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

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Abstract

Studying China's credit market, we find improved price efficiency and, paradoxically, worsening segmentation as perceived government support for state-owned enterprises (SOEs) caused non-SOE credit spreads to explode rather dramatically relative to their SOE counterparts amid government-led credit tightening. Interestingly, the post-2018 credit-market stress helped improve price efficiency within non-SOEs, while SOEs saw no such improvement and instead became sensitive to issuer-level measures of government support, marking a shift of SOE premium beyond the SOE label. We further document the real impact of the deepening credit mis-allocations: non-SOEs in aggregate are losing their long-standing advantage in profitability over SOEs in China.

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1 Introduction

In this paper, we study how perceived government support for state-owned enterprises (SOEs) can shut out non-state firms in China's credit market, causing severe segmentation in credit pricing. While the presence of SOEs in China has been studied extensively in the context of resource misallocations and the ensuing welfare losses, there have been relatively few studies documenting the extent of the misallocation.[1] Anecdotally, SOEs in China are known to have preferential access to bank loans, but the actual magnitudes, in loan volumes and particularly in loan pricing, have not been adequately recorded in the literature owing to limited data on bank loans.[2] Lacking such information, further discussions on the ensuing welfare losses are mostly qualitative in nature. Moreover, as our results show, the extent of the misallocation is itself time-varying due to varying economic conditions and changing government policies, further complicating the message from the existing literature.

Our paper aims to contribute to this important discussion by focusing on the tension between SOEs and non-SOEs in the openness of the credit market. In contrast to the opaqueness of bank loans, market prices are transparent and readily observable, and, unlike loan officers in large SOE banks in China, markets are unburdened by political connections or career concerns, and are instead driven by concerns over risk and return. As such, the SOE credit misallocation documented in our paper is on the most visible slice of a firm's debt financing, which also happens to be the most efficiently priced. And yet, as shown by our results, it is the efficiency of the market that exacerbates the inefficiency of the credit misallocation, especially in times of crisis when market participants turn to government support for safety. More importantly, given the interconnectedness of credit allocations in China, findings from the credit market can be used to uncover the severity of the economy-wide credit condition, including the opaque bank loans and the even more opaque shadow banking.

Our study is made possible by the emergence of China's credit market that involves both SOEs and non-SOEs. From 2008 through 2019, domestic debt securities issued by China's non-financial companies increased from a negligible level to $3.6 trillion, second only to the US.[3] For China's bank-dominated financial system, the presence of this market-based credit

[1] For example, the seminal paper by Hsieh and Klenow (2009) takes as given the misallocations of capital in China and India and study their impact on the total factor productivity at the aggregate level.

[2] 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 confidential 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.

[3] In a time of accommodative monetary policy, US companies have dramatically increased their borrowing

channel has a profound impact – it has allowed firms to access a form of debt financing that is cheaper and more efficient than the traditional bank loans. As a result, the ratio of market-based bonds to bank-based loans increased, for non-financial firms in China, from a mere 3.8% in 2008 to 20.9% in 2019, and, important for our study, SOE as well as non-SOE borrowers have benefited from this shift toward market-based financing.

The SOE Premium – We quantify the extent of SOE's preferential access to the credit market using the SOE premium, measured as the difference in credit spreads between non-SOE and SOE issuers, controlling for credit ratings and other bond characteristics. Prior to 2018, the SOE premium for listed firms in China fluctuated around a stable level of 20 bps, indicating a moderate but non-trivial premium enjoyed by SOEs due to their perceived government support. Post 2018Q2, we find a rapidly worsening segmentation between SOE and non-SOE issuers – the SOE premium exploded, over just one quarter, from 22 bps to an unprecedented 106 bps in 2018Q2. Since November 2018, recognizing the adverse effects on the private sector, the Chinese government offered reassurances and devised policies to support the private sector, but the SOE premium, or the non-SOE discount, deteriorated further, peaking at 165 bps in 2019Q3. It has since come down to below 100 bps and is at 61 bps as of 2020Q2.

Behind this explosive SOE premium were government-led credit tightening policies, including the sequence of de-leveraging campaigns around 2017 and, more importantly, the April 2018 release of "New Regulations on Asset Management," which severely shrunk the financing and re-financing channels of corporate issuers, and weakened the demand for corporate bonds from the asset-management industry in China. Amid heightened concerns over default risk, the non-SOE issuers were perceived as more vulnerable than their SOE counterparts due to the lack of government support. Akin to a run on non-SOEs, investors sought safety in SOE bonds and shunned non-SOE bonds, intensifying the price segmentation and amplifying the SOE premium. Competing with this explanation is the view that the fundamental health of the non-SOE firms was already weak due to their over-borrowing and over-expanding during the credit boom of 2014-2016. As a result, non-SOEs were ill-prepared for the severe credit contraction in 2018.

Explaining the SOE Premium – To better understand the drivers behind the SOE premium, whether it is changing credit quality or increasing importance of government support, we create issuer-level proxies for both credit quality and government support. Focusing first

in the form of debt securities. From 2008 to 2019, debt securities issued by U.S. non-financial corporations increased by $3.02 trillion to a record level of $6.56 trillion. Relative to the global domestic-bond market for non-financial firms, however, the presence of the US market decreased from 53.15% in 2008 to 44.76% in 2019, while that for China increased from 2.94% to 24.64%.

on credit quality, we use the model of Merton (1974) to construct default measures by incorporating information from the firm's financial statements and stock valuations. Central to our default measure is the firm's stock return volatility, book leverage, and asset growth. Intuitively, firms with higher volatility, higher leverage, and lower asset growth are of lower credit quality and their default measures are higher. Studying the SOE premium using our default measures, we find that, although credit quality plays an increasingly important role in credit pricing, it cannot explain the SOE premium. As the non-SOE issuers are in general stronger in credit quality than their SOE counterparts of the same credit ratings, controlling for default measures actually worsens the SOE premium.[4]

Explaining the SOE premium using government support, we construct, from the ground up, an issuer-level measure of government holdings using information on government's equity stakes in SOEs as well as non-SOEs. Compared with the SOE dummy, which treats the SOE sample as a solid block, our measure of government holdings is a continuous variable that captures the strength of government support both across and within the samples of SOEs and non-SOEs. For the SOE sample, our government-holdings measure ranges from 10% to 100%, with a standard deviation of around 17%, indicating a rather large variation across the SOE issuers. In other words, according to our measure of government support, not all SOEs are equal. And yet, prior to 2018Q2, what mattered for credit-market pricing was the label of SOE and the richer information contained in our government-holdings measures bore no significance in explaining credit spreads.

This faith in the SOE label started to crumple post 2018Q2, amid the severe segmentation and the increasing importance of government support. Studying the SOE premium using our government-holdings measure, we find that the sharp increase in the SOE premium was driven by the emergence of credit-market sensitivity to government support. Controlling for government holdings, the SOE premium shrank from the elevated level of 106 bps to essentially zero. Contributing to this significant reduction in SOE premium is the increased sensitivity of credit spreads to government holdings above and beyond the SOE label, which was close to zero before 2018Q2, and became -281 bps (t-stat=-7.82) after 2018Q2. In other words, controlling for credit rating and other bond characteristics, moving the government-holdings measure from 0 to 100% can reduce credit spread by as much as 281 bps post 2018Q2, while the effect was essentially zero before 2018Q2.

Price Discovery – Using our proxies for credit quality and government support, we further

[4]From 2014Q1 to 2018Q1, the SOE premium was 21 bps (t-stat=3.58) before, and 25 bps (t-stat=4.32) after controlling for default measures. The slight increase in SOE premium after the control is due to the fact that non-SOE issuers were in fact stronger in credit quality than their SOE counterparts of the same credit ratings. Likewise, for the time period from 2018Q2 through 2020Q2, controlling for default measures has a negligible effect on the severely elevated SOE premium of 106 bps (t-stat=7.78).

examine the price discovery of China's credit market by focusing on the SOE and non-SOE samples separately. Overall, we find a market of improved price efficiency as investors take into account the developing risk factors – default risk as well as the extent of government support, and price them into the credit market. Prior to 2014, default had never occurred in China's credit market, resulting in the so-called faith-based pricing, where investors held the strong belief that bond would always be paid in full. Not surprisingly, we find that, prior to 2014Q1, default measures were not important in explaining credit spreads above and beyond credit ratings. With the occurrence of the first default in 2014Q1, this faith-based pricing crumpled in China's credit market, and default measure emerged as an important factor in credit pricing for both SOE and non-SOE bonds.[5]

Interestingly, amid the worsening segmentation post 2018Q2, the extent as well as the content of price discovery started to differ between the SOE and non-SOE samples. Among the non-SOE sample, credit spreads became significantly more informative with respect to credit quality. From 2018Q2 to 2020Q2, one standard deviation increase in default measure is associated with an increase in credit spread of 87 bps for non-SOE bonds (t-stat=3.83), a marked improvement in both economic and statistical significance, and the explanatory power of default measure also improved post 2018Q2. By contrast, credit spreads of SOE bonds saw no such improvement. These results are consistent with the observation that, during this severe segmentation, investors are forced to be more discriminating against the non-SOE bonds because of their perceived vulnerability, and credit quality became a more pressing issue for the pricing of non-SOE bonds.

Meanwhile, as investors sought safety in SOE bonds, the extent of government support became the pressing issue for the SOE bonds. Before 2018Q2, our measure of government holdings was unimportant in explaining the SOE credit spreads. Post 2018Q2, one standard deviation increase in government support is associated with a reduction in credit spread of 38 bps (t-stat=6.05), indicating that investors have gone beyond the SOE label in gauging the extent of government support. In a way, this shift beyond the SOE label expands from the differentiation between non-SOEs and SOEs – investors updates their perception of what qualifies as government support, and begins to differentiate weaker SOEs from stronger SOEs. Our result in fact foreshadows what is happening in China right now. As recent as November 2020, China is experiencing a new wave of credit-market defaults, along with significant numbers of failed and canceled new bond issuance, with most of the affected issuers being SOEs sponsored by local governments.[6]

[5]From 2014Q1 to 2018Q1, one standard deviation increase in default measure is associated with an increase in credit spread of 24 bps for non-SOE bonds (t-stat=2.88) and 20 bps for SOE bonds (t-stat=3.84).

