the default measure, canceling out its own effect in the first step.[20] Due to these two opposing forces, an increase in ξ has a small effect on the unified DM, as shown in panel (b) of Figure A.2.

This limited net impact of ξ on our empirical construction of the unified DM does not invalidate the presence of liquidity-driven default, as without our unified model, the relevant information contained in the equity market cannot be fully captured. This can be illustrated by the empirical performance of Merton's DM, which also uses equity market information to back out the asset values and volatilities, but fails to fully capture the increased liquidity-driven default in Phase III.[21]

4.3 Explaining the SOE Premium

Equipped with our unified default measure, we revisit the SOE premium by

[20]In our model, for a given set of asset value and volatility, a higher ξ lowers the default boundary and then lowers equity value and increases equity volatility, as shown in panel (a) of Figure A.2. Reversing this calculation, for a given set of market-observed equity value and volatility, a higher ξ leads to a higher asset value and lower asset volatility.

[21]During Phase III, the equity volatility for non-SOEs further widens relative to SOEs, and the difference in Merton's DM between non-SOEs and SOEs increases mildly and then turns positive post 2019Q2.

$$\text{CreditSpread}_{i,t} = a + b^{\text{NSOE}}\,\text{NSOE}_{i,t} + c\,\text{DM}_{i,t} + d\,\text{Rating}_{i,t} + \sum\nolimits_k \text{Controls}^k_{i,t} + \epsilon_{i,t}\,, \quad (14)$$

where $\text{DM}_{i,t}$ is the model-implied default measure for issuer-i in quarter t. The original SOE premium arises because of the pricing difference between non-SOEs and SOEs, which cannot be explained by credit ratings and other bond and firm characteristics. In fact, the presence of the SOE premium and its explosion after 2018Q2 are the main motivation of our unified model, particularly the introduction of bailout probability π_g and the liquidity parameter ξ. In this section, we study the extent to which the information contained in our unified DM, including that of π_g and ξ, can help price the cross-sectional bond spreads across SOEs and non-SOEs. If our model mechanism is indeed correct, then the inclusion of our unified DM in equation (14) should drive out the SOE premium, resulting in an insignificant coefficient b^{NSOE} for the NSOE dummy, under both the normal liquidity condition of Phase II and the liquidity deterioration of Phase III. Our results in Table 4 show that this is indeed the case.

Focusing first on Phase III, when the SOE premium is the most severe, we see that adding unified DM as an explanatory variable reduces the SOE premium from a staggering 113 bps to a mere 6 bps. By contrast, adding Merton's DM increases the SOE premium slightly from 113 bps to 116 bps. These results indicate that, using our unified DM to explain the cross-issuer credit quality, the severe divide in credit pricing between non-SOEs and SOEs disappears, while using Merton's DM for the same purpose exacerbates the divide. This contrast indicates the main mechanism of our model. Because of the increased importance of government support during this period of heightened liquidity deterioration, the relative credit quality of SOEs as captured by our unified DM becomes significantly higher than that of non-SOEs. By contrast, the "fundamental" credit quality as measured by Merton's DM does not capture this effect.

Our unified default measure works not only amidst the turmoil of Phase III, but also during the relatively calm of Phase II. As shown in Table 4, adding the unified default measure reduces the SOE premium in Phase II from 27 bps (t-stat=4.28) to 6 bps (t-stat=0.82). By contrast, adding Merton's default measure increases the SOE premium from 27 bps to 32 bps (t-stat=5.05). Interestingly, adding government holdings directly as an explanatory variable can explain away the SOE premium in Phase III, and the regression coefficient for government holdings is small and insignificant during Phase II. These empirical results demonstrate the value of having a structural model and reaffirm the importance of our model mechanism. For the pre-default period of Phase I, none of our explanatory variables works and the SOE premium remains at around 20 bps. This is a period when the credit market in China has not yet experienced any default, and, above and beyond credit rating, credit quality does not seem to be important for credit pricing during this early period in China's credit market.

Moving away from the pre-defined Phases and illustrating the SOE premium results more continuously, the bottom panel in Figure 1 further plots the time-series of the SOE premium at the quarterly frequency, after controlling for Merton's DM and our unified DM, respectively. Compared with the original SOE premium plotted in the top panel, we see that while Merton's DM cannot help resolve the SOE premium, the inclusion of our unified DM helps align the cross-sectional pricing in credit spreads and drives out the SOE premium.

Incorporating Heterogeneity in the Liquidity Parameter ξ

We incorporate heterogeneous liquidity parameter ξ by calibrating to the average bond illiquidity (Gamma) measured across non-SOE and SOE bonds by ratings in three phases. Following the convention in China, we treat rating AA+ and above as high quality and AA and below as low quality. As a benchmark, we rescale ξ to be close to 1 in Phase II to match the transaction cost.[22] We re-estimate the unified DM and use them to explain the SOE premium, and find that the remaining unexplained SOE premium is 17 bps (t-stat=1.91), 6 bps (t-stat=0.75) and 17 bps (t-stat=1.22), respectively, in Phase I, II, and III.

Overall, the added heterogeneity in ξ does not result in a significant improvement from our base-case results reported in Table 4. This result might be puzzling, as within the model, a higher ξ would result in a higher default probability. But this is true only if we keep the asset volatility fixed. As discussed in Section 4.2, by matching the model-implied equity value and equity volatility to the data via equation (13), our estimation strategy largely curtails the impact of ξ on the empirical default measure. It is therefore not surprising that allowing ξ to vary across firms does not improve the model performance. It also re-enforces the observation that the market-observed equity volatility contains information not only about the "fundamental" default risk but also the liquidity-driven default risk.[23] To the extent that there is heterogeneity in liquidity, the issuer-level equity value and equity volatility, which are the key inputs in our model estimation, can offer valuable information.

[22]Specifically, in Phase III, we set ξ to 1.34 and 1.79 for high and low quality SOEs, and 2.01 and 3.02 for high and low quality non-SOEs. In Phase II, the respective numbers are 1.03 and 0.95 for high and low quality SOEs, and 0.74 and 0.91 for high and low quality non-SOEs. In Phase I, the respective numbers are 1.47 and 1.18 for high and low quality SOEs, and 1.35 and 0.86 for high and low quality non-SOEs.

[23]One important empirical implication of He and Xiong (2012) is that, for a given set of asset value and volatility, a higher ξ lowers the default boundary and results in lower equity value and higher equity volatility. Empirically, this is consistent with what we find in the data. Cross-sectionally, we find a strong positive correlation between equity volatility and bond illiquidity. Over time, the average difference in equity volatility between non-SOEs and SOEs increases from less than 1% in Phase II to around 8% in Phase III, when the aggregate liquidity worsens.

To further illustrate the role of our model in extracting this valuable information from the equity market, we estimate the asset value and volatility directly from the firm's equity and bond volatilities without using our model, and then use our model to re-estimate the unified default measures and use them to explain the SOE premium.[24] Focusing on Phase III, we find that the remaining unexplained SOE premium is 88 bps (t-stat=4.97) without heterogeneity in ξ and 50 bps (t-stat=2.20) with the incorporation of heterogeneity in ξ as detailed in footnote 22. Two observations are in order. First, compared with our base-case results, this approach can only explain part of the SOE premium in Phase III and leave a large component of the SOE premium (88 bps) unexplained. Second, in this setting, ξ no longer influences the empirical estimation of the asset volatility and becomes a free parameter. Consequently, allowing for heterogeneity in ξ improves the performance, indicating that the information contained in the heterogeneous ξ is helpful in explaining the SOE premium. The fact that our base-case approach can explain a larger fraction of the SOE premium than the alternative approach suggests that by taking our unified model seriously, we can effectively extract liquidity information from equity volatility.

4.4 Price Discovery

We use the unified default measures to study the price discovery in China's credit market by focusing on the SOE and non-SOE samples separately. While the information content of credit spreads has been extensively studied for the U.S. market, our paper is the first comprehensive study of the Chinese market. From 2010 to 2020, this market is informed by two important shocks. The first ever default in 2014Q1 changes investors' perception of credit risk and the 2018Q2 liquidity crisis underscores the importance of government support. Our empirical analysis aims to document their impact on price discovery.

We perform the quarterly panel regression for the SOE and non-SOE samples separately:

$$\mathrm{CreditSpread}_{i,t} = a + \beta\,\mathrm{DM}_{i,t} + c\,\mathrm{Rating}_{i,t} + \sum\nolimits_k \mathrm{Controls}^k_{i,t} + \epsilon_{i,t}\,, \tag{16}$$

where $\mathrm{DM}_{i,t}$ is, for issuer i in quarter t, the model-implied default measure and the corresponding regression coefficient β captures the information content of credit spreads with respect to the default measure.[25] Central to our analysis is our unified measure, which inte-

[24] Following Schaefer and Strebulaev (2007), the asset value is the sum of the market value of equity and the book value of the liability, and the asset volatility is

$$\sigma^A_{i,t} = \sqrt{\left(1 - L_{i,t}\right)^2 \sigma^E_{i,t} + L^2_{i,t}\sigma^D_{i,t} + \left(1 - L_{i,t}\right) L_{i,t}\sigma^E_{i,t}\sigma^D_{i,t}\rho^{ED}} \tag{15}$$

where $L_{i,t}$ is the firm's leverage, $\sigma^E_{i,t}$ and $\sigma^D_{i,t}$ are equity and debt volatility and ρ^{ED} is the correlation between debt and stock returns.

[25] The control variables are the same as the regression specifications in equations (1) and (14) used to

grates the three components of price discovery – credit risk, liquidity risk, and government support. To compare the relative importance of these components, we further use Merton's default measure to proxy for the "fundamental" credit quality that is unrelated to bailout or liquidity, and government holdings to proxy for government support. The main results are summarized in Table 5, where we report only the regression coefficients for the key explanatory variables and the credit ratings. Those for the control variables have been reported in the original SOE premium regression in Table 2 and are omitted for briefness.

Price Discovery and the First Default of 2014Q1

Before the first default in 2014Q1, credit spreads are uninformative with respect to credit quality after controlling for credit ratings. As shown in Table 5, for both the SOE and non-SOE samples, the sensitivity of credit spreads to Merton's DM is of a rather small magnitude and has the wrong sign for the non-SOEs. Introducing unified DM does not have any additional impact. This lack of additional information content in credit spreads can be explained by the fact that, bond investors had never experienced any default before 2014Q1. Their perception of credit risk is such that rating is a sufficient measure of credit risk.

This perception is altered by the first ever default. Moving from Phase I to II, the coefficients for Merton's DM become positive and significant: 1.59 (t-stat=2.70) for non-SOEs and 1.21 (tstat=3.95) for SOEs. As credit-market investors become aware of the possibility of default risk, credit spreads start to incorporate default related information above and beyond credit rating. This includes information from the issuer's financial statements and equity pricing, key inputs to Merton's DM. Gauging the economic significance of this improvement in price discovery, we find that one standard deviation increase in Merton's DM is associated with 24 bps and 23 bps increases in credit spreads, respectively, for non-SOEs and SOEs. During this period, the SOE premium is about 27 bps, and one notch increase in credit rating is associated with an average reduction of 50 bps in credit spread. From this perspective, the economic significance of the improved price discovery is sizable.

Introducing the unified DM, the extent of the price discovery is similar to that of Merton's DM, indicating that the post-default period of Phase II is dominated by information with respect to "fundamental" credit quality. Consistently, government holdings as a direct explanatory variable is not important in explaining credit spreads during this period. Using all three variables together, however, we find that the unified DM remains important, but not Merton's DM. For the SOE sample, where the extent of government support is more

estimate the SOE premium. For briefness, regression coefficients of the control variables are not reported in Table 5, and 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.

important, the regression coefficient for Merton's DM is reduced to 0.47 (t-stat=1.54) while that for unified DM remains large and significant. This result indicates that even during normal liquidity condition, the interaction between bailout probability and the liquidity-driven default still matters in credit pricing.

Price Discovery and the Liquidity Crisis of 2018Q2

The liquidity crisis of 2018Q2 gives us a unique opportunity to study the impact of liquidity on price discovery. For the non-SOE sample, we find a marked improvement in the information content of credit spreads with respect to the "fundamental" credit quality captured by Merton's DM. As shown in Table 5, the regression coefficient associated with Merton's DM increases from 1.59 (t-stat=2.70) to 7.53 (tstat=3.67) for the non-SOE sample, and the corresponding incremental R-squared explained by Merton's DM increases from 0.9% to 2.8%. By contrast, the price discovery for the SOE sample does not exhibit any significant improvement using Merton's DM. The coefficient associated with Merton's DM increases from 1.21 (t-stat=3.95) in Phase II to 2.14 (t-stat=2.42) in Phase III, but the corresponding incremental R-squared explained by Merton's DM decreases slightly from 1.0% to 0.7%. Moreover, the economic significance of Merton's DM, as measured by the increase in credit spread associated with one standard deviation increase in Merton's DM, is 79 bps for the non-SOE sample, a marked improvement from 24 bps in Phase II. By contrast, for the SOE sample, the economic significance decreases slightly from 23 bps to 20 bps.

This contrast in price discovery reflects the key mechanism of our model. Without government support to alleviate the increased default under the worsening liquidity condition, credit spreads of non-SOEs become highly sensitive to credit quality (i.e., Merton's DM). By contrast, SOE issuers are not under the same severe concern over the fundamental credit risk. Under the overall liquidity deterioration, the content of their price discovery has instead become dominated by the information on government support. This increased importance of government support under worsening liquidity, while not captured by Merton's DM, is an important component of our unified DM. As a result, our unified DM can explain the improvement in price discovery for SOEs that is not captured by Merton's DM. As shown in Table 5, moving from Phase II to III, the regression coefficient for our unified DM increases from 2.37 (t=4.26) to 6.86 (t=6.66) for the SOE sample, and the incremental R-squared explained increases from 1.8% to 4.6%. Moreover, the economic significance of our unified DM increases from around 23 bps in Phase II to 51 bps in Phase III, a stark contrast to the lack of improvement using Merton's DM for the SOE sample.

Moreover, by incorporating all three components into one single measure, our unified DM can explain the price discovery for the non-SOE sample as well as SOEs during Phase III.

The coefficient estimate associated with unified DM is 7.40 (t-stat=5.88), compared with 7.53 (t-stat=3.67) for Merton's DM. Comparing their economic significance, one standard deviation increase in unified DM is associated with an increase in the credit spread of 105 bps, compared with 79 bps for Merton's DM. Moreover, the incremental R-squared explained by the unified DM is 4.0%, compared with 2.8% for Merton's DM. Using all three variables together, Merton's DM is no longer significant for the SOE sample, but remains significant for the non-SOEs in Phase III. We find that the additional information contained in Merton's DM is mostly related to the cross-issuer level information on asset growth, which is a key input for Merton's DM but not for our unified DM.[26]

Price Discovery in China's Credit Market, A Graphical Summary

To explain how price discovery in China's credit market evolves over time, we perform the panel regression in equation (16) over an eight-quarter rolling window. The regression coefficients for the default measures are plotted in Figure 4. By reporting the price discovery continuously, this approach serves to complement our results reported in Table 5, where the panel regressions are performed for three phases.

Over time, price discovery in China's credit market is transformed by two important shocks. The first ever default in 2014Q1 changes investors' perception of credit risk. Prior to the shock, using either Merton's DM or our unified DM, the extent of price discovery, after controlling for credit ratings, is essentially zero. After 2014Q1, we see a visible improvement in the regression coefficient, reflecting investors' changing perception of credit risk after the first ever default. Until the end of Phase II, the magnitude of price discovery moves very much in sync for SOEs and non-SOEs, indicating a shared concern over the fundamental credit quality during this post-default period.

The shock introduced by the 2018Q2 credit tightening underscores the importance of government support amidst liquidity deterioration and exacerbates the divide between SOEs and non-SOEs in the credit market. Along with the rapid divergence in credit spreads (i.e., the explosive SOE premium), we also observe a divergence in the content of price discovery. Within the non-SOE sample, credit spreads become significantly more sensitive to the cross-issuer measures of the "fundamental" credit quality. As shown in Figure 4, the sensitivity of credit spreads on Merton's DM increases rapidly after the liquidity shock of 2018Q2,

[26]Suggested by an anonymous referee, we also examine whether the extent of government support is different between inter-bank market and exchanges. Consistent with the intuition that the main investors in the inter-bank market (e.g. banks) would be more likely to extend financial support to SOEs in stressful times, we find that the SOE premium is indeed larger in the inter-bank sample (141 bps in Phase III) than in the exchange sample (91 bps in Phase III). Moreover, the sensitivity of credit spreads on government support and unified DM is also higher in the inter-bank sample than in the exchanges sample.

reflecting the impact of the increased likelihood of liquidity-driven default within this sample. For SOEs, where government support can help alleviate the increased liquidity-driven default, there is no significant increase in price discovery along this dimension. Instead, credit spreads within the SOE sample become more sensitive to the extent of government, reflecting the increased importance of government support under the liquidity deterioration. Our unified DM, which integrates credit, liquidity, and government support into one single measure, can explain the credit spreads for SOEs as well as for non-SOEs, as shown in Figure 4.

5 On the Real Impact

This section studies the real impact of the 2018 credit tightening by comparing the fundamental performance of SOEs and non-SOEs before and after the shock. Our main hypothesis builds on the observation that the rapid widening of the SOE premium after 2018Q2 reflects the worsening credit condition faced by non-SOEs in the broader economy, which subsequently impairs their fundamental performance relative to SOEs. While a complete understanding of the real impact is outside of our model, our attempts to shed light on this important topic, mostly empirical in nature, are as follows. Section 5.1 documents the rapid performance deterioration of non-SOEs relative to SOEs after the 2018 credit tightening. Section 5.2 performs event studies to establish a link between credit deterioration and performance deterioration for non-SOEs. Section 5.3 provides further discussions and offers robustness tests on alternative explanations.

5.1 Post-2018Q2 Performance Deterioration of Non-SOEs

The post-2018Q2 explosion of the SOE premium reflects the deteriorating credit condition faced by non-SOEs relative to SOEs in China. Because of the fluidity of credit dispensation across the credit market, bank loans and shadow banking, the financing difficulties experienced by non-SOEs exist not just in the credit market, but are economy-wide. This motivates us to study the real impact of the credit tightening for a wider range of firms, not just those with active bond trading, where are used to study credit pricing in Section 4. Expanding our sample to include firms with inactive bond trading, we have a collection of large and important non-financial firms in China with access to both the credit and equity market. The summary statistics for this sample of issuers, 821 non-SOEs and 623 SOEs, are reported in the Internet Appendix A.2 because of the lack of space in the main text.[27]

[27]The firm characteristics and cross-issuer distributions are very similar to those reported in Table 1 for the sample used for credit pricing. Using Merton's DM as a proxy of their fundamental credit quality, the

To directly compare and contrast the aggregate performance of non-SOEs against that of SOEs, Figure 5 plots the time-series of the quarterly ROAs averaged across the non-SOE and SOE samples respectively. Focusing first on non-SOEs, we see that, with the exception of the downward trend from 2010 through 2012, the aggregate quarterly ROA of non-SOEs oscillates around a constant level of 1.20% until 2018 and is driven by a strong seasonality, with the first quarter performance lagging significantly behind because of the reduced economic activities during the Chinese New Year celebration. Against this pattern, the post-2018 performance of non-SOEs appears highly unusual. Within one quarter, the aggregate ROA crashes from 1.09% in 2018Q3 to -0.35% in 2018Q4, breaking the worst ever record by a wide margin and driving the aggregate performance of non-SOEs deep into the negative territory. Prior to this event, the aggregate ROA varies within the narrow range between 0.87% to 2.14%. After its crash in 2018Q4, the aggregate ROA bounces back during the first three quarters of 2019, only to plunge back to 0.02% in 2019Q4.