[6]During the most recent quarter, from October 1 to November 16, 2020, there have been 13 defaults

The Real Impact – The increasing importance of government support documented in our paper is not specific just to the credit market. It is in fact a reflection of the broader economy. Absent of detailed information on bank loans and shadow banking, our findings from the credit market help shed light on the economy-wide credit condition in China. Moreover, as the issuers covered in our study are those with access to both bond and equity financing, we are examining the credit allocation among the largest firms in China. Amid the unprecedented explosion in SOE premium, new issuance by such large non-SOEs, which in 2017Q1 accounted for 29% of the total new issuance in the corporate bond market (excluding Chengtou bonds), dropped to a mere 8% in 2019Q3. Prior to 2018Q2, such non-SOE issuers were significantly healthier than their SOE counterparts as measured by our default measure. Post 2018Q2, that advantage disappeared for non-SOEs. Studying other aspects of the firms fundamental, including returns on asset, we find further evidences of the negative impact of this severe segmentation on non-SOEs. For smaller non-SOE firms in China, the credit mis-allocation as well as the real impact could be even worse.

Related Literature – Our paper contributes to the macroeconomics literature on the SOE-related credit misallocations and their 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)).[7] While the literature has so far been focused on the SOE's privileged access to bank loans, our paper is the first to document the extent of the SOE misallocations using pricing information from the credit market. Unencumbered by the opaqueness associated with the distributions of bank loans and shadow-banking activities, we are able to to uncover the otherwise obscure credit allocation between SOEs and non-SOEs in China and trace the worsening misallocation directly to the increased importance of government support. For policy makers in China, our empirical findings should be informative and alarming. This includes the explosive SOE premium post 2018Q2, its destabilizing impact on China's credit market, and the vanishing dominance of non-SOE firms in profitability and financial

totaling 10.1 billions RMB, among which 8 local-government SOE bonds accounted for 76% of the default amount. Over the same time span, a total of 88 bonds in the credit market have been canceled (44 bonds with amount 27.6 billions RMB), failed (38 bonds with amount 35 billions RMB), or postponed (6 bonds with amount 6.8 billions RMB). Among the 82 affected issuers, 61 are local SOEs, 15 are central SOEs, and only 4 are POEs.

[7] Moving beyond the SOE and non-SOE dichotomy, Bai, Hsieh, and Song (2020) examine how "special deals" for favored private firms in resource allocation can contribute to China's growth. Other studies on China's credit allocation include Cong et al. (2019), documenting that the stimulus-driven credit expansion of 2009-2010 disproportionately favored SOEs; Huang, Pagano, and Panizza (2020) on how local public debt can crowd out the investment of private firms while leaving SOEs unaffected; Li, Wang, and Zhou (2018), who find that China's recent anti-corruption campaign helps credit reallocation from SOEs to non-SOEs.

strength over their SOE counterparts.[8]

Our paper contributes to the asset-pricing literature as the first comprehensive study on the information content of credit spreads in China. For the US market, the link between credit spreads and credit quality has been well established – controlling for credit ratings, a significant portion of the variation in credit spreads can be explained by issuer-level variables known to affect the credit quality of a firm.[9] For the Chinese market, however, this topic has not yet been systematic studied, and our paper fills the gap. By using China's first credit-market default in 2014 as a shock, our paper is the first to document how increased awareness of default risk can improve price discovery. Our paper is also the first to study how the tension between SOEs and non-SOEs in the credit market can impact price discovery. Specifically, as investors abandoned non-SOE bonds and sought safety in SOEs, the non-SOE credit spreads became more informative with respect to credit quality while the SOEs saw no improvements.

Our paper is also related to the literature studying the asset-pricing implications of the presence of government support. By focusing on credit pricing, our paper is closely related to that of Berndt, Duffie, and Zhu (2019), who examine the information content of credit spreads of US banks with respect to the likelihood of government bailout. They find large post-Lehman reductions in market-implied probabilities of government bailout, and big increases in debt financing costs for the US banks after controlling for credit quality. In essence, Berndt, Duffie, and Zhu (2019) document the decline of too-big-to-fail after the government allowed Lehman to default. Interestingly, Balasubramnian and Cyree (2011) provide evidence of the emergence of too-big-to-fail after the 1998 government-organized Long-Term Capital Management (LTCM) bailout. The too-big-to-fail phenomenon during the 2008 financial crisis is also documented by Kelly, Lustig, and Nieuwerburgh (2016), using the pricing difference between put options on the financial sector and those on individual banks. Similar to these findings, we show that government support, as perceived by investors in China's credit market, plays a dominant role in driving the SOE premium. Different from the US market, the presence of government support in China is much more pervasive and will remain important in the foreseeable future.

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

[9] Among others, empirical studies on the determinants of credit spreads include Collin-Dufresne, Goldstein, and Martin (2001), Campbell and Taksler (2003), Bao (2009), and Bao, Pan, and Wang (2011).

Finally, our paper is part of the emerging literature on the Chinese credit market.[10] Studying the value of the implicit government guarantee, Jin, Wang, and Zhang (2018) focus on the first large SOE default in 2015, and Bai and Zhou (2018) and Liu, Lyu, and Yu (2017) 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. With the increasing importance of China to the global economy, global investors are looking into China's financial markets for investment opportunities. As such, further academic studies on China's financial markets are not only relevant, but also much needed.

The rest of our paper is organized as follows. Section 2 summarizes the data on China's credit market and provides background information. Section 3 details the constructions of our proxies for credit quality and government support. Section 4 documents the SOE premium, its time-series variation, and its driver. Section 5 examines the information content of the credit spreads with respect to credit quality and government support. Section 6 examines the real impact of the segmentation, and Section 7 concludes. Further details are provided in the appendices.

2 Data and Background Information

In this section, we summarize the sample of corporate bonds employed in our empirical study and provide background information for China's credit market. For the bank-dominated financial system in China, the presence of the market-based credit channel has a profound and lasting impact. On the credit-demand side, it has opened a new channel of debt financing for non-financial firms in China – cheaper and more efficient than the traditional bank loans. On the credit-supply side, it has significantly expanded the investment frontier of asset managers in China 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.

[10] For overviews on the Chinese credit market, see Hu, Pan, and Wang (2019) and Amstad and He (2019). Recent empirical studies include Mo and Subrahmanyam (2019) on China's credit bond liquidity, Chen et al. (2018) on the value of pledgeability in Chinese corporate bonds, Wang, Wei, and Zhong (2015) on the pricing implications of China's yield-chasing retail investors, Ding, Xiong, and Zhang (2020) on the issuance overpricing of Chinese corporate bonds, Gao et al. (2015) on the determinants of loan defaults in China, Huang, Liu, and Shi (2020) on the determinants of short-term credit spreads, Gao, Huang, and Mo (2020) on the effect of credit enhancement on bond pricing.

2.1 The Corporate Bond Sample

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 the top panel of Figure 1, the credit instruments in this market are categorized into four groups: corporate bonds, Chengtou bonds, commercial papers, and other instruments including private placement bonds, convertible bonds, and asset-backed securities. The group of corporate bonds, similar in structure to the US corporate bonds, is the main focus of our paper. It is made up of three types of bonds: Medium-Term Notes account for the largest portion and are traded in the inter-bank market; Corporate Bonds are the second largest and are exchange traded; and Enterprise Bonds, traded in both markets, account for only a very small portion of our sample. By June 2020, the total amount outstanding of our corporate bond sample is RMB 8 trillion, accounting for 34% of the credit market. Chengtou bonds, as shown in Figure 1 to be an important component of the credit market, are excluded from our analysis because of their unique association with local governments in China. Issued by local government financing vehicles (LGFV), Chengtou bonds enjoy a rather special status in China's credit market and are not the best credit instruments for our purpose. We exclude commercial papers from our analysis due to their short duration, and the other credit instruments due to their non-standard structures and limited market size.

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

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

The bottom panel of Figure 1 outlines the overall size of our corporate bond sample, and summarizes the relative size of the four issuer types. The publicly listed issuers, including both listed SOE and listed non-SOE, account for 30% of the corporate sample, while the listed issuers account for the rest. This pattern is contrary to what is observed in the US corporate bond market, where larger listed firms generally have better access to the corporate bond market. Another stark contrast to the US market is the dominance of the SOE issuers. Within the listed sample, a significant gap exists between listed SOE and listed non-SOE. The ratio in amount outstanding of listed SOE to listed non-SOE bonds is 13 in 2010. As the credit market expands in size and diversity, this ratio has decreased steadily to a level close to 1.6 in 2018, but then the improvement flattens out. Not surprisingly, the gap within the unlisted sample is even more astounding: the ratio of SOE to non-NOE is 57 in 2010 and then decreases to 6 in 2018. The fact that the unlisted SOEs continue to dominate the market share is an unhealthy situation for this market. In a way, their presence sucks the oxygen out of an otherwise healthy market.

2.2 Bond-Level Data

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

We only include fixed-rate bonds in the form of medium-term notes, corporate bonds, and enterprise bonds issued by non-financial listed companies. Bonds without any trading during a quarter are excluded from that quarter. Bonds with less than one year to maturity are excluded from our sample. Bonds whose issuer has less than 10 trading days in the equity market during a quarter or has missing financial statements during a quarter are excluded from that quarter. Defaulted bonds are excluded from our data sample starting from the quarter before the actual default date. We adopt this conservative treatment because we are not sure of the accuracy of the official default dates. This is particularly troubling as we observe, for some bonds, extremely large yield spreads even before the actual default date. Moreover, in China, default occurs at the bond level. But we also exclude other, not yet defaulted, bonds issued by the same firm starting from the quarter before the first default date, once the firm has defaulted on at least one bond. The reasoning is similar – we are not sure of the accuracy of the official default dates and the defaulted bonds usually have a spillover effect on other existing bonds issued by the same firms. This treatment has the effect of cutting down extremely large credit spreads and under-biasing our results. In practice, this treatment has a rather negligible effect on our results, given the limited number of defaulted issuers in our sample (28 issuers for the listed non-SOE sample, and 2 issuers for the listed SOE sample). Finally, we winsorize the credit spreads at 0.5% and 99.5% on all the sample.