Meanwhile, the aggregate performance of SOEs also decreases, but not with the same severity. From 2018Q3 to 2018Q4, the quarterly ROA decreases from 0.84% to 0.47%, still above the historical low of 0.31% in 2015Q4. Post 2018Q4, the aggregate ROA bounces back during the first three quarters of 2019 and drops back to 0.44% in 2019Q4. To further contrast their performance difference, we perform the following quarterly regression

$$\mathrm{ROA}_{i,t} = a + b^{\mathrm{NSOE}}\, \mathrm{NSOE}_{i,t} + c\, \mathrm{Equity\ Size}_{i,t} + \epsilon_{i,t}\,, \tag{17}$$

where $\mathrm{ROA}_{i,t}$ is firm-i's ROA in quarter t and NSOE is the non-SOE dummy. We further add equity size and quarter and industry fixed effects to take into account of their influence on ROA. The coefficient for the non-SOE dummy picks up the performance gap between non-SOEs and SOEs in aggregate.

Applying this regression for each quarter, Panel (b) of Figure 5 plots the quarterly performance gap, as measured by b^{NSOE} in the above regression, between non-SOEs and SOEs. To smooth out the seasonality, we further plot the performance gap b^{NSOE} using a rolling window of 8 quarter and plots the smoothed version against the quarterly performance gap. Prior to 2018, the performance gap oscillates around an average level of 0.55% and remains significantly positive, consistent with the common perception that non-SOEs in China, though underprivileged, are more efficient than their SOE counterparts. Post 2018, this performance gap collapses precipitously and becomes indistinguishable from zero, driven mainly by the performance deterioration of non-SOEs, as shown in Panel (a) of Figure 5.[28]

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non-SOE issuers are in general healthier. Not surprisingly, they also have lower government holdings than their SOE counterparts. Using our unified DM, the overall credit quality of non-SOEs is significantly weaker.

[28]Before this more severe deterioration, we see that the performance gap was already shrinking from

Applying this regression for each of our three phases, Panel A of Table 6 further reports the performance gap b^{NSOE} between non-SOEs and SOEs using both ROA and ROE. Before 2018Q2, the profitability gap is fairly stable and b^{NSOE} is estimated at 0.56% and 0.53%, respectively, in Phase I and II, which, in annualized terms, amount to non-SOEs outperforming SOEs by around 2% per year. After 2018Q2, the ROA gap drops to 0.13% and becomes statistically insignificant. At the same time, the coefficient for the equity size, a control variable, also increases sharply, indicating stronger performance deterioration for smaller firms, which are expected to be more vulnerable under credit tightening. We further conduct a propensity score matching (PSM) to control the differences in other dimensions between non-SOEs and SOEs before the New Regulations.[29] We report the new results using the matched sample in Panel B of Table 6. Similarly, we find a sharp decrease in the difference in ROA between non-SOEs and SOEs in Phase III. The same pattern can be observed using ROEs. Overall, amid the severe credit condition, the non-SOE firms in China have on average lost their superior profitability relative to the SOE firms.

We further use our government holdings measure in the regression to capture the extent of government support. As shown in Table 6, the results paint a very similar picture to when the non-SOE dummy is used. Prior to 2018Q2, higher government holdings are in general associated with lower ROA and ROE, and, after 2018Q2, the negative relation weakens significantly in magnitude and becomes statistically insignificant. Putting both the non-SOE dummy and government holdings in the same regression, we find that, in Phase I and II, the non-SOE dummy is important in explaining the variation in ROA while the government holdings are unimportant. This is consistent with our findings in credit pricing. Before 2018Q2, government holdings are not important in explaining credit spreads above and beyond the NSOE dummy. Post 2018Q2, the estimates for both variables become small and insignificant, reflecting the loss of non-SOEs' superior profitability relative to SOEs.

Overall, our results document the post-2018 performance deterioration of non-SOEs relative to SOEs. It should be emphasized that, with access to both credit and equity market financing, the firms included in our sample are among the largest in China. For smaller firms without access to the credit market, the impact could be more severe.

2016 through 2017. Unlike the post-2018 collapse of the performance gap, which is driven by the severe deterioration of non-SOEs, this gradual reduction in the performance gap is in fact driven by the improved SOE performance, resulted from the SOE reform that begins in 2014.

[29]Specifically, we perform one-to-one optimal matching without replacement among all the firms in 2018Q1, consisting of 493 SOEs and 649 non-SOEs. During the matching process, we require any pair of non-SOE and SOE to be in the same industry and then control size, BM, fundamental quality (Merton's DM), and leverage when calculating the scores. As a result, the number of the matched pairs reduce to 169.

5.2 Cross-Sectional Drivers of Performance Deterioration

Focusing on the credit tightening triggered by the 2018 New Regulations, we set 2018Q2 as the event date t and compute the post-event change in performance by

$$\Delta\text{ROA}_{i,t+\tau} = \text{ROA}_{i,t+\tau} - \overline{\text{ROA}}_{i,t-1}\,,$$

where, for firm i, $\text{ROA}_{i,t+\tau}$ is its quarterly ROA realized τ quarters after the event date t, and $\overline{\text{ROA}}_{i,t-1}$ is its pre-event ROA, averaged across the four pre-event quarters $t-j$ for $j = 1$ to 4, to smooth out the seasonality in the quarterly ROAs. Effectively, $\Delta\text{ROA}_{i,t+\tau}$ measures firm-i's change in performance realized τ quarters after the event. Fixing the event date t at 2018Q2, Panel A of Table 7 reports $\Delta\text{ROA}_{i,t+\tau}$ averaged over the first τ quarters after the event for both non-SOEs and SOEs. Consistent with the negative impact of the credit tightening, the average performance changes are negative and significant for both non-SOEs and SOEs, with the magnitudes for non-SOEs significantly larger. Over the first 2 and 8 quarters after 2018Q2, namely $\tau \in [1, 2]$ and $\tau \in [1, 8]$ in Panel A, the respective reduction in quarterly ROA is 0.88% and 0.69% averaged for the non-SOE sample, and 0.16% and 0.17% for the SOE sample.

To formally estimate the difference in performance change between non-SOEs and SOEs, we fix the event date t at 2018Q2, pool together the first τ quarters after 2018Q2, and perform the following panel regression,

$$\Delta\text{ROA}_{i,t+\tau} = a + b^{\text{NSOE}}\,\text{NSOE}_{i,t+\tau} + c\,\text{Equity Size}_{i,t+\tau} + \epsilon_{i,t+\tau}\,, \tag{18}$$

where the coefficient b^{NSOE} for the non-SOE dummy is the difference-in-difference estimate that captures the difference in the changes in performance between non-SOEs and SOEs.[30] As reported under "NSOE - SOE" of Panel A of Table 7, over the first 2 and 8 quarters after the event, the respective diff-in-diff of the quarterly ROA, as measured by b^{NSOE}, is -0.67% and -0.50%, indicating that the performance deterioration of non-SOEs is significantly larger than that of SOEs.

This relative performance deterioration between non-SOEs and SOEs, as measured by b^{NSOE}, is the focal point of our cross-sectional analysis. Specifically, our main objective is to establish a cross-sectional link between the firm-level credit deterioration at 2018Q2 and the subsequent performance deterioration. To capture the firm-level credit deterioration, we use our unified default measure (DM) and compute the change of DM by

$$\Delta\text{DM}_{i,t} = \text{DM}_{i,t} - \overline{\text{DM}}_{i,t-1}\,,$$

[30]We also add equity size and quarter and industry fixed effects to control for their influence on ROA, and for brevity, we only report the regression coefficients for the key variables.

where, for firm i, $\mathrm{DM}_{i,t}$ is its unified default measure at the event time t, and $\overline{\mathrm{DM}}_{i,t-1}$ is its pre-event unified default measure, averaged over the four pre-event quarters. Cross-sectionally, firms with more positive $\Delta\mathrm{DM}_{i,t}$ are experiencing stronger credit deterioration at the event date t. This observation applies equally to SOEs and non-SOEs, as, according to our model, the unified DM integrates the credit, liquidity, and government bailout into one single measure. By contrast, Merton's default measure, which does not consider liquidity or government support, might not be able to fully capture the credit deterioration of 2018Q2.[31]

We use the following predictive regression to test our hypothesis that credit deterioration at 2018Q2 leads to subsequent performance deterioration,

$$\Delta\mathrm{ROA}_{i,t+\tau} = a + \beta^{\mathrm{DM}}\,\Delta\mathrm{DM}_{i,t} + c\,\mathrm{Equity\ Size}_{i,t+\tau} + \epsilon_{i,t+\tau}\,, \tag{19}$$

where the event date t is fixed at 2018Q2 and the panel regression is performed over the first τ quarters after the event date, for $\tau \geq 1$. Central to this regression is the predictor $\Delta\mathrm{DM}_{i,t}$, which uses information up to the event time t to predict the changes in performance $\Delta\mathrm{ROA}_{i,t+\tau}$, realized τ quarters after the event. A negative regression coefficient β^{DM} for $\Delta\mathrm{DM}_{i,t}$ indicates that firms with worse credit deteriorations in 2018Q2, as captured by higher $\Delta\mathrm{DM}_{i,t}$, subsequently experience more severe performance deteriorations.

The results summarized in Panel B of Table 7 confirm this hypothesis for the non-SOE sample and shed further light on the post-2018Q2 performance deterioration along the following four dimensions. First, consistent with the hypothesis that credit deterioration for non-SOEs leads to their subsequent performance deterioration, the regression coefficients β^{DM} are negative and significant, both statistically and economically, for the non-SOE sample. Associated with one standard deviation increase of $\Delta\mathrm{DM}_{i,t}$ at 2018Q2, the subsequent underperformance averaged over the first 2 and 8 quarters after 2018Q2, is 0.35% and 0.22%, respectively, comparable to the magnitude of the diff-in-diff estimator b^{NSOE} that measures the gap in performance deterioration between non-SOEs and SOEs. Second, SOEs are less sensitive to deteriorating credit conditions. The regression coefficients β^{DM} are estimated to be negative for the SOE sample, but statistically insignificant, indicating that the SOEs faced with more credit deterioration in 2018Q2 do not significantly underperform relative to their peers.[32] Third, using Merton's DM to capture the credit deterioration in 2018Q2, we

[31]Conceptually, one might expect credit spreads to be a more direct measure of the firm-level credit deterioration. The usefulness of credit spreads under this setting is limited as our sample shrinks considerably if focusing only on firms with active bond trading. Importantly, the non-SOE firms without active bond trading might be faced with credit squeeze in bond loans or shadow banking, whose pricing we do not observe. In studying the real impact of credit tightening, our interest is focused not only on those largest firms with active bond trading, but also on those relatively smaller non-SOEs with inactive bond trading.

[32]We further estimate the difference in β^{DM} between non-SOEs and SOEs, and, not surprisingly, the

do not find any predictability for either the non-SOE or SOE sample, indicating that the additional information on liquidity and bailout incorporated into the unified DM is important in capturing the true extent of cross-sectional credit deterioration in 2018Q2. Lastly, to isolate the credit risk driven by the liquidity and bailout beyond pure fundamentals, we create a new measure using the difference between Unified $\Delta\mathrm{DM}_t$ and Merton $\Delta\mathrm{DM}_t$ and repeat the predictability test. Not surprisingly, there is a negative relationship between credit deterioration in 2018Q2 and performance deterioration post-2018Q2 for the non-SOE sample, but not for the SOE sample. This confirms that credit deterioration is mainly driven by liquidity and government support beyond fundamentals.

Building on the informativeness of $\Delta\mathrm{DM}_{i,t}$ in capturing the firm-level credit deterioration, we sort all firms, SOEs and non-SOEs, in our sample by their $\Delta\mathrm{DM}_{i,t}$ at t=2018Q2 into two groups. Firms in the high group have higher $\Delta\mathrm{DM}_{i,t}$ at 2018Q2 and are faced with worsening credit conditions, while firms in the low group are less affected. Focusing on the channel of credit deterioration leading to performance deterioration, our hypothesis is that the relative performance deterioration between non-SOEs and SOEs is stronger for the more affected firms. To test this hypothesis, we perform the regression specified in equation (18) for the high and low groups separately.[33] The results are summarized in Panel C of Table 7. First, in both the high and low groups, the diff-in-diff regression coefficients b^{NSOE} are negative and significant, reflecting the prevalence of the performance deterioration of non-SOEs relative to SOEs. In particular, it is present not only for those firms more affected by the credit tightening, but also for those less affected firms in the low group. Second, comparing the magnitude of b^{NSOE} between the high and low groups, we find that, consistent with our hypothesis, the relative worsening profitability between non-SOEs and SOEs is indeed stronger for firms faced with more severe credit deterioration at 2018Q2. Specifically, estimated over the first two quarters after 2018Q2, b^{NSOE} is -0.77% for the high group and -0.40% for the low group, compared with the full-sample estimate of -0.67%.

We further estimate the difference in the performance gap b^{NSOE} between the high and low groups using the following regression,

$$\Delta\mathrm{ROA}_{i,t+\tau} = a + b\,\mathrm{High}_{i,t} + c\,\mathrm{NSOE}_{i,t+\tau} + d\,\mathrm{High}_{i,t} \times \mathrm{NSOE}_{i,t+\tau} + \sum\nolimits_k \mathrm{Controls}^k_{i,t} + \epsilon_{i,t+\tau}\,, \quad (20)$$

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difference is significantly negative, driven by the negative predictability captured within the non-SOE sample. We estimate the difference by introducing the non-SOE dummy to the panel regression specified in equation (19). The coefficient for the interaction term between the non-SOE dummy and $\Delta\mathrm{DM}_{i,t}$ captures the differential sensitivity between non-SOEs and SOEs.

[33] To control for the difference in the sorting variable within the high and low groups, we further add the sorting variable as a control. The average ΔDM in 2018Q2 is 5% for SOEs and 7% for non-SOEs in the high group, -0.2% for SOEs and close to 0 for non-SOEs in the low group. The respective standard deviation of ΔDM is 4.4% for SOEs and 6.5% for non-SOEs.

where, for firm i, $\text{High}_{i,t}$ equals 1 if $\Delta\text{DM}_{i,t}$ is above the median at the event date t. The coefficient d associated with the interaction term is our main focus, which measures the difference in ROA reduction between the high and low groups. Fixing the event date t at 2018Q2 and focusing on the two-quarter window after 2018Q2, the coefficient estimate, as reported under "High - Low" in Panel C, is -0.44% (t-stat=-2.51), indicating that the relative performance deterioration is stronger for the high group, which includes firms that are more affected by the credit tightening at the event date 2018Q2. Examining the difference over a longer window after the event, the differential effect is stable and remains significant.

Finally, using Merton's ΔDM as the sorting variable at 2018Q2, we find the performance gap b^{NSOE} between non-SOEs and SOEs to be negative and significant for both the high and low groups, but the differential effect between the two groups is only marginally significant. Moreover, using the difference between Unified ΔDM_t and Merton ΔDM_t as the sorting variable at 2018Q2, the differential effect between the high and low groups becomes negative and significant. These evidences again confirm that it is firm-level information on the interaction between liquidity and bailout beyond fundamentals that is important in capturing the credit deterioration experienced by the firm in 2018Q2.

5.3 Further Discussions and Robustness Tests

Our model, built on exogenous firm dynamics, is designed for credit pricing. On the topic of the real impact, a hugely complicated yet important issue, our model's role is limited to the estimation of the credit condition faced by non-SOEs relative to SOEs. As to the exact channel through which the credit deterioration of non-SOEs can lead to their performance deterioration, what our model can offer is very much limited. This section offers further discussions on this important issue and offers alternative explanations and robustness tests.

Further Discussions

Within the context of our model, having bailout is always more efficient and improves credit pricing, as it helps to save the bankruptcy costs by lowering the endogenous default boundary. Stepping outside of our model, the efficiency of bailing out SOEs is controversial and opens to extensive debates. Similarly, within the context of our model, the performance deterioration of non-SOEs can be explained by the increasing financing costs faced by non-SOEs in the credit market. In reality, the real impact of the credit deterioration faced by non-SOEs does not stay merely at the level of financing costs, but can penetrate more deeply to affect the firm fundamentals.[34] Faced with the worsening credit condition, non-SOEs might forgo new projects and stop injecting capitals into existing projects, while the less affected SOEs have the capacity to continue their operations and even take over the projects from non-SOEs. To capture this deeper effect, a model that endogenizes the firm's production process is needed.

Moving beyond the economically focused models, the divide between non-SOEs and SOEs can go beyond the realm of finance and economics and central to this divide is the increasing importance of government support. Specifying and testing the channels through which government support can benefit SOEs over non-SOEs are beyond the scope of our paper. By focusing on the credit market, which we can directly observe and measure, our evidence is only one part, albeit an important part, of this society-wide trend moving against non-SOEs. Moreover, the explosion of the SOE premium captured from the credit market can very well reflect the market's expectation of this trend moving in favor towards SOEs.

Over the past several decades, non-SOEs in China, a tremendous engine of growth, have been competing for resources with the more privileged and less efficient SOEs. Our empirical evidence points to an unprecedented reversal of that trend when non-SOEs begin to lose their superior performance to SOEs. Given the central importance of this topic for China's economy, these empirical facts warrant careful documentation and better understanding. Using the firm-level credit shocks realized in the event quarter to predict their subsequent performance deteriorations, we find that the non-SOEs faced with stronger credit deterioration in 2018Q2 subsequently underperform more severely, while SOEs do not exhibit such cross-sectional sensitivities to credit conditions. This is our best attempt at establishing a link between credit deterioration and performance deterioration for non-SOEs. To explore the cross-sectional drivers of the post-2018Q2 performance deterioration of non-SOEs, we further employ a list of explanatory variables, including the firm-level leverage, rollover risk and liquidity capacity at 2018Q2.[35] By far, our unified ΔDM evaluated at 2018Q2 is the best cross-sectional predictor of the performance deterioration of non-SOEs.

US-China Trade War as an Alternative Explanation

Since March 2018, the U.S. and China have been engaged in a contentious and still on-going trade war. If the trade war affects the non-SOE firms more severely than SOEs, then this

[34]Peek and Rosengren (2000) estimate that an exogenous loan supply shock arising from the Japanese banking crisis leads to a decline in real economic activity in the commercial real estate sector in the U.S..

[35]We measure rollover risk by the ratio of current liabilities to total liabilities and measure liquidity capacity by the ratio of liquid assets to current liabilities. Using both measures to capture rollover pressure, we do not find any predictability on the subsequent ROA reductions. Moreover, the post-2018Q2 performance deterioration of non-SOEs relative to SOEs remains significant in the subsample with lower rollover and high liquidity capacity (i.e., healthier firms). The results are omitted for brevity and are available upon request.

event can potentially contribute to the performance deterioration of non-SOEs relative to SOEs. We test this hypothesis by dividing our sample into groups of more- and less-affected firms, using three measures of trade-war exposure.