We choose our sample period to start from January 1, 2010 through June 30, 2020. Prior to 2010, there are not enough listed non-SOE issuers for us to perform our empirical analysis. We further separate our time period into three sub-periods: Phase I, from 2010 through 2013, is the pre-default period; Phase II, from 2014 through 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, captures the second and much more severe wave of defaults.

Table 1 summarizes our bond sample for each of the four groups. Overall, there are 367 listed non-SOE issuers with 923 bonds , 403 listed SOE issuers with 1477 bonds, 403 unlisted non-SOE issuers with 1518 bonds, and 1795 unlisted SOE issuers with 7061 bonds. Table 2 further summarizes our sample by the three sub-periods, and, as we can see, the numbers of issuers and bonds vary over time as well. In addition to credit spreads, the bond-level variables reported in the summary tables include bond characteristics such as rating, maturity, age, issuance size and coupon rate; and bond trading variables such as number of trading days per quarter (TradingDays), percent of zero trading days per quarter (ZeroDays) and quarterly turnover. In addition, we also control for issuers' industry in our analysis using the eleven industry categorization from Wind.

For credit ratings, we merge our sample with the rating dataset of Wind, and update any changes in rating by the major rating agencies in China.[11] We convert the letter grades into numerical grades by assigning 1 to AAA, 2 to AA+, 3 to AA, 4 to AA-, and so on. In China, AAA is the top grade, with AA+ and AA in the middle, and AA- is generally of low quality, and very few bonds are below AA-. As shown in Tables 1 and 2, the average credit ratings varies across the four sub-samples, as well as over the three time periods. Indeed, credit rating is the most important control variable in all of our empirical analysis.

A non-trivial amount of the corporate bonds in China are issued with embedded optionality. For example, a 2+1 bond is issued with a three-year maturity, but, at the end of the second year, investors have the option to sell back the bond at its face value while the bond issuer can choose to modify the coupon rate within a pre-set range to make the bond more or less attractive. We use the dummy variable Embed to single out the bonds with

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

this optionality. As shown in Table 1, the average value of this dummy is 63% for listed non-SOE, 39% for listed SOE, 56% for unlisted non-SOE, and 26% for unlisted SOE. Clearly, the non-SOE issuers are more eager to extend the maturity of their bonds by offering more optionality. As shown further in Table 2, there is an increasing trend in the issuance of such bonds. For example, the ratio of bonds with optionality increases from 38% in Phase I to 53% in Phase II, and to 71% in Phase III for the unlisted non-SOE sample. Throughout our analysis, we control for this optionality since the embedded option has the effect of making bonds more expensive and lowering yields.

Another well established feature in China's bond market is the difference between the inter-bank market, populated by large institutional investors, and the exchanges, populated by small and medium-size investors. Unlike the US corporate bond market, which is dominated by the over-the-counter trading, 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. As shown in Table 1, exchange-traded bonds account for 69% for listed non-SOE, 53% for listed SOE, 48% for unlisted non-SOE, and 21% 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. Throughout our analysis, we use the Exch dummy to control for potential differences in investor behavior between these two markets.

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

Finally, the bond trading variables give us a sense of 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 across the board. As shown in Table 1, for bonds in our sample, the average number of trading days per quarter is 15 for listed non-SOE, 10 for listed SOE, 10 for unlisted non-SOE, and 8 for unlisted SOE. Moreover, there is a dramatic decrease in trading activity over the three time periods, as shown in Table 2. Part of this decreasing trend is due to the crackdown of agent-holding transactions, which is covered extensively in Mo and Subrahmanyam (2019).

2.3 Issuer-Level Equity Data

Focusing on the sample of bonds issued by listed non-SOE and listed SOEs, we construct the issuer-level equity data by merging the bond data with the equity data from Wind. As shown in Table 3, there are in total 367 listed non-SOE issuers and 403 listed SOE issuers, with the numbers varying over the three sub-sample periods.

For each of these firms and during each quarter, we collect information on the total market value of its equity, with EquitySize denoting the logarithm of the equity value. As shown in Table 3, the average size of the firms in our listed non-SOE sample is RMB 13.15 billion, smaller than the average number of RMB 19.82 billion for the listed SOE sample. Compared with the universe of stocks in the Chinese equity market, these firms are larger in size. In fact, a large majority of our equity sample is from the mainboard and they are evenly distributed in the Shanghai and Shenzhen stock exchanges.

To measure the credit quality of a firm, three important inputs are asset growth, leverage and volatility. For each firm, we use its daily stock returns during the quarter to calculate its quarterly equity volatility. As shown in Table 3 the annualized volatility for the listed firms in our sample is on average 40.4% for non-SOE and 36.4% for SOE. To calculate firm leverage, we collect information on the firm's short- and long-term debt and its total asset, using quarterly financial statements. Leverage is calculated as the ratio of total current liabilities plus the total non-current liabilities to the total asset value. As shown in Table 3, the average leverage for non-SOEs is 58.6%, slightly lower than the 61.7% for the SOEs. For each firm within each quarter, we use the average growth rate of the asset value in the past three years to compute the asset growth. As shown in Table 3, the average asset growth for non-SOEs is 23.0%, higher than the 17.2% for the SOEs.

2.4 Corporate Defaults in China

For much of its history, China's credit market was absent of default events, confirming the deep-rooted belief that debt investors will always be bailed out and default was merely a concept in theory. The first ever default in 2014 marks the beginning of an erosion to this strongly held belief. The top panel of Figure 2 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 amount ranging from less than RMB 1 billion to 12.2 billion in 2016Q1. Compared with the total size of the credit market, RMB 16.1 trillion in 2016, this amount of default is rather small. At the same time, the corporate bond market was expanding aggressively with RMB 625 billion new issuance in 2016Q1, as shown in the bottom panel of Figure 2. From 2015Q2 to 2016Q3, the unlisted SOEs were affected more severely than unlisted non-SOEs. It was especially true for the unlisted SOEs in overcapacity industries. Starting from 2016Q4, the total amount of default in the credit market lessened, and the fraction of unlisted SOE defaults reduced rather dramatically, from 83% in 2016Q3 to 10% a quarter later in 2016Q4. From that point on, non-SOEs took most of the blunt.

Starting from 2018Q2, the listed non-SOE issuers, who remained largely intact during the first wave, were severely hit and, at its peak in 2019Q4, accounted for 37% of the total default amount in the credit market. Meanwhile, the magnitude of the default amount has also increased rather 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. 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.

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

3 Measuring Credit Quality and Government Support

3.1 Proxy for Credit Quality: Default Measures

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

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

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

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

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

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

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

where T is the time-horizon of interest.

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

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

The Merton model further translates the distance-to-default to default probability, under the assumption of normal distribution. The probability calculated from the normal distribution, however, is too low. More importantly, the transformation flattens out much of cross-issuer variation in the distance-to-default measure. An alternative approach adopted by Moody's KMV is to calibrate the mapping from distance-to-default to default probability, using the actual default experiences. The construction of this empirical distribution requires a large database of historical defaults, which is not feasible for the Chinese corporate bonds market. In this paper, we use the inverse of the distance-to-default, which we denote as DM (Default Measure), to measure the firm's default risk.

In Table 3, we summarize our sample at the issuer level, including the three key inputs of the models: asset growth μ firm leverage K/V and asset volatility σ_A, as well as the calibrated default measure (DM). Firms in China in general have higher leverage than those in the US: the average level is 58.55% for non-SOEs and 61.67% for SOEs, with SOEs on average more levered than non-SOEs. The average asset volatility, which is backed out from the equity volatility, is around 22.95% for non-SOEs and 17.18% for SOEs, both are higher than that in the US. During Phase II, there is a substantial increase in asset volatility, driven mostly by the 2015 stock-market crash in China. Using these issuer-level measures as inputs to the Merton model, we obtain the issuer-level default measure (DM). The average level of DM is 22.56% for SOEs and 21.18% non-SOEs, indicating an overall stronger credit quality for the non-SOE issuers. In Section 4 we will examine more closely the difference in default measure between SOEs and non-SOEs and its time-series variation.

3.2 Proxies for Government Support

We consider three proxies for government support. The first measure, the NSOE dummy, takes the standard approach of assigning the state affiliation of a firm by the attribution, state or non-state, of its ultimate controller, or end-controller. The second measure, robust government holdings, is our main proxy, which we construct from the ground up using information on the government's equity ownership of the firm. The last proxy, the government end-controller holdings, serves as a robust measure. It focuses on the equity ownership of the end-controller of the firm. Unlike government holdings, which is relevant for both SOEs and non-SOEs, this last proxy is an informative proxy for government support only for the sample of SOE firms.

The Non-SOE Dummy (NSOE)

To understand the extent of government support, one important component of our empirical analysis is to differentiate the state-owned enterprises from the non-state owned firms. For this, we create a non-SOE dummy, which equals one for non-SOE firms and zero for SOEs and this variable is updated quarterly. 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, central SOEs, local SASAC, local government institutions and local SOEs. A firm is classified as non-SOE if its end-controller is not the state. While the majority of the non-SOEs are the privately-owned enterprises (POE), whose end-controllers are individuals or private enterprises in China, the non-SOE sample also includes a mixture of other firms.