Our first measure is at the industry level. Over the course of the trade war, tariffs have been imposed on a list of industries.[36] Following the industry specification of Benguria et al. (2022), we sort firms by their respective industries into high and low groups, with the low group containing firms in industries that are not directly affected by the trade war. To obtain firm-level exposures, we further use information from the equity market. As the equity market can be driven by many factors, we focus on two short episodes when the trade-war news takes the center stage in the Chinese markets. The first episode is June 2018, when the Chinese A-share market falls by over 8%, triggered by the tariff announcements and the anticipation of the eventual launch of the first wave of tariffs that begins on July 6. We assume that firms with high betas during this month are viewed by investors to be affected more by the trade war. The second episode occurs on May 06, 2019, the first trading day after China's Labor Day break, when the A-share market plummets by 5.58%, triggered by President Trump's abrupt escalation of the trade war via Twitter. We assume that firms exhibiting more negative returns on this day have higher exposures.[37]

We perform our robustness tests in the top panels of Table 8 in two dimensions. First, we examine the sensitivity of $\Delta\text{ROA}_{i,t+\tau}$ to the trade-war motivated sorting variables to see if they can explain the cross-sectional variation of changes in ROA within the SOE and non-SOE samples separately. The structure of this table follows that in Panel B of Table 7, except that the sorting variable under the current table is motivated not by credit exposure but trade-war exposure. Overall, we do not find strong evidence that trade war is an important explanatory variable for the subsequent performance deterioration. Focusing on the results when the first-episode beta or the second-episode return are used, we find indication that during the first two quarters after 2018Q2, the sensitivity for SOEs is negative and significant, indicating that SOEs might be more sensitive to the trade war. Further comparing the sensitivity coefficients between SOEs and non-SOEs, as reported under "NSOE - SOE", we do not find any significant difference.

Second, we use the trade-war motivated sorting variable to sort firms into high and low groups, and examine the relative performance deterioration between non-SOEs and

[36]This includes industrial and commercial machinery & computer equipment, electronic equipment, transportation equipment, and light-manufacturing sectors such as food & kindred products, furniture, and fabricated metal products. See Benguria et al. (2022) for further details.

[37]Unlike the previous sorting variables, this variable is observed almost one year after the event date of 2018Q2. To the extent that the trade-war exposure is a firm-level characteristic that does not vary over time, we are using this episode to help us differentiate firms that are more affected from the less affected.

SOEs for the two groups separately. The structure of this table follows that in Panel C of Table 7, except that the sorting variable under the current table is motivated not by credit exposure but trade-war exposure. If the negative impact of the trade war is indeed behind the performance deterioration of non-SOEs, we would expect the difference reported for the low group to be smaller, as it contains firms less exposed to the trade war. Up to the first four quarters after 2018Q2, we do not see any significant results in support of this hypothesis. Extending the post-event window further to include 2019Q4, we see some evidence of this hypothesis. Specifically, using the one-day return on May 6, 2019 to capture the trade-war exposure, the difference in $\Delta\mathrm{ROA}_{i,t+\tau}$ between non-SOEs and SOEs is indeed smaller for the less-affected firms in the low group, over the window defined by $\tau \in [+1, +6]$ and $\tau \in [+1, +8]$. That is, when averaged over the first 6 and 8 quarters after 2018Q2.

Overall, to the extent that we can measure trade-war exposures with accuracy, we find that it cannot fully explain the performance deterioration of non-SOEs relative to SOEs. Our results can be further corroborated by the findings of Benguria et al. (2022). Using export and import data, they construct firm-level tariff exposures and find no significant difference between SOEs and non-SOEs. They further apply textual analyses on the annual reports of publicly listed firms to construct firm-level trade policy uncertainty. They find a trade-war related decline in firm profits only later in 2019Q2 and Q3. Over the 2017Q4-2018Q4 horizon, they do not find significant impact of trade war on firm profits. This includes 2018Q4, when the post-event performance deterioration of non-SOEs is the most severe in our sample. Overall, these evidences indicate that the trade war is unlikely to be the main driver of the post-2018Q2 performance deterioration of non-SOEs relative to SOEs.

The 2016-17 SOE Deleveraging as an Alternative Explanation

Under the deleveraging hypothesis, the 2016-17 government-mandated SOE deleveraging cleans up the balance sheet of SOEs and makes them healthier than non-SOEs. As a result, SOEs are more resilient and can better withstand the credit tightening of 2018, while the over-expansion of non-SOEs during this period makes them vulnerable to the credit shock. Consistent with the timing and nature of the deleveraging campaign, the average leverage, measured by the ratio of book liability to book asset, has declined gradually from 57.4% in 2015Q4 to 55.7% in 2017Q4 for the SOEs in our sample, meanwhile the average leverage of the non-SOEs in our sample has increased from 47.2% to 48.9%. Measuring leverage by book debt over book asset paints a similar picture. Also reflected in these numbers is the fact that SOEs are more levered than non-SOEs, even after the 2016-17 deleveraging campaign.

To test this deleveraging hypothesis, our approach is to compare the post-2018Q2 performance deterioration between the best non-SOEs against the worst SOEs. To capture the potential impact of the deleveraging campaign, especially for SOEs, we use three deleveraging-motivated sorting variables. First, each firm's leverage right before the 2018 credit tightening, averaged over the four quarters before 2018Q2. Second, each firm's change in leverage, calculated as the difference between the four-quarter average before 2018Q2 and the 2015 average. Third, each firm's change in leverage, calculated as the difference between the four-quarter averages before and after October 2016, when the SOE deleveraging is formally announced.[38] To the extent that the deleveraging campaign is effective, SOEs with larger reductions in leverage are those improved SOEs under the hypothesis. Likewise, SOEs with lower levels of leverage right before 2018Q2 are more resilient under the deleveraging hypothesis.

We test the deleveraging hypothesis in two steps. First, we examine the sensitivities of the post-2018Q2 performance deteriorations to the deleveraging-motivated sorting variables. If deleveraging campaign is an important driver of the post-2018Q2 performance deterioration, then we would expect the predictability coefficients β^X, which parallels β^{DM}, to be negative and significant, where X is one of the three deleveraging-motivated sorting variables, to reflect the hypothesis that improved resilience contributes to lower performance deterioration for both non-SOEs and SOEs, but especially for SOEs. The results are reported in Panel B of Table 8. Using the level of leverage right before 2018Q2, the sensitivity coefficients are mostly positive and insignificant. When estimated over the first eight quarters after 2018Q2, the coefficients become positive and weakly significant, indicating that firms with higher leverage in fact deteriorate less. This is not surprising given that leverage is a highly endogenous variable and SOEs' leverage has been consistently higher than that of non-SOEs in part because of their government support. Using the change of leverage during the deleveraging campaign, we find some evidence that SOEs delevered more can subsequently withstand the credit tightening. In particular, using ΔLeverage calculated as the difference between the four-quarter averages before and after Oct 2016, the corresponding predictability coefficients β^X are negative and significant for the SOE sample. For non-SOEs, the deleveraging-motivated sorting variable exhibits no predictability.

Second, we compared the performance deterioration between non-SOEs and SOEs. To minimize the impact of the deleveraging campaign, we take the more resilient SOEs out of the benchmark group and focus on the SOEs less affected by the deleveraging campaign. To further sharpen the contrast, among the non-SOE sample, we take out the weaker non-SOEs and focus on those more resilient non-SOEs, using the same leverage measures. Effectively, we compare the post-2018Q2 performance deterioration between the resilient non-SOEs against the less resilient SOEs, counter to the 2016-17 trend of deleveraging SOEs and leveraging

[38]On October 10th, 2016, China's State Council issued guidelines on cutting the corporate-leverage ratio, marking the beginning of a new phase in the de-leveraging campaign.

non-SOEs. As shown in Panel B of Table 8, the post-2018Q2 performance deterioration of non-SOEs relative to SOEs remains significant. Over the first two quarters after 2018Q2, the relative performance deterioration is 0.54%, 0.42% and 0.35%, respectively, using the three deleveraging-motivated sorting variables. Compared with the full sample result of 0.67%, the relative performance deterioration is less severe, indicating some explanatory ability of this deleveraging hypothesis. Given the lack of these deleveraging-motivated sorting variables in explaining the post-2018Q2 performance deterioration for non-SOEs, however, the deleveraging hypothesis is unlikely to be the main driver of our results on the post-event performance deterioration of non-SOEs relative to SOEs.

6 Conclusions

Motivated by the coexistence of SOEs and non-SOEs in China, we study the relative credit pricing between these two important segments of China's economy using a structural model of default that incorporates bailout probability to the model of He and Xiong (2012). Focusing on the divide of SOEs and non-SOEs in credit pricing, we quantify the extent of the financing disadvantage of non-SOEs relative to SOEs, which worsens dramatically amidst the government-led credit tightening. Under our structural default model that unifies credit, liquidity, and government bailout, this empirically estimated SOE premium captures the value of government support, which increases amidst liquidity deterioration as the presence of government bailout helps alleviate the heightened liquidity-driven default. Moreover, SOEs and non-SOEs are divided not only in the level of bond pricing, but also in the content of their price discovery. The increased importance of government support makes SOEs more sensitive to bailout probability, while the heightened default risk increases non-SOEs' sensitivity to credit quality.

Focusing on the divide of SOEs and non-SOEs in fundamental performance, we find that, after 2018Q2, non-SOEs begin to lose their long-standing performance advantage over SOEs. Using our model-implied default measure to capture the firm-level credit shocks realized in the event quarter, we find that the non-SOEs faced with stronger credit deterioration in 2018Q2 subsequently underperform more severely, while SOEs do not exhibit such cross-sectional sensitivities to credit conditions. This is our best attempt at establishing a link between the credit deterioration of non-SOEs and their subsequent performance deterioration. Nevertheless, we find that the relative performance deterioration of non-SOEs over SOEs is present even among firms less affected by the credit deterioration, albeit with significantly smaller magnitudes than the more affected firms. This result indicates that the disadvantage faced by non-SOEs goes beyond the credit channel. Specifying and testing the additional channels through which government support can benefit SOEs over non-SOEs are beyond the scope of our paper.

Competing with the more privileged SOEs for resource allocation, non-SOEs in China, an indispensable engine of growth, have managed to outperform SOEs for much of the recent economic development in China. From 2010 to 2018Q1, the non-SOEs in our sample consistently overperform the SOEs with a quarterly ROA gap of 0.55%. Post 2018, driven mainly by the severe performance deterioration of non-SOEs, this performance gap collapses precipitously and becomes indistinguishable from zero. As China moves on to the next phase of its development, how to maintain the coexistence of non-SOEs and SOEs is a hugely important topic. Our empirical findings call for government policies to better balance these two important segments of China's economy.

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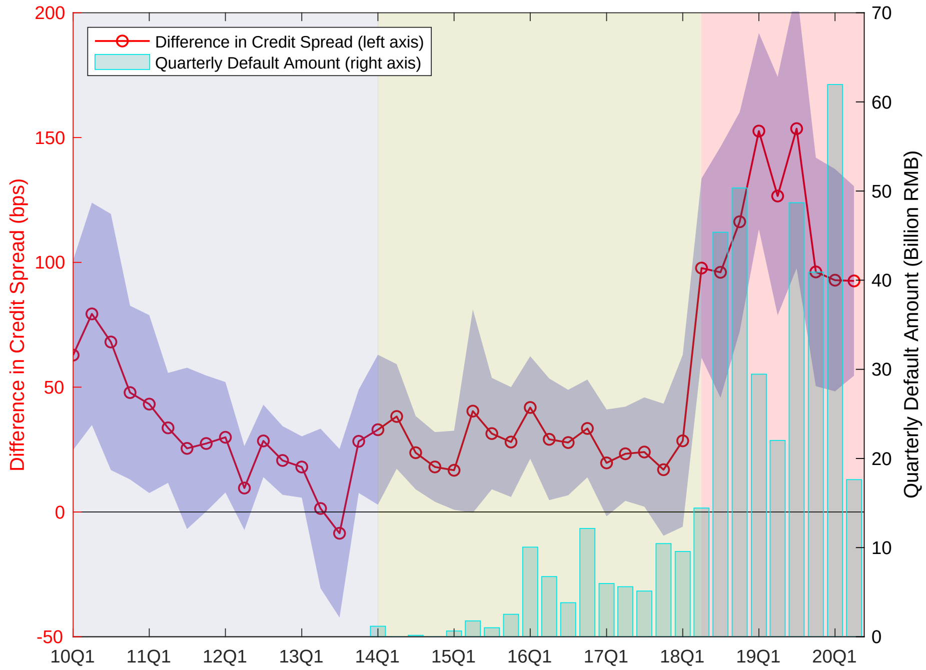
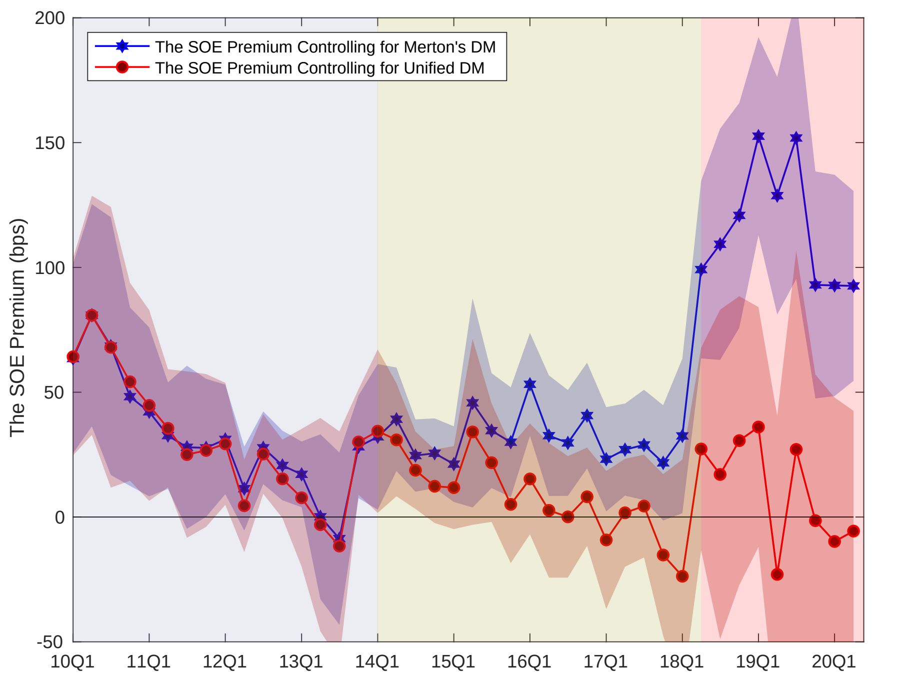
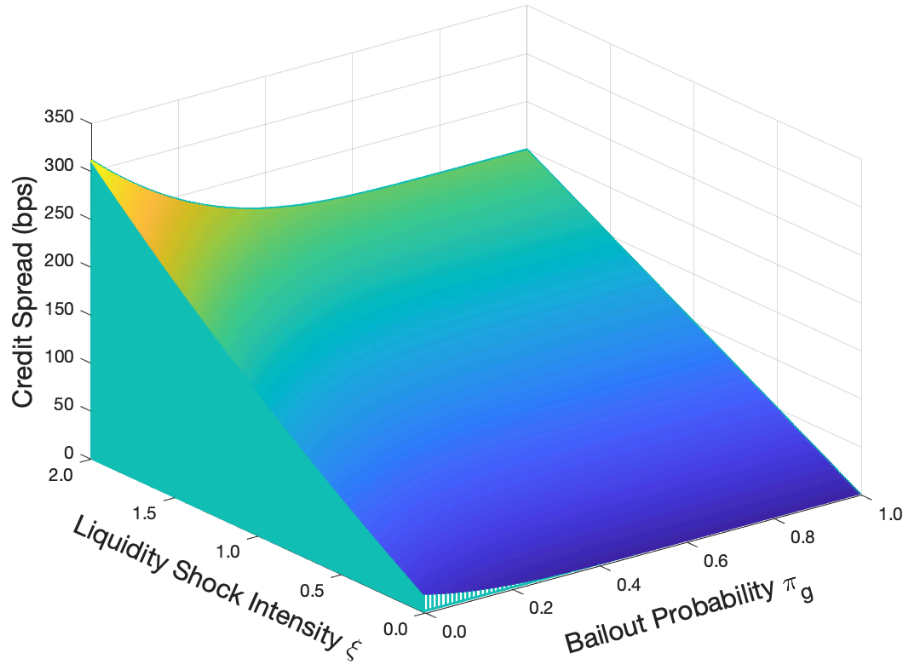


(a) **The SOE Premium**

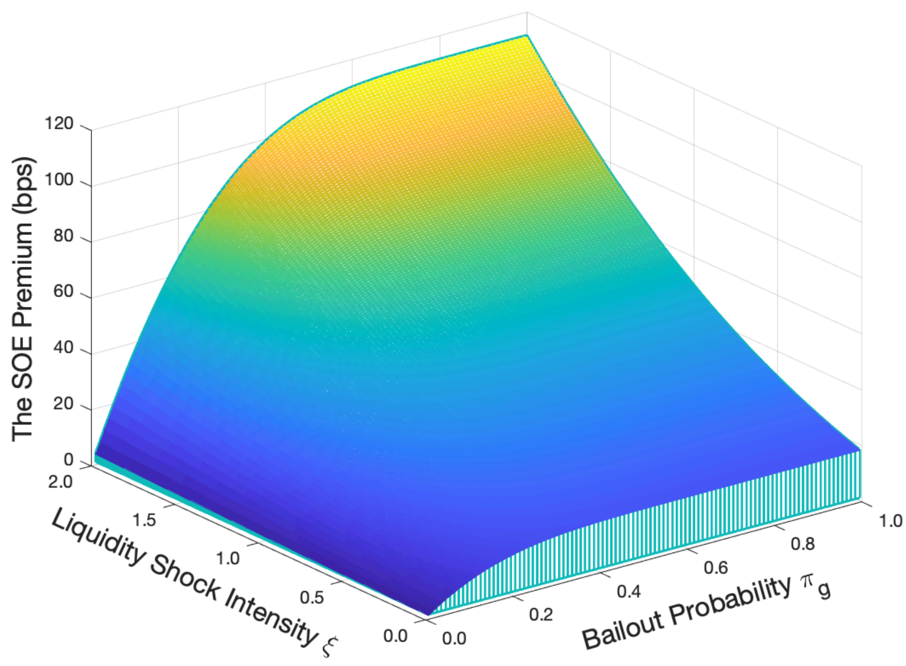


(b) **Explaining the SOE Premium using Model-Implied DM**

Figure 1: Panel (a) plots the difference between listed non-SOEs and listed SOEs in credit spread (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). Panel (b) plots the time-series of the SOE premium after controlling for Merton's DM (blue line) and our unified DM (red line).

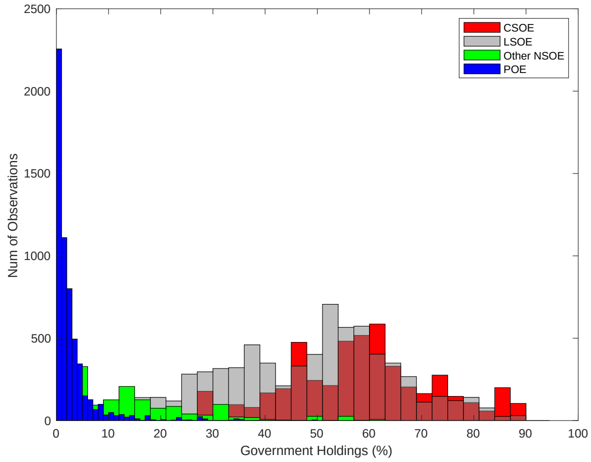


(a) **Credit Spread (bps)**

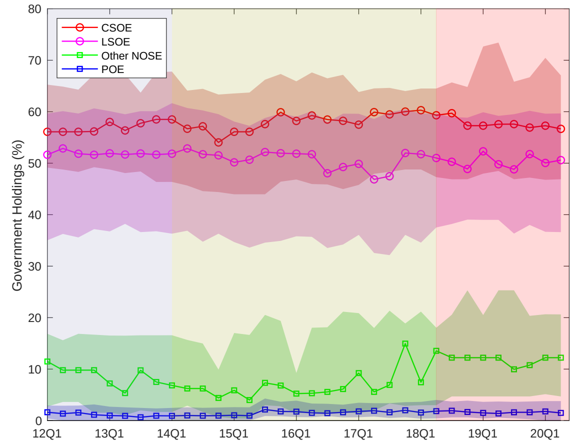


(b) **The SOE Premium (bps)**

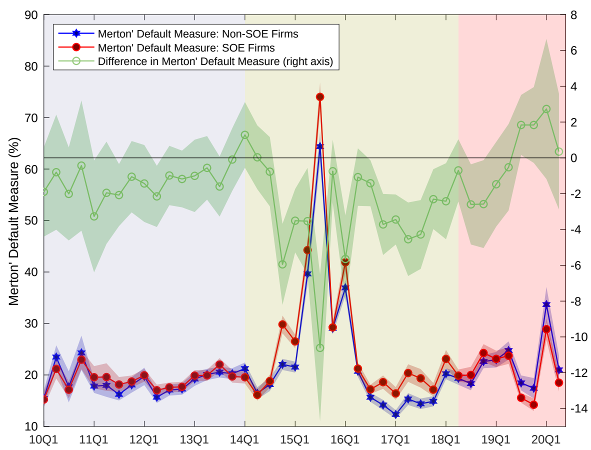
Figure 2: This figure plots the calibration results. The top panel shows the credit spreads with varying bailout probability π_g and liquidity shock intensity ξ. The bottom panel shows the SOE premium with varying bailout probability π_g and liquidity shock intensity ξ. The SOE premium is defined as the difference between non-SOEs ($\pi_g = 0$) and SOEs with positive π_g. For other parameters, see Section 3.2.



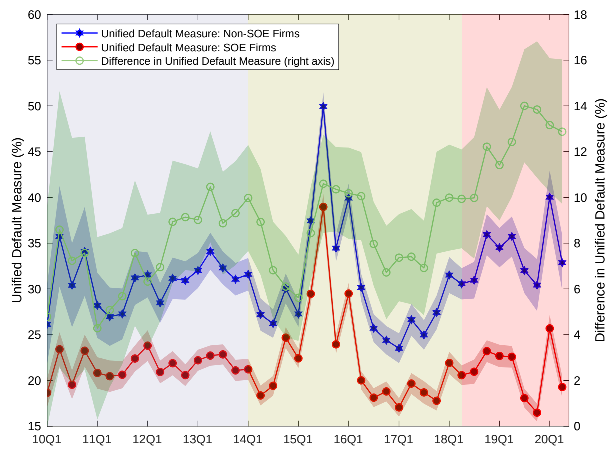
(a) **Distribution of Govt Holdings**



(b) **Govt Holdings: P25, Med and P75**

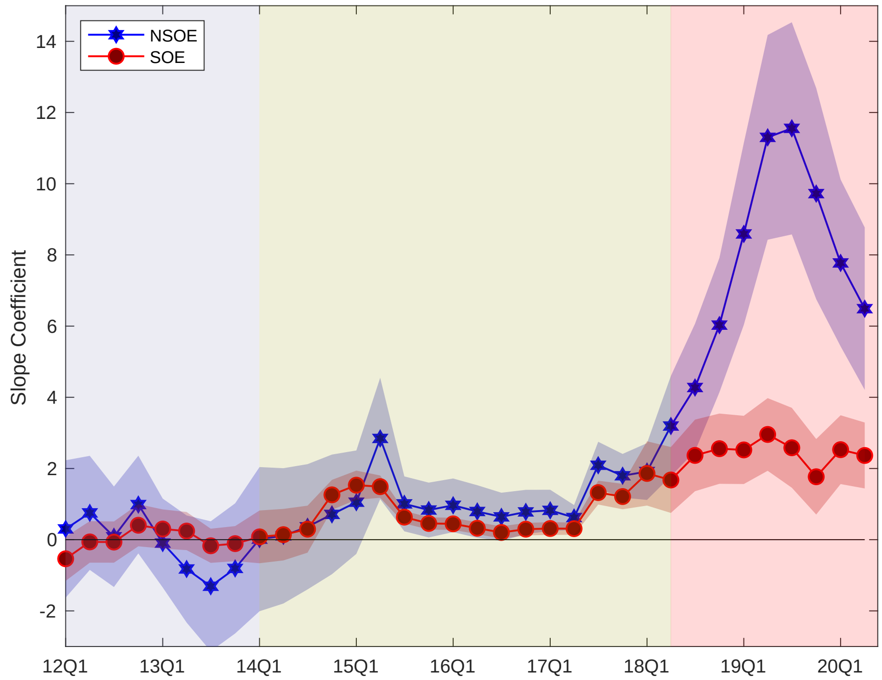


(c) **Merton's Default Measure**

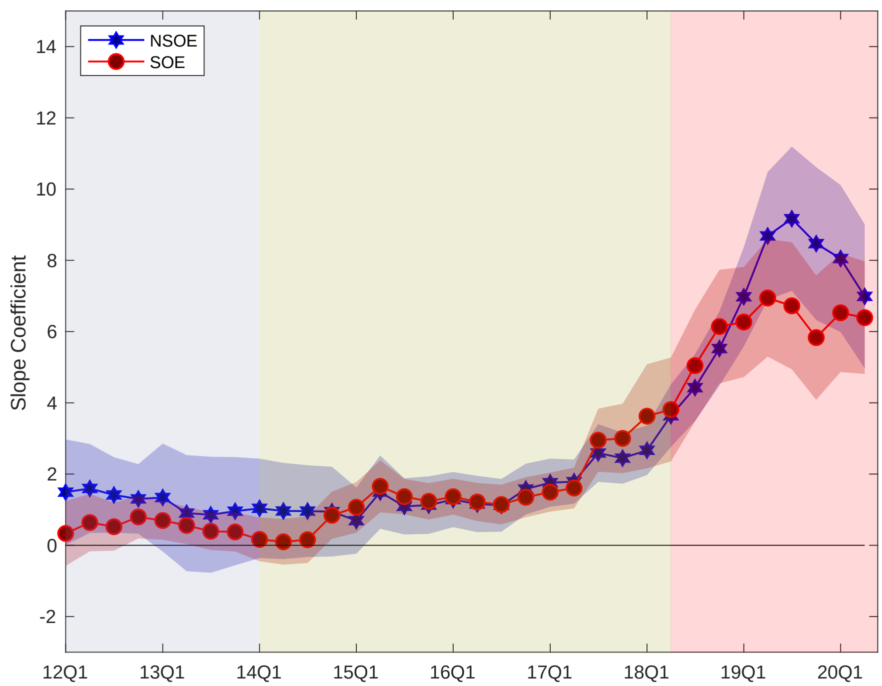


(d) **Unified Default Measure**

Figure 3: This figure plots government holdings and default measures. Panel (a) plots the histogram of the government holdings for four types of firms – central and local SOEs, privately-owned enterprises (POE) and other non-SOEs. Panel (b) plots the time-series of government holdings by type, with dotted lines indicating median values and shaded areas covering the 25 to 75 percentiles. Panels (c) and (d) plot the time-series of default measures of non-SOEs (blue line) and SOEs (red line), with panel (c) using Merton's model and panel (d) using our unified model. The green line further plots the difference in default measure between non-SOEs and SOEs and the shaded areas in both panels cover the 95% confidence intervals.

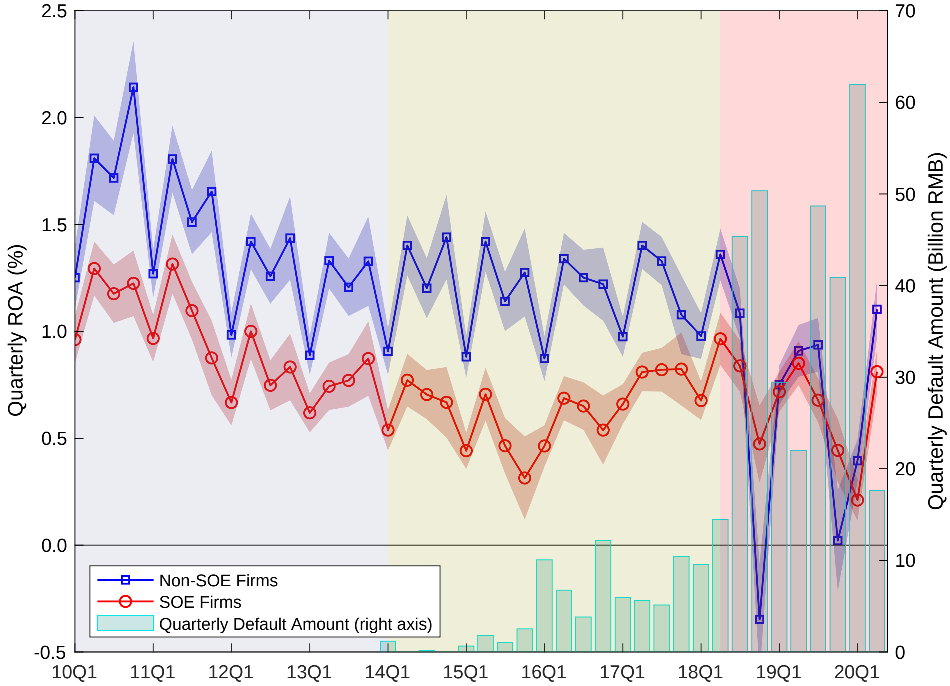


(a) **Credit Spreads on DM Merton**

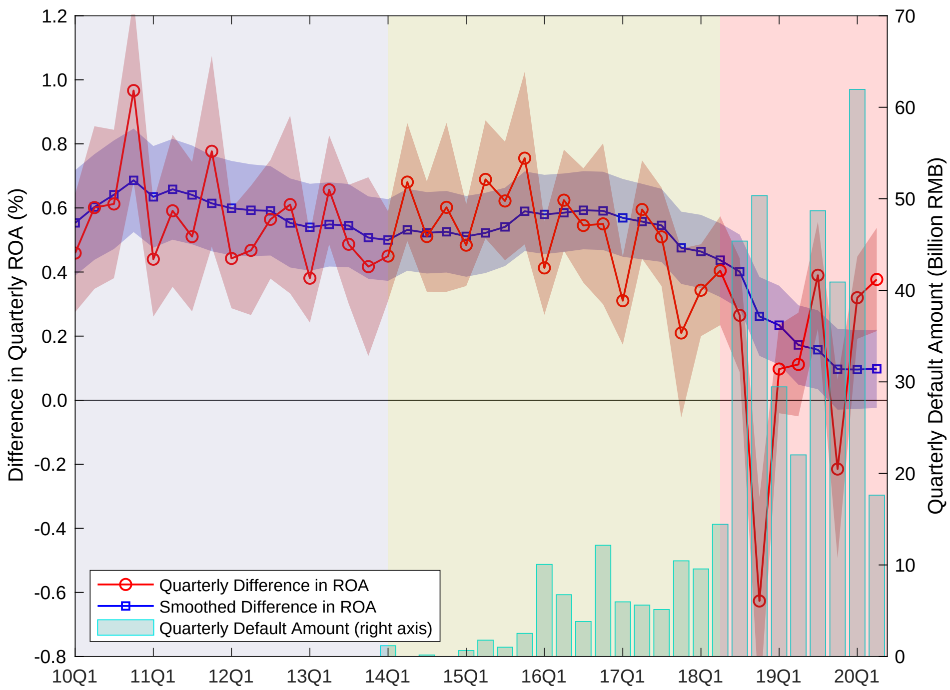


(b) **Credit Spreads on DM Unified**

Figure 4: This figure plots the slope coefficient from the regression of credit spreads on Merton's default measure and unified default measure, respectively, controlling for credit ratings and other bond and firm characteristics. The shaded area indicates the 95% confidence intervals.



(a) **Quarterly Aggregate ROA for Non-SOEs and SOEs**



(b) **Difference in ROA between Non-SOEs and SOEs**

Figure 5: The top panel plots the average quarterly ROA for non-SOEs and SOEs. ROA is net profit divided by lagged book asset. Also reported are the total quarterly default amounts in the credit market (right axis). The bottom panel plots the difference in quarterly ROA between non-SOEs and SOEs, using quarterly regressions, controlling for equity size, quarter and industry fixed effects. To smooth out the seasonality, we further plot the performance gap using a rolling window of 8 quarters. The shaded area indicates the 95% confidence intervals.

Table 1: **Summary Statistics: Sample of Corporate Bonds Used for Empirical Tests on Credit Pricing**

Panel A: Bond-Level Variables

	All				Phase I				Phase II				Phase III			
	NSOE		SOE		NSOE		SOE		NSOE		SOE		NSOE		SOE	
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
NumBonds	915		1471		218		452		636		819		564		884	
CreditSpread (%)	2.46	2.38	1.39	1.41	2.03	1.25	1.21	0.79	2.04	1.40	1.32	1.31	3.54	3.74	1.70	1.89
Rating	2.43	0.85	1.68	0.84	2.73	0.75	1.83	0.86	2.60	0.73	1.79	0.88	1.91	0.91	1.34	0.61
Maturity (yr)	2.96	1.24	3.33	1.70	3.89	1.37	4.17	2.02	2.92	1.16	3.22	1.56	2.43	0.94	2.76	1.31
IssueSize (billions)	1.03	0.89	2.01	2.57	0.94	0.80	2.34	3.18	1.00	0.93	1.90	2.49	1.14	0.85	1.91	2.01
Age (yr)	1.75	1.26	2.01	1.67	1.25	1.04	1.54	1.37	1.81	1.31	2.26	1.69	1.94	1.21	1.98	1.77
Coupon (%)	5.90	1.24	5.12	1.09	6.45	0.99	5.43	0.98	5.94	1.23	5.23	1.09	5.46	1.25	4.65	1.05
Exch	0.69	0.46	0.53	0.50	0.77	0.42	0.56	0.50	0.69	0.46	0.56	0.50	0.63	0.48	0.45	0.50
Callable	0.04	0.20	0.08	0.27	0.00	0.00	0.02	0.14	0.04	0.21	0.08	0.27	0.06	0.24	0.14	0.34
Puttable	0.62	0.49	0.34	0.47	0.55	0.50	0.29	0.45	0.64	0.48	0.37	0.48	0.63	0.48	0.31	0.46
ZeroDays (%)	77.31	26.06	85.75	18.47	62.30	30.00	79.00	21.44	76.71	26.20	85.44	19.29	88.32	15.82	92.36	9.70
Turnover (%)	30.69	62.29	35.39	80.68	44.38	91.30	54.43	118.52	31.44	56.11	30.81	70.16	20.25	46.65	26.50	46.33
TradingDays (day)	15	17	10	12	25	20	14	14	16	18	10	13	8	11	5	6

Panel B: Equity-Level Variables

	All				Phase I				Phase II				Phase III			
NumIssuers	365		401		176		251		314		338		225		252	
EquitySize (log)	23.31	1.03	23.72	1.33	22.57	0.93	23.33	1.40	23.31	0.88	23.72	1.28	23.78	1.08	24.05	1.28
Leverage (%)	58.50	15.30	61.75	14.87	55.75	12.85	61.26	14.63	57.32	15.29	61.30	15.63	62.65	15.98	63.00	13.56
AssetGrowth (%)	24.91	19.40	14.33	13.04	28.55	21.06	19.76	14.27	24.60	19.69	12.85	12.99	23.14	17.27	12.11	10.37
EquityVolatility (%)	40.39	17.95	36.34	18.37	37.55	10.05	32.41	10.80	42.34	21.46	41.55	22.35	38.41	13.33	30.51	12.17
GovtHoldings (%)	5.09	8.40	52.00	16.74	4.98	8.74	52.29	17.32	4.54	7.55	51.26	16.68	6.24	9.57	53.08	16.26
Merton DM (%)	21.19	12.79	22.56	15.16	18.72	6.59	18.33	7.82	22.55	15.02	26.81	18.95	20.14	10.55	18.71	9.26
AssetValue (log)	24.01	1.24	24.66	1.46	23.19	0.97	24.27	1.45	23.90	1.04	24.54	1.40	24.77	1.31	25.23	1.40
AssetVolatility (%)	22.99	15.49	17.12	13.81	22.15	10.35	14.97	9.48	26.14	17.43	21.34	16.23	17.32	12.23	11.46	9.07
Unified DM (%)	33.43	13.46	21.94	9.15	31.71	11.12	21.21	8.06	32.04	13.42	22.96	10.34	37.31	14.17	20.77	7.45
AssetValue (log)	24.16	1.27	24.78	1.51	23.30	0.97	24.36	1.48	24.01	1.05	24.58	1.42	25.01	1.33	25.50	1.45
AssetVolatility (%)	17.50	14.81	16.67	15.54	16.44	10.38	14.07	10.11	20.64	16.73	21.90	18.48	12.01	11.08	9.60	9.06

The sample period is from January 2010 to June 2020. Phase I, from 2010 through 2013, is the pre-default period; Phase II, from 2014 through 2018Q1, captures the first wave of defaults; and Phase III, from 2018Q2 to 2020Q2, captures the second and much more severe wave of defaults. 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. Exch is 1 for exchange-traded bonds. Callable is 1 for bonds issued with callable options. Puttable is 1 for bonds issued with puttable options. 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. EquitySize is the log of the firm's equity size. Leverage is the ratio of total current liabilities plus the total non-current liabilities to the total asset value. AssetGrowth is the average growth rate of the asset value in the past three years. EquityVolatility is the annualized equity volatility. GovtHoldings is the total government equity holdings within firm's top 10 shareholders. Merton DM is the inverse of Merton's distance-to-default. Unified DM is the inverse of the distance-to-default from our unified model. AssetValue and AssetVolatility are model-implied asset value and annualized asset volatility, respectively.