To construct the NSOE dummy, we use data from Wind Financial Information, which collects and updates quarterly the end-controllers of all firms with publicly listed equity or bond issuance. Such firms in China are required to self-report in their annual financial statements the end-controller of the firm and the corresponding attribution – whether or not the end-controller is the state. According to China Securities Regulatory Commission (CSRC),[12] the end-controller of a firm is defined by one of the following criteria: (1) The investor holds more than 50% of the shares; (2) The investor holds more than 30% of the voting rights; (3) The investor can nominate more than half of the board members; (4) The investor can have significant impact on the shareholder meetings; and (5) Others conditions ascertained by the CSRC. For publicly listed firms, Wind collects and organizes such information in "AShareEquityRelationships" dataset (hereafter Controller Dataset). Our overall classification follows that of Wind Financial Information with the exception of six public firms in the other category of non-SOEs, which we consider as SOEs since the respective government holdings, as well as end-controller holdings, of these firms are both greater than 50%. Our results are robust to the re-classification of these six firms.

Government Holdings

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

[12] See Article 84 of the "Listed Companies Takeover Measures" published by CSRC.

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. 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.[13]

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, 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.[14] 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 number of shareholders) and 89.8% (in terms of equity holdings) of the shareholders' attributions from 2010 through 2020Q2. Using this information, we can

[13]Using data from Annual Survey of Industrial Firms (ASIF) of the China's National Bureau of Statistics, Cong, Gao, Ponticelli, and Yang (2019) measure the extent of state ownership from the share of registered capital owned by the government and study its connection with loan allocation during the 2009-2010 credit stimulus. This measure of state-ownership is the same in spirit to our government-holdings measure, but ASIF suffers from many missing observations in the share of government registered capital, even for large SOEs. As such, our robust measure of government holdings, compiled from several of the existing data sources, is valuable for future studies in this area. See Appendix A.1 for further details.

[14]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.

then calculate government holdings for all listed firms in our sample, including SOEs and NSOEs.

Using our own construction as a staring point, we further refine the government holdings measure by taking into account of the information provided by Wind and China Stock Market Accounting Research (CSMAR), respectively, on government holdings within top ten shareholders. Specifically, for each issuer, we have three measures of government holdings from three sources: our own construction, Wind, and CSMAR. If inconsistency arises out of these three data sources, our assumption is that the more accurate measure is the one with the highest government holdings. Underlying this assumption is the fact that the most likely data error occurs out of omission: the failure to assign government attribution to a government-related shareholder. By contrast, mis-identifying a non-state shareholder as government related is a less likely error in the three data sources. Appendix A.1 provides further details in the construction of the government holdings measure and compares the discrepancy among the three data sources. 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.

As reported in Table 3, the average government holdings for the SOE sample is 51.9% with a standard deviation of 16.8% and remains stable over time. To take a close look at the government holdings within SOE, we further divide the SOE sample into central SOE (CSOE) and local SOE (LSOE) based on whether the end-controller is affiliated to the central government or local government. As Panel (a) of Figure 3 shows, the full-sample distribution of government holdings are quite disperse for both CSOE and LSOE groups, ranging from 10% to 100%. In other words, not all SOEs are the same and our government holdings variable contains much richer information than the SOE dummy. Whether or not the credit market values such information (under what kind of economic situation) is the object of our investigation in our empirical analysis.

Moving to the NSOE sample, both Table 3 and Figure 3 show that government holdings are markedly lower than those of SOEs, but there are some interesting cross-issuer variations as well. In particular, within our NSOE sample, there are two groups of firms: privately-owned enterprises (POE) and a mixture of other NSOE firms, some of which are without clear identifications (mixed). As shown in Panel (a) of Figure 3, there is a relatively small variation in POEs and a moderate variation among other NSOE group. The average government holdings is 12.5% with a standard deviation of 12.7% for other NSOE group and 2.8% with a standard deviation of 4.5% for the POE group. Effectively, the information contained in government holdings allows us to differentiate not only the SOEs from NSOEs, but also within the SOE and NSOE samples, respectively.

Finally, Panel (b) of Figure 3 examines the time-series variations of the government holdings. Two points are worth mentioning. First, as expected, moving along the dimension of CSOE, LSOE, mixed, and POE, the government holdings measure exhibits a descending order, with the median being 57.9%, 50.6%, 9.2% and 1.5%, respectively. Second, the median, as well as the bottom and upper 25 percentiles, of the government-holdings measure remains fairly stable over time for these four groups, particularly for the SOEs and POEs.

Government End-Controller Holdings

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 extent 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 a multiple of 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.

To capture the concentration of the government holdings, we compute the total equity holdings by the end-controller. Taking into account the possibility that the end-controller can control the firm through multiple shareholders, we further comb through the layers of equity holdings structure for the top ten shareholders and calculate the effective total holdings by the end-controller. Applied to the SOE group, this measure of end-controller holdings can be used as an alternative proxy for government support. If our government-holdings measure offers an upper bound of the extent of government support by summing up the holdings of all government-related top-ten shareholders, then this new measure of government end-controller holdings provides a lower bound by focusing only on the holdings of the end-controller. All else equal, end-controllers with more at stake would extent more support. By contrast, applying this end-controller holdings measure to the NSOE group, the message would be entirely different from the government holdings measure. As the end-controllers for the NSOE firms are non-state entities, the information content of the end-controller holdings measure for this group is unrelated to government support. In Appendix A.2, these hypotheses will be further tested.

4 Empirical Results: The SOE Premium

The differentiation between the state-owned enterprises (SOEs) and non-state firms (non-SOEs) is among the most important frictions in China's economy. The inefficiency of China's SOEs and their preferential access to banks loans have been widely documented in the academic literature and popular press. At the same time, the contribution of China's private sector to the country's economy has also been widely reported.[15] For credit-market pricing, the most apparent differentiation between an SOE and non-SOE is the perceived government support behind the SOEs. Our focus in this section is to document the extent of this differentiation in credit-market pricing and understand its driver.

4.1 Measuring the SOE Premium

We measure the SOE premium by estimating the difference in credit spreads between a non-SOE bond and an SOE bond of the same credit rating and same bond characteristics. Using the credit spread of bond i in quarter t, we perform the quarterly panel regression:

$$\text{CreditSpread}_{i,t} = a + b\,\text{NSOE}_{i,t} + c\,\text{Rating}_{i,t} + \sum_k \text{Controls}^k_{i,t} + \epsilon_{i,t}\,, \tag{3}$$

where the NSOE dummy, as defined in Section 3.2, captures the attribution of the end-controller of bond-i's issuer in quarter t. The SOE premium is measured by the regression coefficient b associated with the NSOE dummy, taking into account of the differences in credit ratings and other bond characteristics measured by the control variables. This includes bond maturity, issuance size, age, exchange market dummy, optionality, and liquidity. For listed firms, we add the log of their equity sizes as a control variable. The panel regression in equation (3) further includes 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 4, 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.

[15] They contribute 60% of China's GDP, and are responsible for 70% of innovation, 80% of urban employment and provide 90% of new jobs, as summarized in "The China Private Sector Report 2019" by Zeping Ren at Evergrande Research Institute.

The SOE Premium for Listed Firms

Using data from 2010Q1 to 2020Q2, we perform our empirical tests over three time periods defined by two important dates in China's credit market – the first default in 2014Q1 and the onset of the worsening SOE premium in 2018Q2. As reported in Table 4, the SOE premium for the listed sample is 20 bps (t-stat=3.08) and 21 bps (t-stat=3.58), respectively, in the first two time periods before 2018Q2. 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. In other words, the credit-market financing cost for non-SOE issuers is on average 20 bps higher than their SOE counterparts of the same credit rating. The difference is significant both economically and statistically. Moreover, the first default in 2014Q1 does not seem to have any significant adverse effect on the SOE premium. The top panel of Figure 4 further reports the time-series variation of the SOE premium at the quarterly frequency. Prior to 2018Q2, the SOE premium fluctuates around 20 bps. With the exception of 2010 and the first few quarters of 2011, when the credit market is relatively under-developed with a rather small sample of non-SOE bonds, the SOE premium stays well below 50 bps prior to 2018Q2.

Post 2018Q2, the SOE premium explodes rather suddenly. As reported in Table 4, the average SOE premium increases to 106 bps (t-stat=7.78) in the Phase III.[16] As shown in the time-series plot, over just one quarter, the SOE premium rises sharply from 22 bps in 2018Q1 to an unprecedented 104 bps in 2018Q2. Since November 2018, recognizing the adverse effects on the private sector, the Chinese governments 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 165 bps in 2019Q3. It has since come down to below 100 bps and is at 61 bps as of 2020Q2. Behind this dramatic explosion in segmentation is the fast deteriorating credit-market conditions for non-SOE issuers. As shown in Table 1, without controlling for bond characteristics, the average credit spread for non-SOE issuers is 203 bps and 206 bps, respectively, during the first two time periods before 2018Q2. It then jumps to 357 bps post 2018Q2 in the third time period. By contrast, the average credit spread for SOE issuers has a modest increase over the three time periods: 121 bps, 132 bps, and 170 bps, respectively.

Also plotted in the background of Figure 4 are the total quarterly default amounts in

[16]To assess the economic significance of a 100 bps difference in credit spread, it is instructive to look at the difference in credit spread across credit ratings. For the full sample period, the median of credit spreads are 117, 180, and 207 basis points, respectively, for AAA, AA+, and AA rated non-SOE bonds. In other words, the severity of the segmentation during Phase III is equivalent of the difference in pricing of an AAA-rated bond and AA-rated bond. Significant in China is the fact that AA-rated and below are considered speculative grades.

the credit market, which explode to unprecedented levels in 2018Q3 and 2018Q4, following the 2018Q2 explosion of the SOE premium. Among others, the most notable policy event happens at the beginning of 2018Q2 in April 2018, when "New Regulations on Asset Management" was released. Although targeted at the asset-management industry in China, this policy, along with the earlier deleveraging campaigns to rein in the growth of corporate debt, severely limits the firms ability to finance and re-finance their debt. As credit-market investors become more concerned of default risk, they effectively price out the non-SOE bonds and further exacerbate the tension between SOE and non-SOE bonds, by seeking safety in the SOE bonds and abandoning the non-SOE bonds.