Table 2: **Measuring the SOE Premium**

	Listed Sample			Unlisted Sample		
	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III
NSOE	0.20***	0.27***	1.13***	0.25***	0.91***	1.81***
	[2.97]	[4.28]	[7.76]	[5.65]	[15.25]	[17.87]
Rating	0.52***	0.53***	1.19***	0.49***	0.47***	0.48***
	[6.45]	[10.62]	[5.12]	[14.85]	[17.52]	[14.83]
Maturity	0.05***	0.05**	-0.08	0.03***	-0.02	-0.16***
	[2.82]	[2.43]	[-1.41]	[2.96]	[-1.41]	[-12.19]
Age	0.03	0.04**	0.04	0.01	0.00	0.05***
	[1.30]	[2.02]	[0.95]	[0.68]	[0.23]	[3.23]
IssueSize	0.00	-0.04***	-0.08**	-3.03***	-8.24***	-17.76***
	[0.01]	[-2.82]	[-2.09]	[-6.93]	[-9.46]	[-10.17]
ZeroDays	-0.92***	-2.10***	-4.34***	-0.43***	-1.69***	-3.06***
	[-3.92]	[-9.35]	[-5.84]	[-3.79]	[-8.53]	[-8.44]
Exch	0.03	-0.46***	-0.03	-0.09*	-0.36***	-0.07
	[0.39]	[-6.59]	[-0.14]	[-1.86]	[-6.03]	[-0.72]
Callable	-0.24**	1.55***	2.25***	0.17*	2.21***	2.65***
	[-2.00]	[8.17]	[9.08]	[1.78]	[18.22]	[25.55]
Puttable	-0.16**	-0.28***	-0.72***	0.33***	0.12**	0.15**
	[-2.12]	[-3.34]	[-3.72]	[5.04]	[2.53]	[2.19]
EquitySize	-0.15***	-0.19***	-0.26***			
	[-5.15]	[-5.24]	[-4.49]			
Constant	4.26***	6.27***	9.72***	0.93***	1.53***	3.22***
	[4.42]	[7.13]	[5.29]	[5.55]	[6.59]	[8.06]
Obs	4,292	9,967	5,338	16,179	32,240	15,833
Adj R^2	0.546	0.455	0.376	0.561	0.508	0.491

Quarterly panel regressions with credit spreads as the dependent variables, with quarter and industry fixed effects. NSOE 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 2020. Phase I, from 2010 through 2013, is the pre-default Phase; Phase II, from 2014 through 2018Q1, captures the first wave of defaults; and Phase III, from 2018Q2 to 2020Q2, captures the second and much more severe wave of defaults.

Table 3: **Calibration Results**

Panel A: Credit Spread with Varying Bailout Probability π_g and Liquidity Shock ξ

	ξ=1	ξ rises to 2				ξ rises to 3			
	Spread	Spread	$\triangle$Spread	Default Part		Spread	$\triangle$Spread	Default Part	
	(bps)	(bps)	(bps)	(bps)	(fraction)	(bps)	(bps)	(bps)	(fraction)
NSOE: π_g=0	150	312	162	62	38.2%	508	358	158	44.2%
SOE: π_g=0.2	115	246	131	31	23.6%	407	292	92	31.5%
SOE: π_g=0.4	103	213	110	10	9.0%	341	238	38	16.1%
SOE: π_g=0.6	100	201	101	1	1.3%	309	209	9	4.2%
SOE: π_g=0.8	100	200	100	0	0.0%	301	201	1	0.3%
SOE: π_g=1.0	100	200	100	0	0.0%	300	200	0	0.0%

Panel B: The SOE Premium with Varying Bailout Probability π_g and Liquidity Shock ξ

	ξ=1	ξ rises to 2			ξ rises to 3		
	Premium	Premium	$\triangle$Premium		Premium	$\triangle$Premium	
NSOE $-$ SOE	(bps)	(bps)	(bps)	(multiplier)	(bps)	(bps)	(multiplier)
π_g=0 - π_g=0.2	35	66	31	1.9	101	66	2.9
π_g=0 - π_g=0.4	47	99	52	2.1	167	120	3.5
π_g=0 - π_g=0.6	50	111	61	2.2	199	149	4.0
π_g=0 - π_g=0.8	50	112	62	2.2	207	157	4.2
π_g=0 - π_g=1.0	50	112	62	2.2	208	158	4.2

Panel C: One-Year Default Probability with Varying Bailout Probability π_g and Liquidity Shock ξ

	ξ=1	ξ rises to 2		ξ rises to 3	
	Prob (bps)	Prob (bps)	$\triangle$Prob (bps)	Prob (bps)	$\triangle$Prob (bps)
NSOE: π_g=0	23.0	78.3	55.3	224	201
SOE: π_g=0.2	6.06	28.9	22.8	107	101
SOE: π_g=0.4	0.83	6.75	5.92	37.8	37.0
SOE: π_g=0.6	0.03	0.69	0.66	7.70	7.67
SOE: π_g=0.8	0.00	0.01	0.01	0.53	0.53
SOE: π_g=1.0	0.00	0.00	0.00	0.00	0.00

Panel D: The SOE Premium with Varying Liquidity Shock ξ and Maturity m When π_g^{SOE}=0.6

	ξ=1	ξ rises to 2			ξ rises to 3		
	Premium	Premium	$\triangle$Premium		Premium	$\triangle$Premium	
NSOE $-$ SOE	(bps)	(bps)	(bps)	(multiplier)	(bps)	(bps)	(multiplier)
m=1	50	111	61	2.2	199	149	4.0
m=3	48	82	34	1.7	119	71	2.5
m=6	44	64	20	1.5	82	38	1.9
m=10	40	53	13	1.3	65	25	1.6

This table reports the credit spread (Panel A), SOE premium (Panel B) and one-year default probability (Panel C) with varying bailout probability π_g and liquidity shock ξ. Panel D reports the SOE premium with varying liquidity shock ξ and maturity m when π_g^{SOE}=0.6. The SOE premium is defined as the difference between non-SOEs ($\pi_g = 0$) and SOEs with positive π_g. We set the risk-free rate r to be 4%, the tax rate τ to be 25%, the bond recovery rate α to be 50%, the payout rate δ to be 1%, asset volatility σ to be 15%, asset growth μ to be 15%, the maturity of the bond m to be one year, the trading cost k to be 1%, and the current fundamental value of the firm to be 100.

Table 4: **Explaining the SOE Premium**

	Phase I				Phase II				Phase III			
NSOE	0.20***	0.20***	0.21**	0.17**	0.27***	0.32***	0.17	0.06	1.13***	1.16***	-0.04	0.06
	[2.97]	[2.84]	[2.57]	[1.96]	[4.28]	[5.05]	[1.51]	[0.82]	[7.76]	[7.88]	[-0.21]	[0.38]
Merton DM		-0.12				1.36***				4.60***		
		[-0.38]				[4.52]				[4.92]		
GovtHoldings			0.04				-0.26				-2.86***	
			[0.23]				[-1.24]				[-6.95]	
Unified DM				0.34				2.27***				7.23***
				[0.91]				[6.26]				[9.92]
Rating	0.52***	0.52***	0.52***	0.52***	0.53***	0.53***	0.52***	0.52***	1.19***	1.11***	1.15***	1.23***
	[6.45]	[6.35]	[6.30]	[6.61]	[10.62]	[10.93]	[10.47]	[10.67]	[5.12]	[5.06]	[4.91]	[5.91]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.26***	4.30***	4.25***	3.99***	6.27***	5.42***	6.33***	4.93***	9.72***	7.42***	9.52***	3.59*
	[4.42]	[4.71]	[4.40]	[3.58]	[7.13]	[6.19]	[7.32]	[5.38]	[5.29]	[3.90]	[5.15]	[1.90]
Obs	4,292	4,292	4,292	4,292	9,967	9,967	9,967	9,967	5,338	5,338	5,338	5,338
Adj R^2	0.546	0.546	0.546	0.547	0.455	0.465	0.456	0.476	0.376	0.392	0.390	0.423

Quarterly panel regressions of credit spreads on non-SOE Dummy (NSOE), Merton's default measures (Merton DM), government holdings (GovtHoldings), unified default measures (Unified DM) and other Controls with quarter and industry fixed effects. NSOE is one for bonds issued by non-SOEs and zero for SOEs. Merton DM is the inverse of Merton's distance-to-default. GovtHoldings is the total government equity holdings within firm's top 10 shareholders. Unified DM is the inverse of the distance-to-default from our unified model. Other Controls include bond maturity, issuance size, age, exchange market dummy, optionality, liquidity and equity size. Reported in square brackets are tstat's using standard errors clustered by bond and quarter. The sample extends from January 2010 to June 2020. Phase I, from 2010 through 2013, is the pre-default Phase; Phase II, from 2014 through 2018Q1, captures the first wave of defaults; and Phase III, from 2018Q2 to 2020Q2, captures the second and much more severe wave of defaults.

Table 5: **Price Discovery: Credit Spreads on Default Measures and Government Holdings**

NSOE	Phase I						Phase II						Phase III					
Merton DM		-0.12			-0.10	-0.32		1.59***			1.60***	0.87		7.53***			7.66***	6.00***
		[-0.14]			[-0.11]	[-0.32]		[2.70]			[2.72]	[1.30]		[3.67]			[3.82]	[3.64]
GovtHoldings			0.52		0.52	0.73			-0.02		-0.13	0.26			-6.00***		-6.16***	-4.09***
			[1.14]		[1.13]	[1.56]			[-0.05]		[-0.28]	[0.60]			[-4.70]		[-5.26]	[-3.48]
Unified DM				0.68		0.85				1.86***		1.58***				7.40***		4.90***
				[1.03]		[1.13]				[4.61]		[3.12]				[5.88]		[5.03]
Rating	0.78***	0.78***	0.79***	0.77***	0.79***	0.78***	0.41***	0.41***	0.41***	0.42***	0.41***	0.43***	1.61***	1.41***	1.55***	1.61***	1.35***	1.41***
	[3.12]	[3.12]	[3.20]	[3.17]	[3.19]	[3.26]	[4.44]	[4.56]	[4.49]	[4.60]	[4.58]	[4.72]	[4.35]	[4.13]	[4.27]	[4.93]	[3.96]	[4.47]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	7.55***	7.57***	7.53***	6.69***	7.55***	6.50***	11.60***	10.77***	11.60***	9.83***	10.76***	9.67***	15.19***	13.21***	11.44***	4.44	9.34***	3.95
	[3.80]	[3.93]	[3.82]	[2.64]	[3.97]	[2.62]	[7.28]	[6.97]	[7.23]	[5.58]	[6.90]	[5.63]	[4.69]	[4.22]	[3.37]	[1.26]	[2.89]	[1.16]
Obs	1,367	1,367	1,367	1,367	1,367	1,367	4,116	4,116	4,116	4,116	4,116	4,116	2,085	2,085	2,085	2,085	2,085	2,085
Adj R^2	0.494	0.494	0.495	0.496	0.494	0.498	0.373	0.382	0.373	0.388	0.382	0.391	0.363	0.391	0.381	0.403	0.410	0.424
SOE	Phase I						Phase II						Phase III					
Merton DM		0.10			0.09	0.17		1.21***			1.21***	0.47		2.14**			1.54*	-0.89
		[0.67]			[0.62]	[0.98]		[3.95]			[3.95]	[1.54]		[2.42]			[1.76]	[-1.17]
GovtHoldings			-0.15		-0.14	-0.21			-0.30		-0.31	0.20			-2.23***		-2.08***	-0.89**
			[-1.03]		[-1.02]	[-1.48]			[-1.37]		[-1.43]	[0.93]			[-5.41]		[-5.27]	[-2.36]
Unified DM				0.04		-0.26				2.37***		2.17***				6.86***		6.52***
				[0.17]		[-0.96]				[4.26]		[3.28]				[6.66]		[5.86]
Rating	0.40***	0.40***	0.39***	0.40***	0.39***	0.39***	0.54***	0.54***	0.53***	0.52***	0.53***	0.53***	0.55***	0.53***	0.51***	0.54***	0.50***	0.53***
	[11.25]	[11.22]	[11.13]	[11.36]	[11.11]	[11.06]	[9.01]	[9.37]	[8.97]	[9.37]	[9.30]	[9.41]	[4.52]	[4.41]	[4.48]	[4.81]	[4.40]	[4.80]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.33***	3.29***	3.38***	3.30***	3.35***	3.53***	4.78***	3.95***	4.81***	3.31***	3.98***	3.10***	8.16***	6.80***	8.49***	3.33**	7.49***	4.27***
	[3.74]	[3.76]	[3.91]	[3.44]	[3.94]	[3.83]	[5.48]	[4.52]	[5.62]	[3.49]	[4.65]	[3.32]	[5.55]	[4.34]	[6.07]	[2.03]	[5.03]	[2.60]
Obs	2,925	2,925	2,925	2,925	2,925	2,925	5,851	5,851	5,851	5,851	5,851	5,851	3,253	3,253	3,253	3,253	3,253	3,253
Adj R^2	0.541	0.541	0.542	0.541	0.542	0.542	0.488	0.498	0.489	0.506	0.499	0.508	0.380	0.387	0.404	0.426	0.408	0.430

Quarterly panel regressions of credit spreads on Merton's default measures (Merton DM), government holdings (GovtHoldings), unified default measures (Unified DM) and other Controls with quarter and industry fixed effects for non-SOEs sample (top panel) and SOEs sample (bottom panel), respectively. Merton DM is the inverse of Merton's distance-to-default. GovtHoldings is the total government equity holdings within firm's top 10 shareholders. Unified DM is the inverse of the distance-to-default from our unified model. Other Controls include bond maturity, issuance size, age, exchange market dummy, optionality, liquidity and equity size. Reported in square brackets are tstat's using standard errors clustered by bond and quarter. The sample extends from January 2010 to June 2020. Phase I, from 2010 through 2013, is the pre-default Phase; Phase II, from 2014 through 2018Q1, captures the first wave of defaults; and Phase III, from 2018Q2 to 2020Q2, captures the second and much more severe wave of defaults.

Table 6: **The Relative Performance Between Non-SOEs and SOEs**

	Panel A: NSOE Dummy					
	ROA (%)			ROE (%)		
	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III
NSOE	0.56***	0.53***	0.13	1.08***	1.20***	-0.01
	[7.80]	[8.94]	[1.09]	[6.70]	[8.00]	[-0.03]
EquitySize	0.19***	0.19***	0.35***	0.78***	0.74***	1.09***
	[6.08]	[6.34]	[8.68]	[10.86]	[11.05]	[7.58]
Constant	-3.56***	-4.05***	-7.03***	-16.25***	-16.66***	-21.40***
	[-4.86]	[-4.95]	[-8.51]	[-9.75]	[-9.43]	[-7.94]
Obs	15,677	18,487	10,844	15,677	18,487	10,844
Adj R^2	0.065	0.064	0.095	0.051	0.046	0.085
	Panel B: NSOE Dummy under PSM					
	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III
NSOE	0.45***	0.38***	-0.09	0.94***	0.96***	-0.41
	[4.06]	[4.24]	[-0.62]	[3.59]	[4.44]	[-0.87]
EquitySize	0.19***	0.22***	0.42***	0.69***	0.62***	1.24***
	[3.25]	[3.99]	[5.29]	[4.36]	[5.17]	[4.15]
Constant	-3.23**	-4.31***	-8.41***	-13.22***	-12.76***	-25.92***
	[-2.55]	[-3.50]	[-4.72]	[-3.72]	[-4.67]	[-3.80]
Obs	4,573	5,362	2,970	4,573	5,362	2,970
Adj R^2	0.052	0.049	0.110	0.052	0.035	0.083
	Panel C: Government Holdings					
	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III
GovtHoldings	-0.89***	-0.91***	-0.26	-1.81***	-2.09***	0.07
	[-6.46]	[-7.93]	[-1.03]	[-5.77]	[-6.77]	[0.10]
EquitySize	0.17***	0.21***	0.36***	0.76***	0.78***	1.09***
	[5.74]	[6.84]	[9.14]	[10.99]	[11.64]	[8.20]
Constant	-2.73***	-3.84***	-7.01***	-14.73***	-16.17***	-21.35***
	[-3.76]	[-4.61]	[-8.34]	[-9.40]	[-9.09]	[-7.85]
Obs	15,677	18,487	10,844	15,677	18,487	10,844
Adj R^2	0.056	0.057	0.095	0.047	0.041	0.085
	Panel D: NSOE Dummy and Government Holdings					
	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III
NSOE	0.63***	0.59***	0.10	1.12***	1.33***	0.07
	[6.74]	[6.56]	[0.73]	[4.32]	[5.59]	[0.20]
GovtHoldings	0.18	0.14	-0.09	0.08	0.31	0.21
	[0.97]	[0.86]	[-0.32]	[0.17]	[0.64]	[0.30]
EquitySize	0.18***	0.19***	0.35***	0.78***	0.73***	1.09***
	[6.02]	[6.17]	[8.61]	[10.99]	[11.08]	[7.80]
Constant	-3.60***	-4.04***	-7.04***	-16.27***	-16.63***	-21.37***
	[-4.86]	[-4.93]	[-8.50]	[-9.63]	[-9.42]	[-8.00]
Obs	15,677	18,487	10,844	15,677	18,487	10,844
Adj R^2	0.065	0.064	0.095	0.051	0.046	0.085

Quarterly panel regressions with ROA, ROE as the dependent variables on non-SOE Dummy (NSOE), government holdings (GovtHoldings) and equity size with quarter and industry fixed effect. Panel B reports the results within the matched sample using propensity score matching (PSM). ROA is the ratio of the net profit to the lag book asset. ROE is the net profit to the lag book equity. NSOE is one for bonds issued by non-SOEs and zero for SOEs. GovtHoldings is the total government equity holdings within firm's top 10 shareholders. Reported in square brackets are tstat's using standard errors clustered by firm and quarter. Phase I is from 2010 through 2013; Phase II is from 2014 through 2018Q1; and Phase III is from 2018Q2 to 2020Q2.

Table 7: **Cross-Sectional Tests on the Credit Channel**

	Panel A: Sample Averages of Post-Event Performance Change, $\Delta\text{ROA}_{t+\tau}$ with t=2018Q2							
	$\tau \in [1,1]$	$\tau \in [1,2]$	$\tau \in [1,3]$	$\tau \in [1,4]$	$\tau \in [1,5]$	$\tau \in [1,6]$	$\tau \in [1,7]$	$\tau \in [1,8]$
NSOE	-0.14***	-0.88***	-0.74***	-0.63***	-0.58***	-0.74***	-0.76***	-0.69***
	[-3.02]	[-12.14]	[-14.38]	[-15.08]	[-16.21]	[-19.61]	[-22.71]	[-22.50]
SOE	0.02	-0.16***	-0.13***	-0.08***	-0.08***	-0.12***	-0.20***	-0.17***
	[0.53]	[-3.28]	[-3.50]	[-2.58]	[-2.93]	[-4.81]	[-8.34]	[-7.46]
NSOE − SOE	-0.17**	-0.67***	-0.57***	-0.52***	-0.47***	-0.58***	-0.53***	-0.50***
	[-2.41]	[-7.31]	[-8.55]	[-9.56]	[-10.03]	[-12.29]	[-12.41]	[-12.72]

	Panel B: Predicting Post-Event Performance Change with ΔDM at 2018Q2											
	Predictability β^{DM} (Unified ΔDM)				Predictability β^{DM} (Merton ΔDM)				Predictability β^{DM} (Unified - Merton ΔDM)			
	$\tau \in [1,2]$	$\tau \in [1,4]$	$\tau \in [1,6]$	$\tau \in [1,8]$	$\tau \in [1,2]$	$\tau \in [1,4]$	$\tau \in [1,6]$	$\tau \in [1,8]$	$\tau \in [1,2]$	$\tau \in [1,4]$	$\tau \in [1,6]$	$\tau \in [1,8]$
NSOE	-5.45***	-3.71***	-4.01***	-3.36***	-2.04*	-0.90	-0.79	-0.54	-2.49	-2.83***	-3.48***	-3.20***
	[-4.31]	[-5.15]	[-5.98]	[-6.25]	[-1.80]	[-1.42]	[-1.32]	[-1.16]	[-1.63]	[-3.31]	[-4.37]	[-4.96]
SOE	-1.45	-1.01	-1.16*	-0.67	-0.61	-0.20	-0.07	-0.02	0.32	-0.24	-0.61	-0.41
	[-1.05]	[-1.27]	[-1.67]	[-1.15]	[-0.98]	[-0.50]	[-0.20]	[-0.06]	[0.32]	[-0.36]	[-1.06]	[-0.84]
NSOE - SOE	-4.28**	-2.80**	-3.03***	-2.70***	-1.48	-0.72	-0.81	-0.53	-2.90	-2.57**	-2.74***	-2.76***
	[-2.28]	[-2.57]	[-3.11]	[-3.37]	[-1.16]	[-0.96]	[-1.17]	[-0.95]	[-1.64]	[-2.47]	[-2.88]	[-3.51]

	Panel C: Difference in Post-Event Performance Change between Non-SOEs and SOEs											
	ROA Gap b^{NSOE} (Unified ΔDM)				ROA Gap b^{NSOE} (Merton ΔDM)				ROA Gap b^{NSOE} (Unified - Merton ΔDM)			
	$\tau \in [1,2]$	$\tau \in [1,4]$	$\tau \in [1,6]$	$\tau \in [1,8]$	$\tau \in [1,2]$	$\tau \in [1,4]$	$\tau \in [1,6]$	$\tau \in [1,8]$	$\tau \in [1,2]$	$\tau \in [1,4]$	$\tau \in [1,6]$	$\tau \in [1,8]$
High ΔDM	-0.77***	-0.60***	-0.67***	-0.60***	-0.86***	-0.62***	-0.73***	-0.62***	-0.79***	-0.64***	-0.67***	-0.60***
	[-5.44]	[-7.35]	[-9.22]	[-10.03]	[-5.93]	[-7.51]	[-9.93]	[-10.42]	[-5.97]	[-8.08]	[-9.72]	[-10.49]
Low ΔDM	-0.40***	-0.32***	-0.37***	-0.31***	-0.50***	-0.44***	-0.47***	-0.40***	-0.53***	-0.37***	-0.48***	-0.37***
	[-3.21]	[-4.34]	[-5.84]	[-5.72]	[-4.36]	[-6.15]	[-7.53]	[-7.73]	[-4.05]	[-4.95]	[-7.05]	[-6.68]
High - Low	-0.44**	-0.32***	-0.34***	-0.33***	-0.28	-0.12	-0.16*	-0.14*	-0.40**	-0.38***	-0.32***	-0.35***
	[-2.51]	[-3.11]	[-3.68]	[-4.31]	[-1.63]	[-1.17]	[-1.76]	[-1.78]	[-2.36]	[-3.80]	[-3.55]	[-4.67]

Panel A reports the average post-event performance change in quarterly ROA ($\Delta\text{ROA}_{t+\tau}$) for non-SOEs and SOEs separately. "NSOE - SOE" reports the difference in the change of ROA between non-SOEs and SOEs, estimated from regression (18). $\Delta\text{ROA}_{t+\tau}$ is computed as the difference between ROA realized τ quarters after the event date t=2018Q2 and its pre-event ROA averaged across the four pre-event quarters. Panel B reports the predictability regression of change in quarterly ROA at quarter $t+\tau$ ($\Delta\text{ROA}_{t+\tau}$) on change in default measure at quarter t (ΔDM_t), estimated from regression (19). ΔDM_t is computed as the difference between the default measure at the event time t, and its pre-event unified default measure averaged across the four pre-event quarters. "NSOE - SOE" reports the difference in predictability between non-SOEs and SOEs. Panel C reports the difference in post-event performance change between non-SOEs and SOEs following in regression (18) for high and low groups separately, sorted by their change in default measure at t. "High - Low" reports the difference in the performance gap between the high and low groups, estimated using the regression (20). ROA is the ratio of the net profit to the lag book asset. Merton DM is the inverse of Merton's distance-to-default. Unified DM is the inverse of the distance-to-default from our unified model. Reported in square brackets are tstat's using standard errors clustered by firm and quarter.

Table 8: **Robustness Tests on Alternative Explanations**

	Panel A: US-China Trade War as an Alternative Explanation											
	X=Trade-War-Affected Industries				X=Trade-War CAPM Beta				X=Trade-War Return			
	Sensitivity β^X				Sensitivity β^X				Sensitivity β^X			
	$\tau \in [1,2]$	$\tau \in [1,4]$	$\tau \in [1,6]$	$\tau \in [1,8]$	$\tau \in [1,2]$	$\tau \in [1,4]$	$\tau \in [1,6]$	$\tau \in [1,8]$	$\tau \in [1,2]$	$\tau \in [1,4]$	$\tau \in [1,6]$	$\tau \in [1,8]$
NSOE	0.52**	0.26*	0.17	0.15	0.04	-0.03	-0.00	-0.08	-2.99	-1.76	1.32	2.05*
	[1.96]	[1.78]	[1.21]	[1.31]	[0.21]	[-0.35]	[-0.01]	[-1.06]	[-1.15]	[-1.16]	[0.96]	[1.81]
SOE	0.04	0.21	0.10	0.14	-0.25**	-0.12*	-0.08	-0.05	-3.55*	0.79	0.09	-0.46
	[0.17]	[1.10]	[0.66]	[1.07]	[-2.05]	[-1.71]	[-1.25]	[-0.87]	[-1.95]	[0.57]	[0.08]	[-0.52]
NSOE − SOE	-0.03	-0.17	-0.15	-0.10	0.15	0.01	-0.01	-0.10	2.29	-1.55	2.24	3.23**
	[-0.14]	[-1.55]	[-1.59]	[-1.31]	[0.76]	[0.09]	[-0.10]	[-1.14]	[0.76]	[-0.80]	[1.37]	[2.38]
	Performance Gap b^{NSOE}				Performance Gap b^{NSOE}				Performance Gap b^{NSOE}			
High X	-0.71***	-0.62***	-0.65***	-0.54***	-0.58***	-0.47***	-0.56***	-0.51***	-0.71***	-0.51***	-0.66***	-0.60***
	[-4.88]	[-7.26]	[-8.74]	[-8.79]	[-4.64]	[-6.26]	[-8.29]	[-9.19]	[-6.14]	[-7.56]	[-10.51]	[-11.61]
Low X	-0.68***	-0.47***	-0.54***	-0.47***	-0.59***	-0.44***	-0.47***	-0.38***	-0.58***	-0.52***	-0.50***	-0.39***
	[-5.52]	[-6.44]	[-8.48]	[-9.00]	[-4.75]	[-5.96]	[-7.23]	[-7.02]	[-4.14]	[-6.09]	[-6.86]	[-6.47]
High − Low	-0.03	-0.17	-0.15	-0.10	-0.05	-0.08	-0.11	-0.14*	-0.13	-0.01	-0.20**	-0.25***
	[-0.14]	[-1.55]	[-1.59]	[-1.31]	[-0.31]	[-0.78]	[-1.18]	[-1.92]	[-0.74]	[-0.13]	[-2.14]	[-3.26]
	Panel B: The 2016-17 SOE Deleveraging as an Alternative Explanation											
	X=Leverage (17Q2-18Q1 avg)				X=ΔLeverage (17Q2-18Q1 − 15Q1-Q4)				X=ΔLeverage (17Q1-Q4 − 15Q4-16Q3)			
	Sensitivity β^X				Sensitivity β^X				Sensitivity β^X			
NSOE	0.20	0.30	0.25	0.39*	-0.25	-0.41	-0.19	-0.16	-0.62	-0.68	-0.52	-0.58
	[0.40]	[1.08]	[0.99]	[1.93]	[-0.39]	[-1.13]	[-0.59]	[-0.60]	[-0.74]	[-1.46]	[-1.20]	[-1.63]
SOE	-0.21	0.10	0.11	0.27*	-0.86	-0.04	-0.01	0.39	-1.71*	-0.55	-0.62	-0.06
	[-0.66]	[0.46]	[0.63]	[1.78]	[-1.41]	[-0.13]	[-0.02]	[1.51]	[-1.85]	[-1.02]	[-1.27]	[-0.16]
NSOE - SOE	0.43	0.24	0.23	0.17	0.41	-0.49	-0.36	-0.68*	0.69	-0.39	-0.24	-0.76
	[0.79]	[0.75]	[0.83]	[0.71]	[0.46]	[-0.96]	[-0.81]	[-1.84]	[0.56]	[-0.55]	[-0.37]	[-1.43]
	Performance Gap b^{NSOE}				Performance Gap b^{NSOE}				Performance Gap b^{NSOE}			
Low X NSOE	-0.54***	-0.47***	-0.56***	-0.51***	-0.42***	-0.35***	-0.43***	-0.39***	-0.35**	-0.32***	-0.42***	-0.35***
− High X SOE	[-3.86]	[-5.81]	[-7.69]	[-8.53]	[-2.77]	[-4.09]	[-5.59]	[-6.20]	[-2.34]	[-3.75]	[-5.29]	[-5.42]

Panel A reports the sensitivity regression of change in quarterly ROA at quarter $t+\tau$ ($\Delta\text{ROA}_{t+\tau}$) on three measures of trade-war exposure. "NSOE - SOE" reports the difference in sensitivity between non-SOEs and SOEs. "Performance Gap" columns report the difference in post-event performance change between non-SOEs and SOEs following regression (18) for high and low groups, sorted by the three measures of trade-war exposure. "High - Low" reports the difference between the high and low groups, estimated from the regression (20). Panel B reports the sensitivity regression of change in quarterly ROA at quarter $t+\tau$ ($\Delta\text{ROA}_{t+\tau}$) on three deleveraging-motivated sorting variables. The last row reports the difference between the best non-SOEs in the low group against the worst SOEs in the high group. ROA is the ratio of the net profit to the lag book asset. Reported in square brackets are tstat's using standard errors clustered by firm and quarter.

Internet Appendix
"The SOE Premium and Government Support in China's Credit Market"
Zhe Geng and Jun Pan

A Appendix

A.1 Technical Proofs

Proof of Proposition 1

When $\pi_g = 0$, He and Xiong (2012) show that

$$\begin{aligned} E_t &= V_t - \frac{\delta V_B}{z\sigma^2}\frac{e^{-\gamma v_t}}{\gamma+1} - \frac{(1-\pi)C + \left(1-e^{-(r+\xi k)m}\right)\left[p - \frac{c}{r+\xi k}\right]}{z\sigma^2}\left[\frac{1}{\eta} + \frac{(1-e^{-\gamma v_t})}{\gamma}\right] \\ &+ \frac{1}{z\sigma^2}\left\{e^{-(r+\xi k)m}\left(p - \frac{c}{r+\xi k}\right)A(a) - \left(\frac{\alpha V_B}{m} - \frac{c}{r+\xi k}\right)A(\widehat{z})\right\}. \end{aligned} \tag{21}$$

where A follows equation (A7) in He and Xiong (2012). By replacing the recovery rate $\frac{\alpha V_B}{m}$ with $\frac{\alpha V_B}{m}(1-\pi_g) + \frac{P}{m}\pi_g$ under bailout probability π_g, we can solve for V_B following equation (A6) in their appendix,

$$\begin{aligned} 0 = &-\frac{\delta V_B}{\eta - 1} + \left[(1-\pi)C + \left(1-e^{-(r+\xi k)m}\right)\left(p - \frac{c}{r+\xi k}\right)\right]\frac{1}{\eta} + \frac{\sigma^2}{2}l \\ &+ e^{-(r+\xi k)m}\left(p - \frac{c}{r+\xi k}\right)\left[\begin{array}{c} \frac{\left\{N(-a\sigma\sqrt{m}) - e^{rm}N(-z\sigma\sqrt{m})\right\}}{\eta} \\ +\frac{\left\{N(a\sigma\sqrt{m}) - e^{rm}N(-z\sigma\sqrt{m})\right\}}{\gamma} \end{array}\right] \\ &+ \left[\frac{\alpha V_B}{m}(1-\pi_g) + \frac{P}{m}\pi_g - \frac{c}{r+\xi k}\right]\left[\begin{array}{c} -\frac{\left\{N(-\widehat{z}\sigma\sqrt{m}) - e^{\frac{1}{2}\left[z^2 - \widehat{z}^2\right]\sigma^2 m}N(-z\sigma\sqrt{m})\right\}}{a - \widehat{z} + \eta} \\ -\frac{\left\{N(\widehat{z}\sigma\sqrt{m}) - e^{\frac{1}{2}\left[z^2 - \widehat{z}^2\right]\sigma^2 m}N(-z\sigma\sqrt{m})\right\}}{a + \widehat{z} + \eta} \end{array}\right]. \end{aligned}$$

So,

$$V_B(\pi_g) = \frac{\frac{(1-\pi)C + \left(1-e^{-(r+\xi k)m}\right)(p - \frac{c}{r+\xi k})}{\eta} + (p - \frac{c}{r+\xi k})[b(-a) + b(a)] + (\frac{c}{r+\xi k} - p\pi_g)[(B(-\widehat{z}) + B(\widehat{z})]}{\frac{\delta}{\eta - 1} + \frac{\alpha}{m}[B(-\widehat{z}) + B(\widehat{z})](1-\pi_g)},$$

where

$$a \equiv \frac{r-\delta-\sigma^2/2}{\sigma^2}, z \equiv \frac{\left(a^2\sigma^4+2r\sigma^2\right)^{1/2}}{\sigma^2}, \eta \equiv z-a>1, \widehat{z} \equiv \frac{\left[a^2\sigma^4+2(r+\xi k)\sigma^2\right]^{1/2}}{\sigma^2},$$
$$b(x) = \frac{1}{z+x} e^{-(r+\xi k)m} \left[N(x\sigma\sqrt{m}) - e^{rm} N(-z\sigma\sqrt{m})\right],$$
$$B(x) = \frac{1}{z+x} \left[N(x\sigma\sqrt{m}) - e^{\frac{1}{2}\left[z^2-x^2\right]\sigma^2 m} N(-z\sigma\sqrt{m})\right].$$

A.2 Data Description

Overview of China's Credit Market

Excluding financial bonds, the Chinese credit market for non-financial companies stands at RMB 23 trillion by the end of June 2020. As shown in panel (a) of Figure A.3, 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, including Medium-Term Notes, Corporate Bonds and Enterprise Bonds. By June 2020, the total amount outstanding of our corporate bond sample is RMB 8 trillion, accounting for 34% of the credit market.[39]

We sort the corporate bond sample by issuer type along two dimensions. First and foremost, we consider whether the bond issuer is a state-owned enterprise (SOE) or non-SOE. Second, we consider whether the bond issuer is publicly listed or unlisted. Our empirical study focuses mostly on the listed firms, which are larger and more important to the economy and whose financial statements and equity market information help us measure the credit quality as well as the potential government support of the bond issuers. Panel (b) of Figure A.3 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 listed SOE and listed non-SOE, account for 30% of the corporate bond sample, while the unlisted issuers account for the rest.[40] Another unique aspect of China's bond market is the dominance of the SOE issuers, especially during the early sample period. Over time, the non-SOE issuers catch

[39]Chengtou bonds, as shown in panel (a) of Figure A.3 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.

[40]Suggested by an anonymous referee, some SOEs with large bond amounts outstanding at the interbank market are not listed due to the strategic concern of the government, which contributes to the dominance of unlisted issuers in China's bond market.

up steadily in size and the ratio of listed SOEs to listed non-SOEs in amount outstanding decreases from 13 in 2010 to a level close to 1.6 in 2018.

The Panel (c) of Figure A.3 plots the quarterly default amount in 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 amounts ranging from less than RMB 1 billion to 12.2 billion in 2016Q1. At the same time, the corporate bond market was expanding aggressively with RMB 625 billion new issuances in 2016Q1, as shown in Panel (d) of Figure A.3. Starting from 2018Q2, more than 90% of the default is driven by non-SOE 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 listed SOEs also seem quite safe. Throughout our sample period, there are only two default events for the listed SOEs with a total default amount of 6.5 billion.

We provide further details in collecting the bond sample issued by listed firms, as shown in Table 1. 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, including CCXI, China Lianhe, DaGong Global, and Shanghai Brilliance. For Exch dummy, exchange-traded bonds account for 69% for listed non-SOE, and 53% for unlisted 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. For bond trading variables, there is a dramatic decrease in trading activity over the three time periods, as shown in Table 1. Part of this decreasing trend is due to the crackdown of agent-holding transactions, which is covered extensively in Mo and Subrahmanyam (2020). In addition, we also control for issuers' industry in our analysis using the eleven industry categorization from Wind.

Summary Statistics of Unlisted Firms: Bond-Level Data

Panel A of Table A.1 summarizes our bond sample issued by unlisted firms. Overall, there are 395 unlisted non-SOE issuers with 1497 bonds, and 1418 unlisted SOE issuers with 5943 bonds. We further summarize our sample by the three sub-periods, and, as we can see, the numbers of issuers and bonds vary over time as well. The exchange-traded bonds account for 47% for unlisted non-SOEs, and 16% for unlisted SOEs. For embedded optionality, within our sample, we find 56% (27%) of unlisted non-SOE (SOE) bonds are puttable while 4% (9%) of unlisted non-SOE (SOE) bonds are callable. As SOEs issue more callable bonds with negative option values for investors, while non-SOEs issue more puttable bonds with positive option values for investors, adjusting for this optionality would on average decrease the credit spreads for SOEs and increase those for non-SOEs, further widening the SOE premium. Comparing the non-SOE and SOE samples further, we see that SOE bonds in general have higher ratings, larger issuance size, and with longer maturity and older in age, higher turnover but less frequent tradings, consistent with the general pattern in the listed sample.

Summary Statistics of Listed Firms with Participation in Credit Market

Focusing on the sample of listed firms with participation in the credit market, which we focus on to study the real impact, we report the equity-level summary statistics in Panel B of Table A.1. There are in total 821 non-SOE issuers and 623 SOE issuers. The non-SOE sample on average has a smaller equity size than that of the SOE sample. The average leverage for non-SOEs is 46.7%, lower than 56.5% for the SOEs. The annualized volatility for this sample is on average 44.3% for non-SOE and 39.6% for SOE. The average asset growth for non-SOEs is 28.7%, higher than the 16.2% for the SOEs. The average government holdings are 3.6% for non-SOEs and 48.0% for SOEs. We also report the summary statistics of the Merton DM and unified DM, as well as the respective estimates of asset value and volatility. Similar to the pattern in Table 1, we find that SOEs in general have higher Merton DM and thus are less healthy than non-SOEs. Merton's DM is on average 23.4% for SOEs and 21.9% for non-SOEs. However, our unified DM indicates that SOEs are significantly healthier than non-SOEs. The unified DM is on average 21.5% for SOEs and 28.6% for non-SOEs. For ROA and ROE, we find that non-SOEs on average have higher ROA and ROE than SOEs, especially in Phase I and II. Moving to Phase III, we see a reversal pattern as SOEs now have higher profitability than non-SOEs.