Perhaps the most alarming message captured by our time-series plot of the SOE premium is the fact that the credit misallocation between the two segments of China's economy can erupt rather suddenly in times of crisis. Such a severe segmentation in pricing is a reflection of the dire economic reality faced by the non-SOE firms in China. As shown in Figure 2, along with the unprecedented amounts of default post 2018Q3, the non-SOE issuers account for an overwhelming fraction. Meanwhile, new issuance by listed non-SOEs as a percentage of the total new issuance in the corporate bond market (excluding Chengtou bonds) has decreased from its peak level of 18% to a mere 3% in 2019Q3. The results captured by our SOE premium can be viewed as a credit-market version of the "state advancing and private retreating" picture described by Lardy (2019) for bank loans in China. Given the transparency of the credit market, as well as its price efficiency, the segmentation captured in our paper is much more severe in magnitude and alarming in its speed of explosion.

Difference in Default Measure

Accompanying the results on credit spreads, we also report in Table 4 the difference in default measure between non-SOEs and SOEs by performing the quarterly panel regressions in equation 3 by replacing credit spreads by $DM_{i,t}$, the default measure for firm i in quarter t. In this panel regression, parallel to the segmentation regression (at the issuer level), the coefficient b associated with the NSOE dummy captures the difference in default measure between the non-SOE and SOE issuers. As shown in Table 4, the difference in default measure is negative during all three time periods: -1.50% (t-stat=-2.95), -3.08% (t-stat=-4.23), and -0.55% (tstat=-0.91), indicating that the non-SOEs are in general healthier than the SOEs, but that advantage shrinks precipitously post 2018Q2. The same pattern of the shrinking gap in default measure can also be found in the bottom panel of Figure 4. These results point to the possibility that the post-2018Q2 credit-market stress begins to impact the balance sheet and equity performance of the non-SOEs firms. We will examine more closely the real impact of the severe segmentation on non-SOE issuers in Section 6.

The SOE Premium for Unlisted Firms

Along with the alarming segmentation in the listed sample, segmentation between non-SOE and SOE issuers also exists in the unlisted sample. Table 4 also reports the SOE premium for bonds issued by unlisted firms: 16 bps in Phase I, 79 bps in Phase II, and 154 bps in Phase III. Compared with our findings for the listed sample, the most interesting difference is that the segmentation coefficient actually 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 the unlisted firms.

Control Variables

Focusing next on the control variables, for credit ratings, unsurprisingly, bonds with higher credit ratings (and lower numerical rating measure) have lower credit spreads. In the first two periods, a letter-grade improvement in credit rating is on average associated with a reduction in credit spread of around 50 bps, a larger magnitude compared to the SOE premium in the same time period. In Phase III, the sensitivity of credit spreads to credit rating becomes larger, with one-letter grade improvement in credit rating associated with a reduction of 124 bps, which is slightly higher than the contemporaneous SOE premium. For maturity and exchange-traded dummy, the evidences are mixed and vary over time. For age, we do not find any significant result. With respect to issuance size and embedded optionality dummy, we find insignificant results in Phase I and significant results in Phase II and III during which time bonds with small issuance size or embedded optionality have high credit spreads. The liquidity proxy ZeroDays are consistently negative correlated with the credit spreads, indicating a potential reaching-for-yield story. Issuers with larger equity size enjoy lower credit spreads. A more detailed discussion on the control variables refer to Section **??**.

4.2 Explaining the SOE Premium

To better understand the SOE Premium, particularly its explosion since 2018Q2, we introduce two important drivers for the credit-market pricing in China: credit quality and government support. As detailed in Section 3, we use the default measure, DM, constructed from the Merton model as a proxy for credit quality, and we build, from the ground up, a new measure of government holdings, GovtHoldings, as a proxy for the extent of government support.

Using these two new measures, namely DM and GovtHoldings, Table 5 reports the results of the quarterly panel regressions:

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

Effectively, the regression coefficient b measures the SOE premium after controlling for DM and GovtHoldings, and the coefficients c and d measure the importance of DM and GovtHoldings in explaining the credit spreads in China. Our focus in this section is on the drivers of the SOE premium, particularly its explosion since 2018Q2. A full discussion on the the price discovery of China's credit market with respect to credit quality and government support can be found in Section 5.

As reported in Table 5, controlling for default measure cannot help explain the SOE premium. From 2014 through 2018Q1, the SOE premium was at 21 bps (t-stat=3.58). After controlling for DM, the premium increased slightly to 25 bps (t-stat=4.32), as the default measures of non-SOE issuers were in fact stronger than their SOE counterparts of the same credit ratings. Likewise, from 2018Q2 through 2020Q2, the SOE premium was estimated to be 106 bps (t-stat=7.78), and controlling for default measures does not have much of an impact.

By contrast, our measure of government holdings is found to be instrumental in explaining the explosive SOE premium post 2018Q2. As shown in Table 5, GovtHoldings was not important in explaining the pre-2018Q2 credit spreads, and the SOE premium remained largely unchanged after controlling for GovtHoldings during Phases I and II. Post 2018Q2, however, the richer information contained in our government holdings data started to matter. Controlling for GovtHoldings, the elevated level of the SOE premium shrank from 106 bps (t-stat=7.78) to -9 bps (t-stat=-0.48). Contributing to this significant reduction in SOE premium is the increased sensitivity of credit spreads to government holdings, which was -8 bps (t-stat=-0.37) from 2014 through 2018Q1, and became -281 bps (t-stat=-7.82) from 2018Q2 through 2020Q2.

Our results indicate that, prior to the onset of the severe segmentation of 2018Q2, the concept of government support is important for credit pricing at the level of whether or not the end-controller of a firm is government. Investors view SOE and non-SOE as two solid blocks – one with government support and the other without. For them, labeling a firm as SOE or non-SOE is sufficient information for the purpose of credit pricing. Any further information with respect to the government ownership of a firm is unimportant and does not get priced in. In times of crisis, however, the extent of government support becomes more important and investors react by further differentiating bond issuers using the richer information contained in government holdings. And this further differentiation gives rise to the explosive SOE premium post 2018Q2. In this sense, it is ironic that this severe credit misallocation was driven by the investors efficiently pricing their concerns for default risk in the credit market. More broadly, our results, gathered from the openness of the credit market, can be viewed as the tip of an iceberg, revealing the economy-wide credit misallocations in China, with bank loans and shadow banking as the two other important components not captured in our paper.

5 Empirical Results: Price Discovery

We study in this section the price discovery with respect to credit quality and government support by focusing on the samples of SOEs and non-SOEs separately. For each sample, we perform the quarterly panel regression:

$$\text{CreditSpread}_{i,t} = a + b\,\text{DM}_{i,t} + c\,\text{GovtHoldings}_{i,t} + d\,\text{Rating}_{i,t} + \sum_k \text{Controls}^k_{i,t} + \epsilon_{i,t}\,, \quad (4)$$

where the credit spread of bond i in quarter t is regressed on the corresponding default measure (DM) and government support (GovtHoldings) controlling for credit rating and other bond and firm characteristics. The regressions further include quarter fixed effect and industry fixed effect to control for potential market-wide fluctuations and industry differences in credit spreads. The reported t-stat's use standard errors double clustered by quarter and bond to take into account of cross-sectional as well as time-series correlations in credit spreads. The main results are summarized in Table 6 and the more detailed results are given in Table A.2 for the non-SOE sample and Table A.3 for the SOE sample.

5.1 Price Discovery: Credit Quality

To capture the information content of credit spreads on credit quality, we focus on the coefficient associated with the default measure, DM, in the panel regression summarized by equation (4). While the information content of credit spreads has been extensively studied for the US market, our paper is the first comprehensive study of the Chinese market. Given the known segmentation in this market, we perform this regression for our listed non-SOE and listed SOE samples separately. Moreover, recognizing that this is a market in transition, we perform the panel regressions over three time periods: Phase I, from 2010Q1 through 2013Q4, is the pre-default period; Phase II, from 2014Q1 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.

The Shock of First Default in History: 2014Q1

During Phase I, prior to the first default of 2014Q1, credit spreads are uninformative with respect to credit quality above and beyond the information contained in credit ratings. As shown in Table 6, for both the SOE and non-SOE samples, the sensitivity of credit spreads to default measures is of rather small magnitude, with the wrong sign for the non-SOE sample. Given that investors had never experienced a default prior to 2014Q1, this lack of connection between credit spread and default measure makes intuitive sense. During this period, investors control for credit quality by focusing on credit rating, and credit spreads do not contain any additional information about the credit quality of the issuer. For all practical purposes, there is very little incentive for the credit-market investors to move beyond credit rating since their belief is such that default never happens.

This situation is improved during Phase II, after the first default in the Spring of 2014. For both the non-SOE and SOE samples, the coefficients for DM are positive and statistically significant: 1.63 (t-stat=2.88) for non-SOEs and 1.04 (tstat=3.84) for SOEs. This indicates that, as credit-market investors become aware of the potential default risk, credit spreads start to incorporate default related information above and beyond credit rating. In particular, information related to the issuer's financial statements and equity market valuation starts to get incorporated into credit spreads. To gauge the economic significance of our results, we use the sample standard deviation of DM during Phase II reported in Table 3, which is 0.15 and 0.19, respectively, for the non-SOE and SOE samples. This implies that one standard deviation increase in DM is associated with 24 bps and 20 bps increases in credit spreads for non-SOEs and SOEs, respectively, comparable to the average SOE premium during this period. Inferring from the regression coefficients for credit rating during Phase II, associated with an improvement of one letter grade in credit rating is an average reduction of 50 bps in credit spread. From this perspective, the economic significance of the price discovery with respect to credit quality is sizable.

While this improvement in price discovery is decisively welcoming for a young market in transition, the explanatory power of our default measure remains limited. As shown in Table 6, during Phase II, the additional adjusted R-squared attributable to the default measure is 1.0% for the non-SOE sample and 0.8% for the SOE sample. Such small magnitudes in the explanatory power are in stark contrast with the findings for the US credit market, where, as documented by Collin-Dufresne, Goldstein, and Martin (2001), a significant portion of the variation in credit spreads can be explained by issuer-level variables known to affect the credit quality of a firm. At the same quarterly frequency, Bao (2009) reports that default measures constructed using models of Merton (1974) and Black and Cox (1976) can explain as much as 45% of the cross-sectional variation in credit spreads for the US sample.

The Shock of Worsening Segmentation: 2018Q2

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

For the non-SOE sample, we find a marked improvement in the information content of credit spreads. As shown in Table 6, the regression coefficient associated with DM increases from 1.63 (t-stat=2.88) to 7.89 (tstat=3.83) for the non-SOE sample. During this period, the standard deviation of DM for listed non-SOE issuers is 0.11. This implies that, associated with one standard deviation increase in DM, credit spreads on average increase by 87 basis points. During this stressful time period for non-SOE issuers, associated with an improvement of one letter grade in credit rating is an average reduction of 144 bps in credit spread. From this perspective, the default measure has an economically significant impact on the credit spread. Moreover, the adjusted R-squared of the panel regression improves by 3% with the inclusion of the default measure during this period. Compared to the US market, the explanatory power of the default measure is rather small, but it is by far the best performance of the default measure among our results.

For the SOE sample, the coefficient associated with DM increases from 1.04 (t-stat=3.84) in Phase II to 2.09 (t-stat=2.65) in Phase III. For the SOE sample, the standard deviation of DM is 0.09 during Phase III, as compared with 0.19 during Phase II. This implies that one standard deviation increase in DM translates an increase in credit spread of 20 bps in Phase II and 19 bps in Phase III. In other words, the economic significance of the DM coefficient remains more or less the same for the SOE sample, while its statistical significance reduces. Overall, in stark contrast to the non-SOE sample, there is no improvement in the information content of credit spreads for the SOE sample. Given that most investors seek safety in SOE bonds while abandoning the non-SOE bonds amidst the credit turmoil, the price discovery for non-SOE bonds is forced to be more informative, while SOE bonds with their outside government support are under no such pressure.

The Time-Series Variation of Price Discovery

To better capture how the price discovery evolves over time, the left panels of Figure 5 report the time-series variation of the extent of price discovery with respect to credit quality using the panel regression specified in equation (4) over a rolling window of 8 quarters. The top-left panel reports the slope coefficients on the default measure while the bottom-left panel reports the additional adjusted R-squared explained by the default measure. Prior to 2014Q1, the price discovery is essentially zero as captured by both the regression coefficient and the explanatory power. After the shock of the first default in the history of China's credit market, we see a visible improvement in both the regression coefficient and the explanatory power. The gradual nature of the plot is due to the smoothing done by the rolling window of 8 quarters. It is also interesting to observe that during Phase II, the time-series movements are similar for both the SOE and non-SOE samples.

Post 2018Q2, however, we see a rapid improvement in the price discovery for the non-SOE sample while the estimates for the SOE sample stays relatively flat. As a result, the slope coefficient for non-SOEs diverges significantly from that for SOEs, and the same pattern can be seen in terms of incremental R-squared. For non-SOEs, the incremental explanatory power increases rather rapidly from 1% to the peak value of 9% on 2019Q3. Meanwhile, explanatory power for SOE fluctuates around 1%.

Difference-in-Difference Test in Price Discovery

To formally test our observation that, since 2018Q2, credit spreads of non-SOEs become significantly more informative than those of SOEs, we perform the difference-in-difference test by running the following quarterly panel regression with two time shocks,

$$
\begin{aligned}
\text{CreditSpread}_{i,t} &= a + b_1\,\text{DM}_{i,t} + b_2\,\text{NSOE}_{i,t} + b_3\,\text{Post}_{i,t} + c_1\,\text{DM*NSOE}_{i,t} + c_2\,\text{DM*Post}_{i,t} \\
&+ c_3\,\text{NSOE*Post}_{i,t} + d\,\text{DM*NSOE*Post}_{i,t} + e\,\text{Rating}_{i,t} + \sum_k \text{Controls}^k_{i,t} + \epsilon_{i,t}
\end{aligned}
$$

where Post is the event shock. For the default shock in 2014Q1, we define Post as 1 for the time period from 2014Q1 through 2018Q1 and 0 for the time period from 2010Q1 to 2013Q4. For the segmentation shock in 2018Q2, we define Post as 1 for the time period from 2018Q2 through 2020Q2 and 0 for the time period from 2014Q1 to 2018Q1. Effectively, the coefficient d associated with DM*NSOE*Post, captures the additional informativeness of default measure on credit spreads for NSOE compared to SOE after each shock.

	Shock = **First Default**		Shock = **Segmentation**	
	Phase I 2010Q1-2013Q4	Phase II - I	Phase II 2014Q1-2018Q1	Phase III - II
SOE	0.09	1.30***	1.01***	1.28
	[0.57]	[3.60]	[3.76]	[1.47]
NSOE-SOE	-0.41	0.88	0.38	5.57**
	[-0.52]	[1.06]	[1.06]	[2.16]

As summarized above, after the first default shock, the informativeness of credit spreads with respect to credit quality improves for the SOE sample and the difference in the DM coefficient is 1.30 (t-stat=3.60). Relative to the SOE sample, there is no further improvement for the non-SOE sample, and the difference-in-difference coefficient is 0.88 (t-stat=1.06). By contrast, after the segmentation shock, the SOE sample actually sees no improvement in price discovery and the difference in the DM coefficient is 1.28 (t-stat=1.47). Relative to the non-SOE sample, however, there is a rather significant improvement in price discovery for the non-SOE. The difference-in-difference estimate is 5.57 with t-stat 2.16.

5.2 Price Discovery: Government Support

While the connection between credit spreads and credit quality has been extensively studied in the literature, price discovery with respect to government support has not been broadly explored for the credit market. The closest paper in the literature of that of Berndt, Duffie, and Zhu (2019), who examine the information content of credit spreads of US banks with respect to the likelihood of government bailout. They find large post-Lehman reductions in market-implied probabilities of government bailout, and, after controlling for credit quality, they find big increases in debt financing costs for the US banks. Conceptually, our message follows that of theirs – weaker government support results in higher credit spreads. Our approach, however, differs from theirs in that we take a reduced-form approach by constructing proxies for government support using information on government ownership. Taking advantage of the large cross-issuer variation in our proxy, we gauge the importance of government support in credit pricing. In Berndt, Duffie, and Zhu (2019), the extent of government support is built explicitly into a structural model and the key identifying shock is the time-variation in government support for US banks: stronger before the 2007-08 financial crisis and weaker afterwards. Similar to Berndt, Duffie, and Zhu (2019), we also cover two regimes with the segmentation shock in 2018Q2 as the turning point. Relative to this shock, we can examine the before and after sensitivities of credit spreads to government support among the SOE and non-SOE samples.

Before 2018Q2: Only the SOE Label Matters

To capture the information content of credit spreads on government support, we focus on the coefficient associated with the government holdings, GovtHoldings, in the panel regression summarized by equation (4). As shown in the Table 6, the coefficient on the government holdings for the non-SOE sample is 0.45 (t-stat 1.06) in Phase I and 0.24 (t-stat 0.52) in Phase II. For the SOE sample, the loading on the government holdings is -0.17 (t-stat -1.26) in Phase I and -0.11 (t-stat -0.52) in Phase II. Overall, these results indicate that the richer information contained in government holdings are not important for credit pricing. In credit-market pricing, investors take into account of the extent of government support up to the SOE labels, and the magnitude of that effect is captured by our SOE premium of around 20 bps. Prior to 2018Q2, the extent of government support above and beyond the SOE labels does not get priced into the market. This result is also consistent with our findings reported in Table 5, where panel regression is performed using the full sample of both SOEs and non-SOEs.

Post 2018Q2: Faith in the SOE Label Crumples

Post 2018Q2, amid the rapidly worsening segmentation and the increasing importance of government support, the SOE label is no longer sufficient for credit pricing and our government-holdings measure becomes important. For the SOE sample in Table 6, the coefficient estimate is -2.32 (t-stat=-6.05), indicating that one standard deviation increase in government holdings is associated with a reduction of 38 bps in credit spreads. The top-right panel of Figure 5 further captures the timing of the "crumpling" of the SOE label. The slope coefficient of the government holdings turns negative and significant right after the second quarter of 2018 and becomes stronger afterwards. Meantime, bottom right panel of Figure 5 plots the R-squared explained by the government holdings, which increases sharply from 0.3% to 3.0% post 2018Q2. These evidences indicate that the extent of government support as measured by government holdings has become increasingly important in explaining the credit spreads within SOE sample.

Interestingly, government holdings also matter for the non-SOE sample post 2018Q2. As shown in Table 6, the coefficient estimate is -5.52 (t-stat=-4.56), indicating that one standard deviation increase in government holdings is associated with a reduction of 53 bps in credit spreads (t-stat=4.56) for the non-SOE sample. Compared with the magnitudes for

SOEs, the larger slope coefficient for non-SOEs is mostly due to the larger variations in credit spreads within the non-SOE sample.[17] In terms of explanatory power, the importance of government-holdings measure for the SOE sample is more apparent, as shown by the bottom right panel of Figure 5. For the non-SOE sample, the price discovery with respect to credit quality remains more important, as captured by the bottom left panel of Figure 5.

Effectively, our results show an interesting pattern of divergence, with the price discovery for SOEs focusing more on government support, while the price discovery for non-SOEs focusing more on credit quality. In other words, the rapid segmentation not only divides SOEs from non-SOEs in terms of credit pricing, it also divides the contents of their price discovery, moving one segment of the market toward price discovery with respect to credit quality and the other segment toward price discovery with respect to government support. In the end, however, the focal point is the same: the probability of default. And the unifying theme is the emerging importance of government support, which differentiates non-SOEs against SOEs, and also differentiates the SOEs with weaker government support against those with stronger government support.