A.3 Construction of Government-Holdings Measure

Key to the SOE classification is whether or not the end-controller (i.e., the ultimate controller) of a firm is the state, which includes the state-owned assets supervision and administration commission of the state council (central SASAC), central government institutions, local SASAC and local government institutions. To capture the extent of government support above and beyond the non-SOE dummy, we use information on government holdings of listed firms. For each publicly listed firm, our government-holdings variable measures the sum of equity holdings by all government-related entities within the top ten shareholders. Compared with the non-SOE dummy, which treats SOEs and non-SOEs as two solid blocks, our measure of government holdings is a continuous variable with richer information on the variation in the strength of government support both across and within the SOE and non-SOE blocks.

In constructing the government holdings measure, we piece together shareholder information from three separate datasets from Wind Financial Information. The first dataset is the "AShareInsideHolder" dataset (hereafter Shareholder Dataset), which contains the basic information of the top 10 shareholders of a listed firm, including their names and holdings. This dataset is available because the publicly listed firms in China are required to disclose such information in their financial reports. Using this information, we find that, on average, the top 10 shareholders hold 61.2% of the firms and this holding percentage remains stable over time during our sample period. For our purpose, the main drawback of this dataset is it does not contain information on the shareholder's attribution – whether or not a top-ten shareholder is government related.

To identify the government-related attributions of the top-ten shareholders, we further merge the Shareholder Dataset with two other datasets from Wind that contains such attribution information. One is the Controller Dataset used earlier to help us construct the NSOE dummy, and the other is the "CompIntroduction" dataset (hereafter Firm Dataset). While the Controller Dataset gives us dynamic information on firms' attribution, its collection of firms is limited as it contains only firms that serve as end-controllers or are related to end-controllers. The Firm Dataset helps us expand the sample substantially as it contains attribution information for different types of firms, including listed and unlisted firms.[41] Merging the three datasets together, we are able to piece together a rather comprehensive picture of the shareholder structures for the listed firms in our sample. Our methodology can match 64.7% (in terms of the number of shareholders) and 89.8% (in terms of equity holdings) of the shareholders' attributions from 2010 through 2020Q2. Using this information, we can then calculate government holdings for all listed firms in our sample, including SOEs and non-SOEs.

In addition to the initial construction (labeled as Raw), we further incorporate two separate databases that provide similar information. The first dataset is from Wind, which provides the total holdings (in shares) for all the government-related shareholders within the top ten shareholders. Their approach is effectively the same as our construction. Comparing their measures against ours, we find a substantial amount of inconsistencies, with missing observations being the main driver. For example, China's biggest manufacturer of air-conditioners - Gree Electric is owned and controlled by Zhuhai SASAC before December 2019, but its government holdings information is missing in Wind before 2008. Even for firms

[41]The main disadvantage of the Firm Dataset is that information on attribution is more likely to be static, recorded at the entry point of the firm. Nonetheless, this is the best we can do given the data limitations.

whose government holdings are recorded as positive in Wind, we still find many instances when Wind fails to account for all the government-related shares.

The second data source used in our compilation is CSMAR, which provides the attribution information for each top ten shareholders, without calculating the total government holdings. We find three potential drawbacks in their data. First, they do not separate the holdings by National Social Security Fund (NSSF), a government-run investment fund established primarily to provide a reserve of funds for China's social security system. Given the investment objective of NSSF, it is unlikely that their holdings will be informative for the purpose of gauging the extent of government support. For this reason, we exclude NSSF's holdings from the measure of government holdings. Second, prior to 2014, CSMAR has many missing observations in the first and third quarters of each year. It is possible that they focus their attention more on the semi-annual and annual reports. Finally, even in recent years, as CSMAR improves its data coverage, we still find that a significant portion of inaccurate estimates.

Overall, all three data sources provide valuable and yet imperfect information on government holdings. Our objective is to compile the most robust measure of government holdings using the information contained in these data sources. Our algorithm in merging the three datasets is as follows. For quarters when the government holdings values are missing in all three data sources, we fill in the nearest value from the previous quarters. For quarters when all three data sources provide values, we adopt the maximum algorithm by choosing the highest government holdings among the three. Underlying this choice is the observation that the most prevalent errors in these data sources are missing observations: the failure to assign government attribution to a government-related shareholder. For quarters when one or two estimations are missing, we modify our algorithm as follows. Suppose the government holdings value for a firm is 45% from Wind, 50% from our raw estimation, and missing from CSMAR for one particular quarter. We then check the values from all three sources reported for the previous quarter. If, during the previous quarter, both Wind and Raw have the same holdings as in the current quarter, while CSMAR has a non-missing value, say 55%, we will fill in the value of 55% for CSMAR for the current quarter and choose the maximum among the three estimates. In other words, our robust government holdings will pick up CSMAR's estimation (55%) in this case. By contrast, if either Wind or Raw indicates a change in value from the previous quarter to the current quarter, we will then choose the maximum only between Wind and Raw. In this case, our robust government holdings will pick up Raw's estimation (50%). Since both CSMAR and Wind have many missing values in Q1 and Q3 from 2010 to 2013, this modification is necessary for our construction.

The key underlying assumption for our construction is that most of the errors occurred in the three data sources are due to omissions: the failure to assign state attributions to government-related entities. By contrast, the errors of wrongly assigning state attributions to non-state entities are less likely. To verify our strategy, we further randomly choose ten examples in which the government holdings measure provided by the three data sources are inconsistent and manually check their shareholder's attribution. We find that it is always the case that the maximum holdings have a larger and more accurate coverage than the rest. As long as the three data sources do not systematically mis-specify the attribution information for a given shareholder, this is the most effective way for us to compile the non-overlapping information contained in the three data sources. In this respect, we believe that our robust measure of government holdings is a more precise and robust measure of government support compared with the ones adopted in the literature.[42] Using either the initial construction or the refined version, the main message of our findings remains robust, although the refined version does help reduce noise and sharpen our findings.

To better assess the data quality across different sources, we use two measures to compare their data quality against our robust measure of government holdings. For firm i in quarter t, we measure the absolute difference in government-holdings measure between each of the data sources and our robust measure. From this deviation, we further calculate the quarterly error rate and the mean error for each of the data sources: the quarterly error rate calculates the percent of incidents when the deviation is more than 1%, while the mean error reports the average of the deviation for each of the data sources. Effectively, the first measure focuses on the number of incidents when errors take place, while the second measure cares more about the overall magnitudes of the errors.

Figure A.4 plots the quarterly error rates and mean errors for Wind, CSMAR, and our initial construction (labeled as Raw). Panel (a) reports the error rates for the three data sources. Overall, CSMAR outperforms both Wind and Raw in all periods, with improving data quality over time. The error rate is around 17% in Phase I and 8% in Phase III. For Wind, the error rates are on average 20% in Phase I, followed by a big jump in 2015Q3, driven mainly by the stock crash in July 2015 amid the government's effort to rescue the market. As for Raw, the error rates are on average 27% in phase I and then decrease to 17% and remain stable afterwards.

Panel (b) of Figure A.4 reports the mean error for the three data sources. We see

[42]For example, Cong et al. (2019) use the share of registered capital effectively owned by the government as the measure of state-ownership from Annual Survey of Industrial Firms (ASIF) of China's National Bureau of Statistics. Their measure of state ownership is in spirit to our government holdings, but ASIF suffers from many missing observations in the share of government-registered capital, even for large SOEs. In the example of Gree Electric, the shares of government-registered capital in ASIF are zero for the period from 1998 through 2013.

a significant decline in mean error, indicating an overall convergence in the information contained in the three data sources. By 2020, the mean error rate is less than 1% for Wind and CSMAR. Indeed, post 2018, we see a pattern of expanded data coverage and improving data quality by both CSMAR and Wind. Consistent with our findings of the emerging importance of government support for credit pricing, the professional data providers are also making more effort to differentiate the affiliations, state and non-state, of the top-ten shareholders, At the same time, we observe a slight increase in the mean error of our raw estimation, as the additional information from Wind and CSMAR becomes more valuable in helping us construct the robust measure. Moreover, our initial construction tends to have high error rates but relatively low mean errors because of our inability to identify those small shareholders with low holdings among the top ten shareholders. Indeed, this is where professional data services such as Wind and CSMAR can add value.

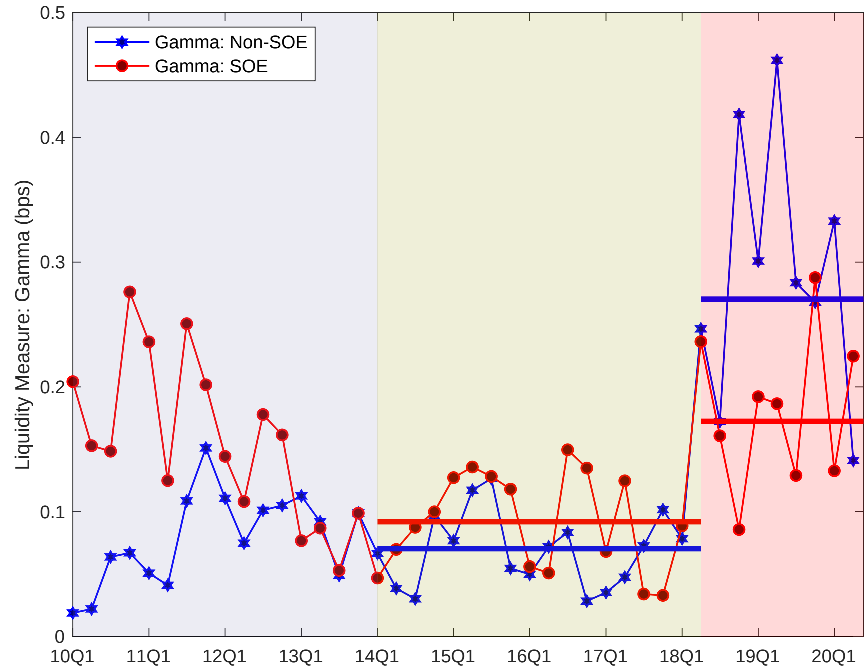
Overall, by compiling the information from the three data sources with varying degrees of information and imperfection, the robust version of our government holdings measure is so far the most comprehensive when it comes to proxies for government support. It could be useful for other research settings in the future.

By using our government holdings measure as a proxy for government support, our underlying hypothesis is that, with a higher stake invested in a firm, the government is more likely to extend support, especially in times of crisis. Following this intuition, one important aspect that can be further explored is the concentration of government holdings. For example, two firms both with 50% of government holdings might differ quite significantly in government support if one is held by one government entity while the other is held by multiple government entities. In particular, the one with concentrated government ownership is more likely to receive government support in times of crisis, while the one with more diverse government ownership might need more coordination from the various government entities.

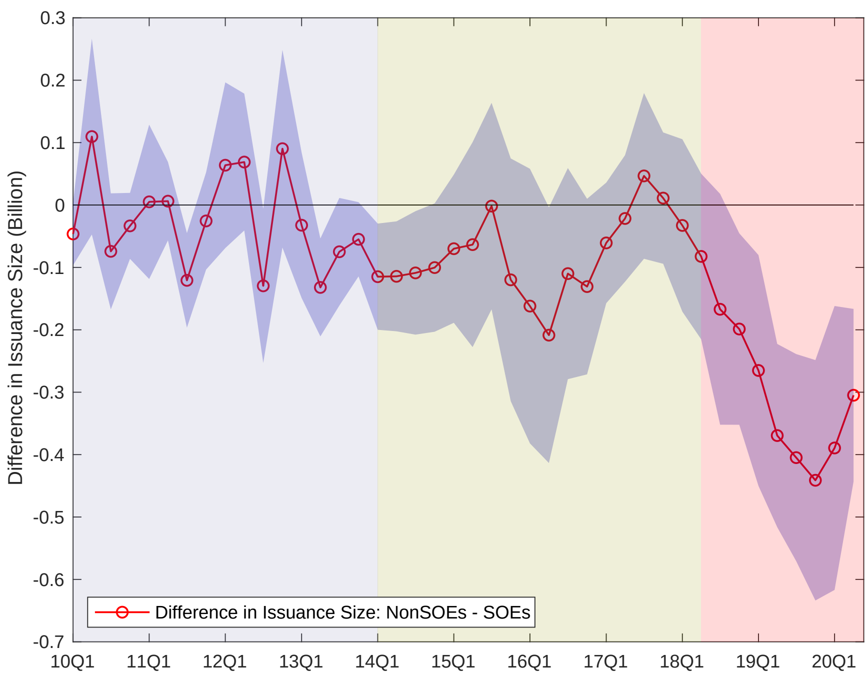
A.4 Alternative Unified Default Measures

In Section 4.1, we use the quartic function $y = 1-(x-1)^4$ to translate government holdings (x) into bailout probability (y). In this subsection, we provide alternative mappings using linear ($y = x$), quadratic ($y = 1-(x-1)^2$), cubic ($y = 1-(x-1)^3$) function forms, as well as the binary mapping via the non-SOE dummy. We follow the same procedure in constructing the unified default measures and report the SOE premium after controlling for the unified DM in Panel A of Table A.2. From left to bottom, the SOE premium in Phase III is 6 bps (t-stat=0.38) for quartic, 23 bps (t-stat=1.63) for cubic, 40 bps (t-stat=2.80) for quadratic, 72 bps (t-stat=5.07) for linear and 3 bps (t-stat=0.16) for binary function forms. Moving to the adjusted R-Squared, we find that the quartic function gives the highest R-Square while the binary function has the lowest R-Square. Overall, our unified DM can explain a large fraction of the SOE premium across different function forms, especially for quartic, cubic and binary functions in Phase II and III. For the binary function, the low SOE premium and the low R-Squared suggest that although the binary function can explain away the credit spread difference between non-SOEs and SOEs (between-groups effect), its explanatory power on the cross-sectional variation (within-groups effect) is weaker compared to other functional forms.

Panel B and C report the price discovery results for non-SOEs and SOEs, respectively. From left to right, we see a decreasing trend for both coefficient estimates and adjusted R-Squared in Phase III. For example, for the SOEs sample, the coefficients associated with the Unified DM are 6.86 (t-stat=6.66) for quartic, 5.82 (t-stat=6.55) for cubic, 5.04 (t-stat=7.04) for quadratic, 3.86 (t-stat=6.73) for linear and 4.76 (t-stat=5.05) for binary. Meantime, the adjusted R-Squares are 0.426 for quartic, 0.421 for cubic, 0.422 for quadratic, 0.415 for linear and 0.399 for binary. Across different mappings, we can see that the quartic (binary) function performs the best (worst) in terms of adjusted R-Squared. To sum up, the more concave the mapping between government holdings and bailout probability is, the better performance of our unified DM will be. In general, regardless of the mappings, our unified default measure can explain a large fraction, if not all, of the SOE premium and improve the extent of the price discovery.

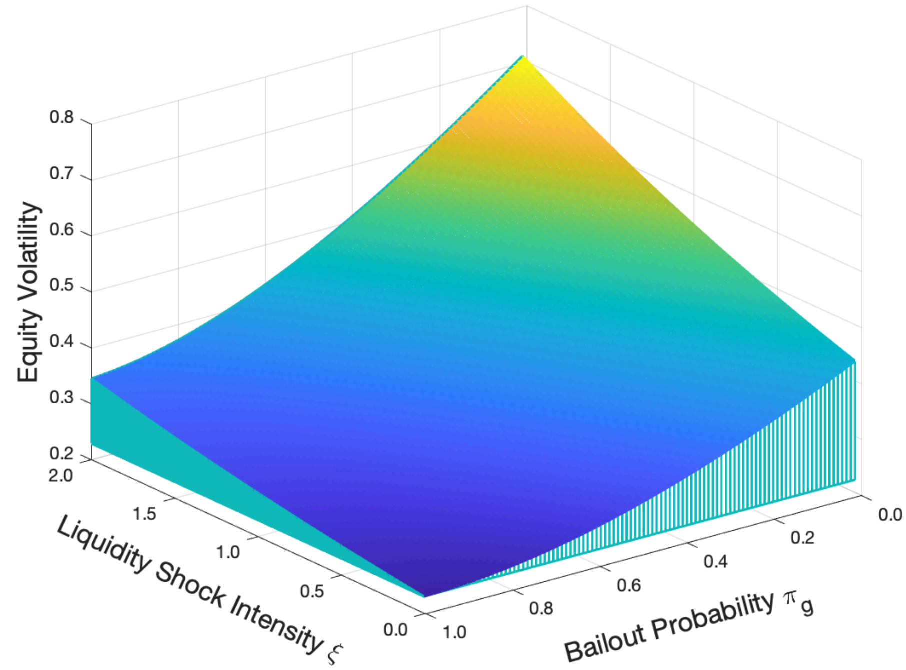


(a) **Liquidity Measure Gamma**

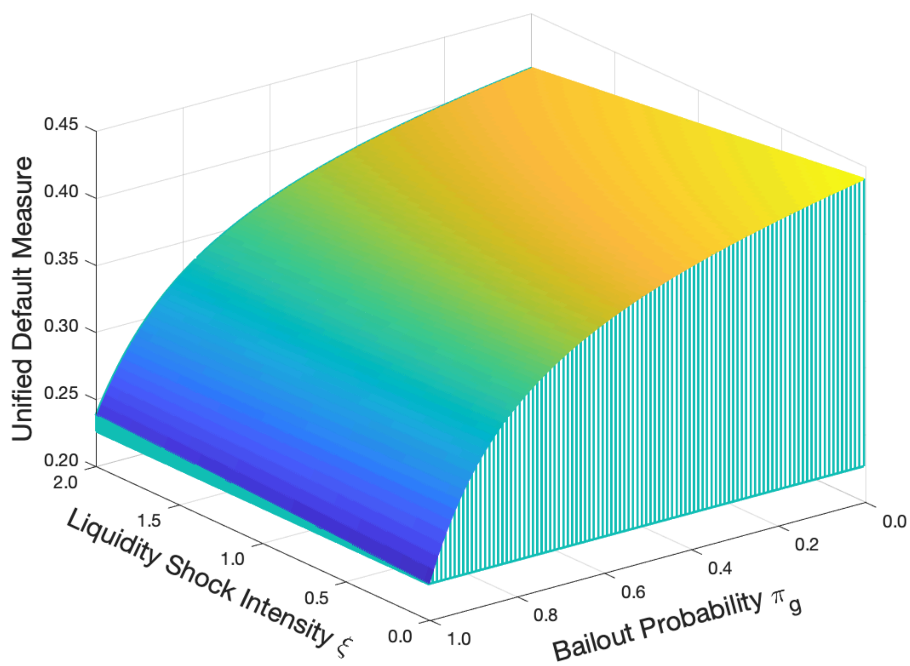


(b) **Issuance Size Difference**

Figure A.1: Panel (a) plots the quarterly average of the illiquidity proxy – Gamma from Bao, Pan, and Wang (2011) for non-SOEs (blue line) and SOEs (red line). To control for rating and maturity effects, we include bonds with ratings between AA and AAA and maturity between 2 years and 5 years. Panel (b) plots the difference between listed non-SOEs and listed SOEs in issuance size, estimated using quarterly regressions, controlling for size and industry. The shaded area indicates the 95% confidence intervals.