Overall, studying the information content of credit spreads with respect to default measures and government holdings, we find a market of improved price efficiency as investors take into account the developing risk factors – default risk as well as the extent of government support, and price them into the credit market. Paradoxically, as investors react to the emerging importance of government support, the segmentation between the SOE and non-SOE further deepens. In other words, the efficiency of market prices results in further inefficiency in resource allocations, which could have real economic consequences on the non-SOE issuers as shown in Section 6.

6 Empirical Results: The Real Impact

The increasing importance of government support documented in our paper is not specific just to the credit market. It is in fact a reflection of the broader economy. Absent of detailed information on bank loans and shadow banking, our findings from the credit market are important and informative, as they serve to uncover the economy-wide credit condition in China. In this section, we further examine the real economic impact of the severe segmentation on non-SOEs in China. It should be emphasized that the issuers covered in our study are those with access to both bond and equity financing. In a way, we are examining

[17]As shown in Table 2, the standard deviations of credit spread are comparable during Phase II: 1.39% for non-SOEs and 1.31% for SOEs. Moving to Phase III, the numbers diverge significantly: 3.78% for non-SOEs and 1.89% for SOEs.

the credit allocation among the largest firms in China. For smaller non-SOE firms in China, the credit mis-allocation as well as the real impact could be even worse.

6.1 Performance Difference Between Non-SOEs and SOEs

To examine the real consequences of the severe segmentation in credit pricing, we extent our sample to include all listed firms with any types of bond issuance in history and are left with a larger sample. We focus our analysis on firm profitability, as captured by quarterly returns to asset (ROA) and quarterly return to equity (ROE). We measure ROA by net profit divided by lagged book asset, and ROE by net profit divided by lagged book equity.

Table A.4 reports the summary statistics for the sample of listed issuers with participation in the credit market. There are in total 821 non-SOE issuers and 623 SOE issuers, with an increasing number of issuers in the non-SOEs sample and relatively stable number of issuers in SOEs sample over time. Similar to the summary statistics in Table 3, compared to the SOE issuers, the non-SOE issuers on average have smaller equity size, higher equity volatility, lower leverage, and higher asset growth rate. Focusing on their fundamental health and profitability, we see that non-SOE issuers are in general stronger in credit quality as measured by the default measure, and have higher ROAs and ROEs. Not surprisingly, they also have lower government holdings and end-controller holdings than their SOE counterparts.

Examining the time-series variations, we again focus on the three time periods: Phase I, from 2010Q1 through 2013Q4, is the pre-default period; Phase II, from 2014Q1 through 2018Q1, captures the first wave of defaults; and Phase III, from 2018Q2 to 2020Q2, captures the severe segmentation in pricing between SOEs and non-SOEs. As shown in Table A.4, during Phases I and II, the non-SOE issuers are in general healthier than SOE issuers with lower default measures. This pattern reversed in Phase III, when SOE issuers became slightly healthier with a lower default measure (22.91%) than non-SOE issuers (24.21%). The comparison in profitability exhibits a similar pattern. During the first two phases, the ROA and ROE of non-SOE issuers are on average over 40 bps higher than those of SOE issuers. Moving to Phase III, the difference in ROA turns to almost zero and that in ROE turns negative – SOE issuers on average have a higher ROE (1.50%) than non-SOE issuers (0.98%) during Phase III.

Figure 6 further captures how the profitability for non-SOEs and SOEs evolves over time, by plotting the quarterly ROAs and ROEs for both non-SOEs and SOEs. Prior to 2018Q4, there has always been a positive gap between the profitability of non-SOEs and SOEs, confirming the commonly held view that non-SOEs are more profitable than SOEs. Starting from 2018Q4, however, we see a sharp decrease in the profitability of non-SOEs, while those of SOEs remain relatively intact. Since then, the positive profitability gap enjoyed by the non-SOEs drops to near zero and turns negative in some quarters, suggesting that the shrinking non-SOE advantage in profitability is driven mainly by non-SOEs' worsening profitability. So far, our analyses are based on the raw data. In the next section, we examine the performance difference more carefully by controlling for firm characteristics and industry effect.

6.2 Performance Difference via Panel Regressions

Table 7 reports the performance difference between non-SOEs and SOEs via quarterly panel regressions, controlling for firm size and with quarter and industry fixed effects to control for time-variation as well as industry variation in firm profitability. Focusing first on ROA and ROE, we find that non-SOEs in China are in general more profitable than SOEs. During the pre-2018Q2 periods (Phases I and II), the profitability gap is fairly stable and statistically significant. The difference in quarterly ROAs between non-SOEs and SOEs is on average 0.56% (t-stat=7.80) in Phase I and 0.53% (t-stat=8.94) in Phase II. In annualized terms, this gap in ROA is around 2%. Post 2018Q2, the ROA gap drops rather dramatically to 0.13% (t-stat=1.09) and is statistically insignificant. The same pattern can be observed using ROEs. Before 2018Q2, the ROE gap between non-SOEs and SOEs is on average 1.08% (t-stat=6.70) in Phase I and 1.20% (t-stat=8.00) in Phase II, and then decreases sharply to -0.01% (t-stat=-0.03) in Phase III. Post 2018Q2, amid the severe credit condition, the non-SOE firms in China have on average lost their superior profitability relative to the SOE firms.

To provide further evidence, we also use our robust government-holdings measure (GovtHoldings) to capture the extent of government support. As shown in Panel B of Table 7, higher government holdings are in general associated with lower ROA and ROE, similar to the findings in Panel A. Compared with the results in Panel A, where the extent of government support is captured by the SOE dummy, the results in Panel B using GovtHoldings paint a very similar picture. The sensitivity of ROA to GovtHoldings is -0.89% and -0.91%, respectively, in Phase I and II, and then drops quickly to -0.26% post 2018Q2 and becomes statistical insignificant. Consider two firms: one non-SOE firm with zero government ownership and one SOE firm with 100% government ownership. Pre 2018Q2, the quarterly ROA of the non-SOE firm is on average 0.90% higher than that of the SOE firm and statistical significance of the performance gap is strong. Post 2018Q2, however, the superior performance drops to a statistically insignificant 0.26%. Regressing ROE on GovtHoldings gives a similar result. During Phases I and II, the quarterly ROE of the non-SOE firm (with zero government ownership) is 1.81% and 2.09% higher than that of the SOE firm (with 100% government ownership), respectively. Post 2018Q2, this superior performance in ROE diminishes to near zero.

In addition to the shrinking gap in profitability, our results also document a shrinking gap in credit quality. As shown in Panel A of Table 7, the non-SOE firms are stronger in credit quality and with lower default measure than the SOE firms. The difference in default measure between non-SOEs and SOEs is on average -2.21% (t-stat=-6.65) and -3.49% (t-stat=-4.44) during Phase I and II, respectively. Post 2018Q2, during Phase III, the difference drops to -0.41% and is indistinguishable from zero. The same pattern can be observed when we use government holdings as a proxy for government support. As shown in Panel B of Table 7, firms with higher government holdings have higher default measures and lower credit quality. Again, consider two firms: one SOE firm with 100% government ownership and one non-SOE firm with zero government ownership. During Phase I, the difference in their default measures is 2.55% and is statistical significant, indicating that non-SOEs are stronger in credit quality than SOEs. Moving to Phase II, the difference actually increases to 6.49% with strong statistical significance. In other words, after the first default in 2014, as investors become more aware of credit risk, the non-SOEs with access to the credit market actually become markedly healthier than SOEs. Post 2018Q2, however, the non-SOE firm becomes weaker than the SOE, although the difference of -0.05% in default measure is statistical insignificant.

Overall, our results document the extent to which the severe segmentation in credit pricing could harm the fundamentals of the non-SOE firms in China. It should be emphasized that our sample of non-SOEs are publicly listed firms with access to the bond market. Our numbers show that, post 2018Q2, even these large non-SOEs with access to the capital markets are struggling in performance. In addition to the severe credit-market squeeze documented in this paper, post 2018, the non-SOE firms, from small to large, are also known to have difficulties in financing and re-financing via other credit channels, including bank loans and shadow banking. As shown in our results, such severe credit conditions are affecting the fundamentals of the non-SOE firms. The rapidly shrinking gap in profitability and credit quality between non-SOEs and SOEs observed in this paper could serve as an alarming alert to policy makers in China.

6.3 Robustness Check on the Effect of the US-China Trade War

One potential concern is that the worsening profitability and fundamentals for non-SOEs could be driven instead by the US-China trade war, which started in early 2018. To address this issue, we perform robustness checks by dividing our sample into two: one focuses on firms in industries that are affected by the trade war, and the other on industries that are less affected, using the industry specifications given by Benguria, Choi, Swenson, and Xu (2020).[18]

Table 8 re-examines the performance difference between non-SOEs and SOEs within the two subsamples separately. Panel A focuses on the SOE and non-SOE firms less affected by the trade war, while Panel B focuses on those more affected. The patterns are in general very similar to our full-sample results. Regardless of the firms' exposures to the trade war, the superior performance of non-SOEs over SOEs are always present in Phases I and II. As shown in Panel A for firms less affected, the quarterly ROA gap is on average 53 bps in both Phases I and II. As shown in Panel B for firms more affected, the quarterly ROA gap is on average 60 bps in Phase I and 52 bps in Phase II. Likewise, the sharp reduction post 2018Q in non-SOEs' performance advantage can also be observed for both subsamples. For the less affected, the gap in ROA decreases to 8 bps and is statistically insignificant in Phase III, while for the affected, the gap in ROA decreases to 20 bps and also statistically insignificant.