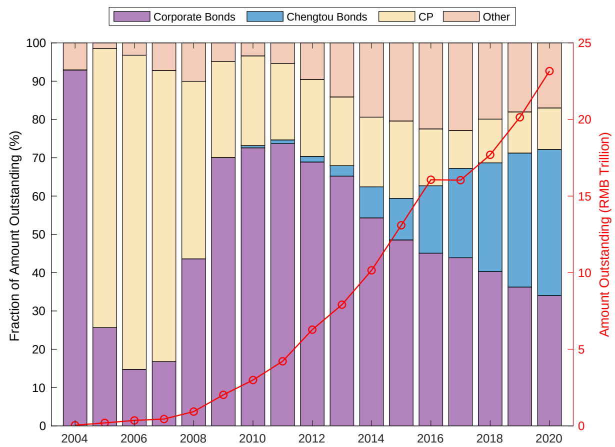


(a) **Equity Volatility, Fixing Asset Value and Volatility**

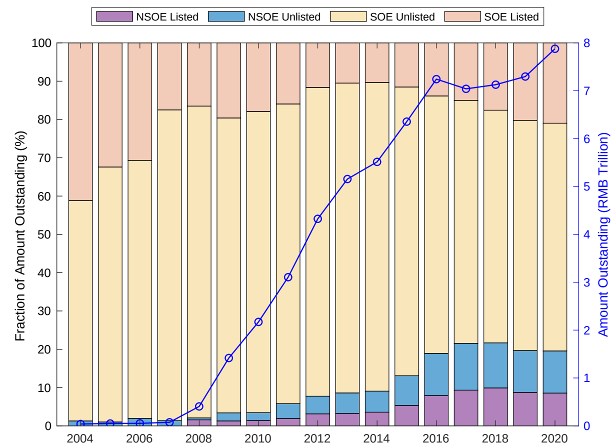


(b) **Unified Default Measure, Fixing Equity Value and Volatility**

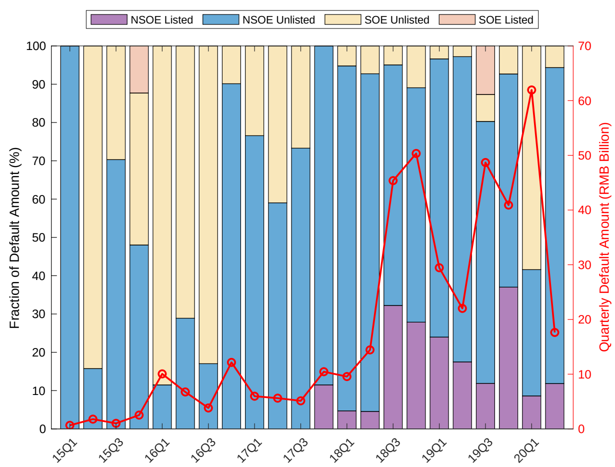
Figure A.2: This figure plots the calibration results. The top panel shows the equity volatility with varying bailout probability π_g and liquidity shock intensity ξ, given the fixed asset value $V_0 = 100$ and asset volatility $\sigma_A = 15\%$. The bottom panel shows the unified default measure with varying bailout probability π_g and liquidity shock intensity ξ, given the fixed equity value $E = 38$ and equity volatility $\sigma_E = 55\%$. The equity value and volatility are calculated when $\xi = 1$ and $\pi_g = 0$. For other parameters, see Section 3.2.



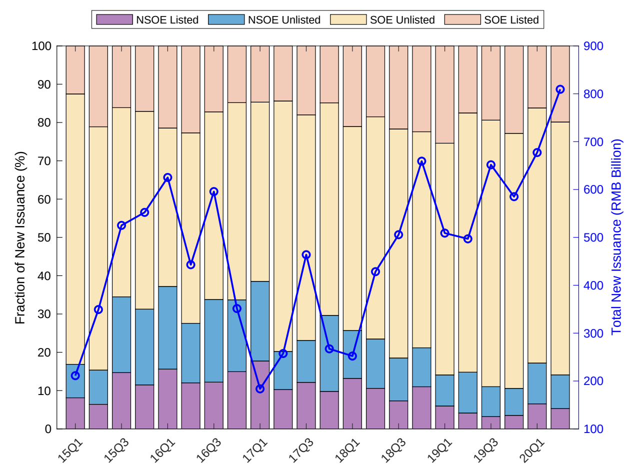
(a) **China's Credit Market**



(b) **China's Corporate Bond Market**

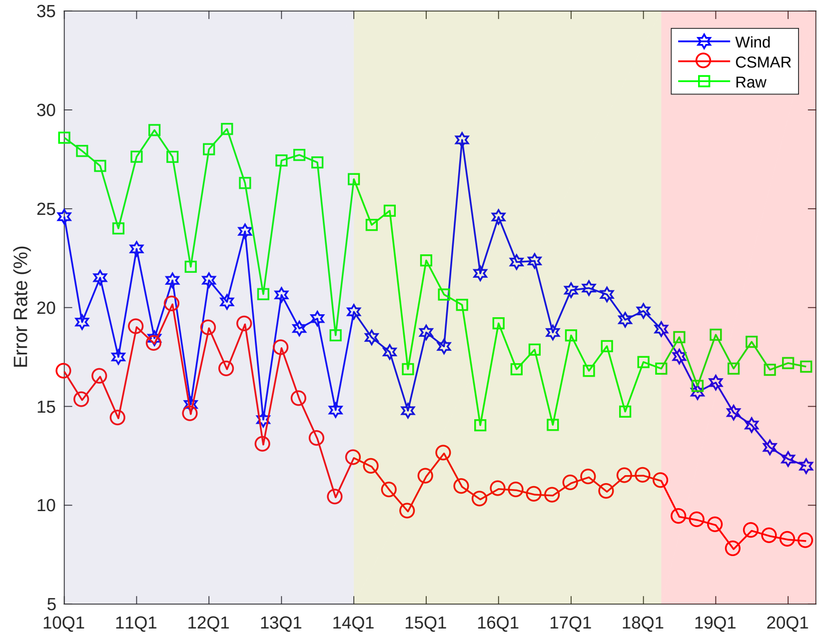


(c) **Quarterly Default**

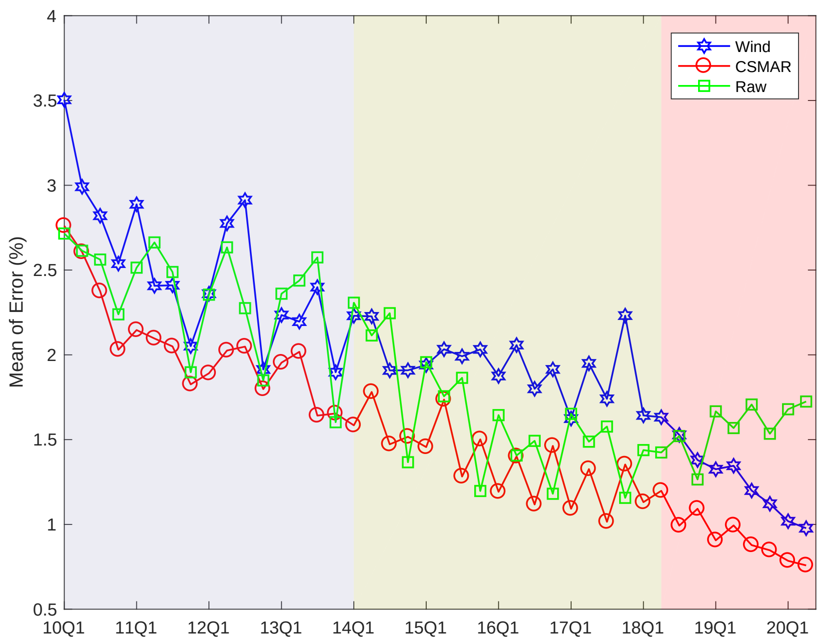


(d) **Quarterly New Issuance**

Figure A.3: Panel (a) plots the total amount outstanding of the Chinese credit market (right axis) and the fraction by instrument type (left axis). Panel (b) plots the total amount outstanding of the corporate bond market (right axis) and the fraction by issuer type (left axis). Data for 2020 is as of end of the second quarter. Panel (c) plots the quarterly default amount (right axis) and the fraction by issuer type (left axis) and defaults by all instruments in the credit market are included. Panel (d) plots quarterly new issuance of corporate bonds (right axis) and the fraction by issuer type (left axis) and corporate bonds issued by Chengtou are excluded.



(a) **Error Rate (%)**



(b) **Mean of Error (%)**

Figure A.4: This figure plots the quarterly error rates in the construction of government holdings from three sources, namely Wind, CSMAR and our raw government holdings (Raw). The quarterly error rates are defined as the ratio of the number of errors to the number of total firms in any given quarter. Any difference between the robust government holdings and the estimation from Wind, CSMAR or Raw beyond 1% is considered as errors. The robust government holdings is the maximum government holdings among Wind, CSMAR and Raw. Panel (a) reports the result for all the listed firms and Panel (b) reports the mean of difference between robust government holdings and Wind, CSMAR and Raw.

Table A.1: **Summary Statistics: Unlisted Sample and Listed Firms with Participation in Credit Market**

Panel A: Unlisted Sample Bond-Level Variables

	All				Phase I				Phase II				Phase III			
	NSOE		SOE		NSOE		SOE		NSOE		SOE		NSOE		SOE	
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
NumIssuers	395		1418		147		804		353		1249		274		952	
NumBonds	1497		5943		298		2046		1053		3659		937		3400	
CreditSpread (%)	2.81	1.84	1.50	1.24	2.02	0.87	1.43	0.87	2.52	1.52	1.40	1.14	3.68	2.31	1.80	1.69
Rating	2.32	0.81	1.79	0.86	2.76	0.69	1.90	0.87	2.45	0.77	1.90	0.87	1.91	0.76	1.44	0.72
Maturity (yr)	3.08	1.44	3.40	1.88	3.96	1.79	4.34	2.03	3.18	1.39	3.19	1.73	2.51	1.07	2.75	1.54
IssueSize (billions)	1.09	0.93	1.90	2.49	0.99	0.66	2.06	2.88	1.09	0.89	1.84	2.49	1.15	1.08	1.83	1.90
Age (yr)	1.63	1.29	2.10	1.88	1.03	0.90	1.76	1.63	1.56	1.26	2.36	1.93	2.01	1.35	1.95	1.96
Coupon (%)	6.10	1.31	5.37	1.12	6.32	1.04	5.48	1.04	6.18	1.32	5.55	1.12	5.87	1.38	4.84	1.06
Exch	0.47	0.50	0.16	0.37	0.16	0.37	0.16	0.36	0.46	0.50	0.13	0.34	0.64	0.48	0.23	0.42
Callable	0.04	0.21	0.09	0.28	0.01	0.09	0.01	0.12	0.04	0.21	0.08	0.26	0.06	0.24	0.20	0.40
Puttable	0.56	0.50	0.27	0.44	0.38	0.49	0.35	0.48	0.52	0.50	0.26	0.44	0.69	0.46	0.20	0.40
ZeroDays (%)	85.55	19.63	88.63	15.45	81.55	20.18	81.64	20.96	85.16	20.95	90.64	12.95	88.05	16.35	92.74	8.10
Turnover (%)	48.02	115.58	67.62	148.50	124.04	209.82	122.81	223.91	43.48	97.46	51.53	111.14	21.67	54.43	35.85	62.44
TradingDays (day)	10	13	8	10	12	13	12	14	10	14	6	9	8	11	5	5

Panel B: Listed Firms with Participation in Credit Market

	All				Phase I				Phase II				Phase III			
NumIssuers	821		623		570		544		693		543		791		562	
EquitySize (log)	22.35	1.06	22.79	1.05	21.73	0.98	22.45	1.02	22.71	0.89	23.04	0.98	22.52	1.06	22.93	1.06
Leverage (%)	46.72	18.70	56.46	18.00	43.15	20.12	56.65	18.01	47.34	17.95	57.08	18.05	50.08	17.32	55.02	17.79
AssetGrowth (%)	28.68	31.56	16.18	23.14	38.81	36.73	22.33	26.51	27.22	29.92	13.46	21.06	18.64	22.32	10.39	17.25
EquityVolatility (%)	44.27	18.00	39.64	17.18	41.83	10.89	37.92	11.06	47.05	22.94	43.20	22.18	42.70	14.94	36.24	14.22
GovtHoldings (%)	3.60	7.59	48.02	16.20	3.77	7.79	47.39	16.51	3.51	7.39	48.36	15.85	3.52	7.65	48.49	16.24
Merton DM (%)	21.88	12.76	23.39	14.20	18.58	6.94	20.36	8.33	22.92	14.84	26.60	18.36	24.21	13.76	22.91	12.41
AssetValue (log)	22.80	1.11	23.48	1.15	22.16	1.04	23.12	1.12	23.09	0.96	23.69	1.09	23.09	1.10	23.73	1.17
AssetVolatility (%)	30.53	16.75	22.71	14.61	28.92	12.11	21.85	11.48	34.26	20.39	25.65	17.64	26.38	13.43	18.90	12.21
Unified DM (%)	28.60	11.49	21.54	8.50	27.87	11.01	21.17	7.38	27.93	11.75	21.98	9.60	30.58	11.42	21.39	8.20
AssetValue (log)	22.88	1.12	23.52	1.18	22.23	1.04	23.14	1.13	23.16	0.96	23.69	1.10	23.24	1.10	23.87	1.21
AssetVolatility (%)	26.22	16.81	22.81	16.21	25.00	12.98	21.83	12.36	30.17	20.08	26.66	19.75	21.28	13.19	17.60	13.01
ROA (%)	1.07	1.77	0.78	1.45	1.34	1.58	0.96	1.46	1.12	1.58	0.64	1.42	0.67	2.17	0.71	1.46
ROE (%)	1.85	4.74	1.48	4.72	2.37	3.63	1.94	4.61	2.11	3.69	1.09	4.97	0.79	6.85	1.37	4.35

The sample period is from January 2010 to June 2020. Phase I, from 2010 through 2013, is the pre-default period; Phase II, from 2014 through 2018Q1, captures the first wave of defaults; and Phase III, from 2018Q2 to 2020Q2, captures the second and much more severe wave of defaults. 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. Exch is 1 for exchange-traded bonds. Callable is 1 for bonds issued with callable options. Puttable is 1 for bonds issued with puttable options. 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. EquitySize is the log of the firm's equity size. Leverage is the ratio of total current liabilities plus the total non-current liabilities to the total asset value. AssetGrowth is the average growth rate of the asset value in the past three years. EquityVolatility is the annualized equity volatility. GovtHoldings is the total government equity holdings within firm's top 10 shareholders. Merton DM is the inverse of Merton's distance-to-default. Unified DM is the inverse of the distance-to-default from our unified model. AssetValue and AssetVolatility are model-implied asset value and annualized asset volatility, respectively.

Table A.2: **Robustness Checks: Alternative Approaches to Constructing Unified Default Measure**

Panel A: Explaining the SOE Premium (x: Govt Holdings, y: Bailout Probability)															
	$y = 1-(1-x)^4$			$y = 1-(1-x)^3$			$y = 1-(1-x)^2$			$y = x$			$y = 0.8$ for SOEs		
	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III
NSOE	0.17**	0.06	0.06	0.18**	0.11	0.23	0.19**	0.17**	0.40***	0.20***	0.24***	0.72***	0.16	0.02	0.03
	(1.96)	(0.82)	(0.38)	(2.21)	(1.50)	(1.63)	(2.56)	(2.44)	(2.80)	(2.89)	(3.80)	(5.07)	(1.61)	(0.23)	(0.16)
Unified DM	0.34	2.27***	7.23***	0.28	2.13***	6.95***	0.18	2.07***	6.38***	0.17	1.96***	5.57***	0.37	2.24***	6.14***
	(0.91)	(6.26)	(9.92)	(0.84)	(6.16)	(9.77)	(0.61)	(6.33)	(9.52)	(0.63)	(6.66)	(8.89)	(0.93)	(7.45)	(7.49)
Obs	4,292	9,967	5,338	4,292	9,967	5,338	4,292	9,967	5,338	4,292	9,967	5,338	4,292	9,967	5,338
Adj R^2	0.547	0.476	0.423	0.547	0.476	0.421	0.546	0.477	0.418	0.546	0.477	0.413	0.547	0.475	0.408
Panel B: Price Discovery in NSOE Sample (x: Govt Holdings, y: Bailout Probability)															
	$y = 1-(1-x)^4$			$y = 1-(1-x)^3$			$y = 1-(1-x)^2$			$y = x$			$y = 0.8$ for SOEs		
	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III
Unified DM	0.68	1.86***	7.40***	0.68	1.79***	7.39***	0.68	1.86***	7.26***	0.68	1.82***	6.93***	0.68	1.81***	6.70***
	(1.03)	(4.61)	(5.88)	(1.06)	(4.50)	(5.65)	(1.07)	(4.72)	(5.62)	(1.12)	(4.75)	(5.42)	(1.16)	(4.79)	(5.14)
Obs	1,367	4,116	2,085	1,367	4,116	2,085	1,367	4,116	2,085	1,367	4,116	2,085	1,367	4,116	2,085
Adj R^2	0.496	0.388	0.403	0.496	0.388	0.403	0.496	0.389	0.400	0.497	0.388	0.396	0.497	0.388	0.393
Panel C: Price Discovery in SOE Sample (x: Govt Holdings, y: Bailout Probability)															
	$y = 1-(1-x)^4$			$y = 1-(1-x)^3$			$y = 1-(1-x)^2$			$y = x$			$y = 0.8$ for SOEs		
	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III
Unified DM	0.04	2.37***	6.86***	0.03	2.14***	5.82***	-0.02	2.00***	5.04***	-0.01	1.85***	3.86***	0.00	2.51***	4.76***
	(0.17)	(4.26)	(6.66)	(0.14)	(4.39)	(6.55)	(-0.14)	(4.73)	(7.04)	(-0.08)	(5.29)	(6.73)	(0.02)	(5.54)	(5.05)
Obs	2,925	5,851	3,253	2,925	5,851	3,253	2,925	5,851	3,253	2,925	5,851	3,253	2,925	5,851	3,253
Adj R^2	0.541	0.506	0.426	0.541	0.506	0.421	0.541	0.507	0.422	0.541	0.509	0.415	0.541	0.505	0.399

This table reports the SOE premium (Panel A) and price discovery (Panel B and C) under alternative unified default measures. From left to right, we use $y = 1-(x-1)^4$, $y = 1-(x-1)^3$, $y = 1-(x-1)^2$, $y = x$ and the binary mapping to translate government holdings (x) into bailout probability (y). NSOE is one for bonds issued by non-SOEs and zero for SOEs. Unified DM is the inverse of the distance-to-default from our unified model. Reported in square brackets are tstat's using standard errors clustered by bond and quarter. The sample extends from January 2010 to June 2020. Phase I, from 2010 through 2013, is the pre-default Phase; Phase II, from 2014 through 2018Q1, captures the first wave of defaults; and Phase III, from 2018Q2 to 2020Q2, captures the second and much more severe wave of defaults.