Repeating the same analyses for ROEs and default measures, we draw the same conclusion as the full-sample results. In other words, trade-war exposure is not the driver behind the diminishing performance advantage of non-SOEs post 2018Q2. Using government holdings as an alternative proxy to measure the extent of government support gives us the same conclusion. Interestingly, comparing the magnitudes of our results between two sub-samples, we can see that it is in fact the subsample that is less affected by the trade war that exhibits stronger reductions in average ROA and ROE post 2018Q2. By contrast, within the subsample more affected by the trade war, the post-2018Q2 ROA gap is not as severe: 20 bps (t-stat=1.53) when the NSOE dummy is used, and 54 bps (t-stat=2.13) when the government-holdings measure is used.[19] These results point to the possibility that SOEs in those more affected industries may incur heavier losses due to the trade war. In other words, the effect of the trade war could be opposite to that of the worsening segmentation. Overall, our results are robust after controlling for the impact of the US-China trade war.

[18]Starting in March 2018, the Trump administration imposed trade barriers and a broad round of tariffs on Chinese products in the name of protecting the intellectual property rights held by U.S. companies. Then a sequence of tariffs has been imposed by both US and China from July 2018 to May 2019, which had a negative impact on firms in certain industries. The detailed background information about the US-China trade war can be found in Benguria, Choi, Swenson, and Xu (2020). The affected industries include industrial and commercial machinery & computer equipment, electronic equipment, transportation equipment, and light-manufacturing sectors such as food & kindred products, furniture, and fabricated metal products.

[19]For brevity, the full sub-sample analyses using government-holdings measures are not reported.

7 Conclusions

In this paper, we study the allocative efficiency as well as the price efficiency of China's credit market. Unlike the opaque bank loans and the even more opaque shadow banking activities, the transparency of credit market offers a unique opportunity for us to study the credit allocation in China. Focusing mostly on firms with access to both bond and equity financing, we are examining the credit allocation among the largest firms in China. And yet, our results uncover severe allocative inefficiency between the two important segments in China: the state-owned enterprises (SOEs) and the non-state owned firms. The explosive increase in the SOE premium post 2018Q2 indicates a credit market under severe distress, as investors abandoned non-SOE bonds and sought safety in SOEs. Using government equity holdings as a proxy for the extent of government support, we further identify the sole driver of this explosive SOE premium – the increased importance of government support in credit pricing. Studying the real impact of this allocative inefficiency, we find that the non-SOEs are losing their advantage in profitability and fundamental strength over the SOEs.

Interestingly, studying the price discovery of China's credit market, our results indicate a market with improved price efficiency. Using Merton's default model to construct a proxy for credit quality, we find that, controlling for credit ratings, credit spreads were uninformative with respect to credit quality before the first default in 2014Q1. It was only after 2014Q1, credit spreads of both SOEs and non-SOEs became informative, with comparable informational content. With the explosion of the SOE premium post 2018Q2, the magnitude of the price discovery as well as its content started to diverge. Because of the heightened awareness of credit risk, investors priced the non-SOE bonds with more differentiation with respect to their credit quality. As a result, the non-SOE credit spreads became markedly more informative with respect to credit quality post 2018Q2. In other words, while worsening across the SOE and non-SOE divide, the allocative efficiency actually improved within the non-SOE issuers. By contrast, the SOE credit spreads saw no such improvement, and instead became sensitive to the extent of government support. This very fact that, post 2018Q2, investors started to differentiate the extent of government support above and beyond the SOE label is an indication that the unquestionable faith in the SOE label was dissipating. Indeed, as recent as November 12, 2020, China began to see a new wave of defaults by local-government SOEs.

As China further opens up its financial system, this onshore credit market is well positioned to become a key component of the global fixed-income market, offering prospective international investors exposures to the real China. If the rapid growth of China's economy was 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 could very well be the story of the coming decade. Against this backdrop, our findings on both the allocative efficiency and price efficiency in China's credit market provide useful and perhaps alarming information to policy makers and regulators in China. The increased importance of government support in credit pricing has brought distortions to both credit allocation and price discovery. If left unchecked, it could cause instability in China's credit market in the short run, and drag down China's economic growth in the long run.

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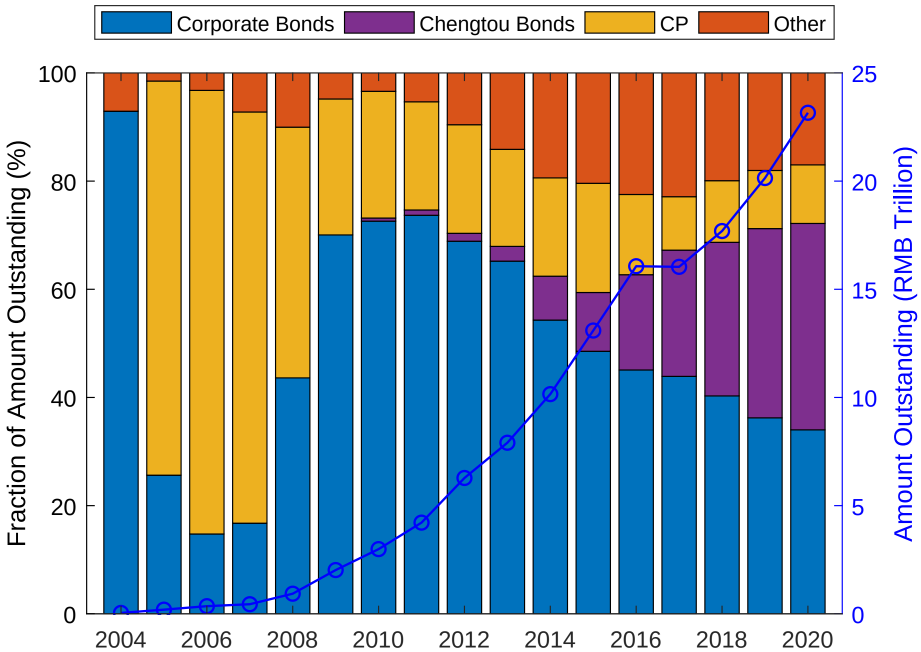
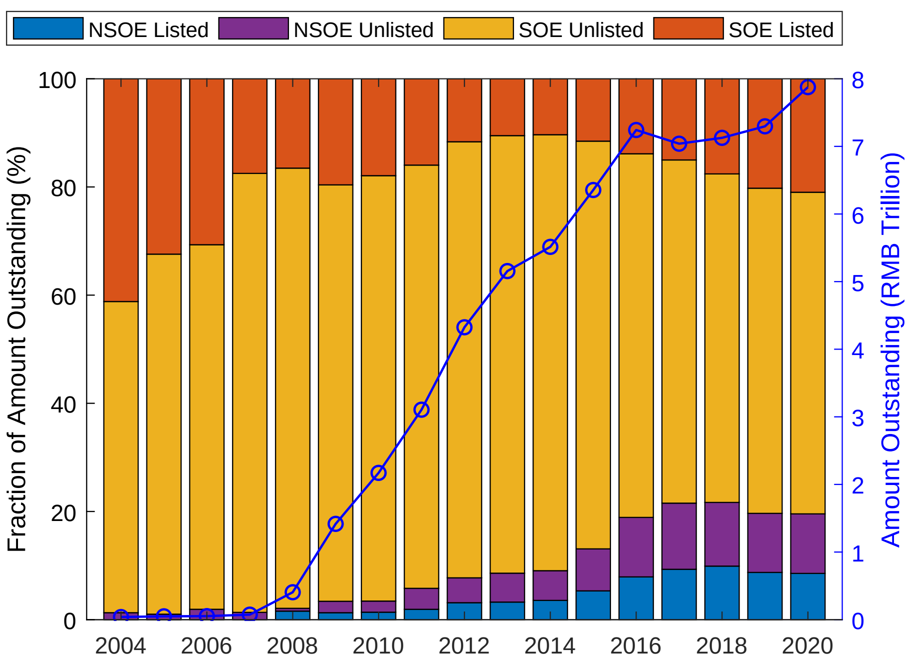
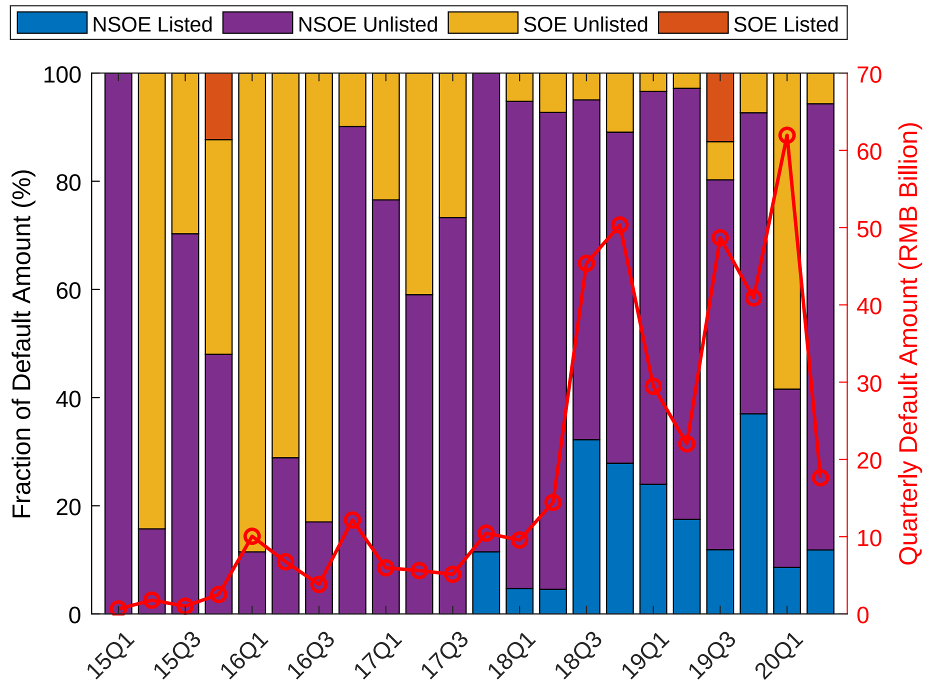


(a) **China's Credit Market**

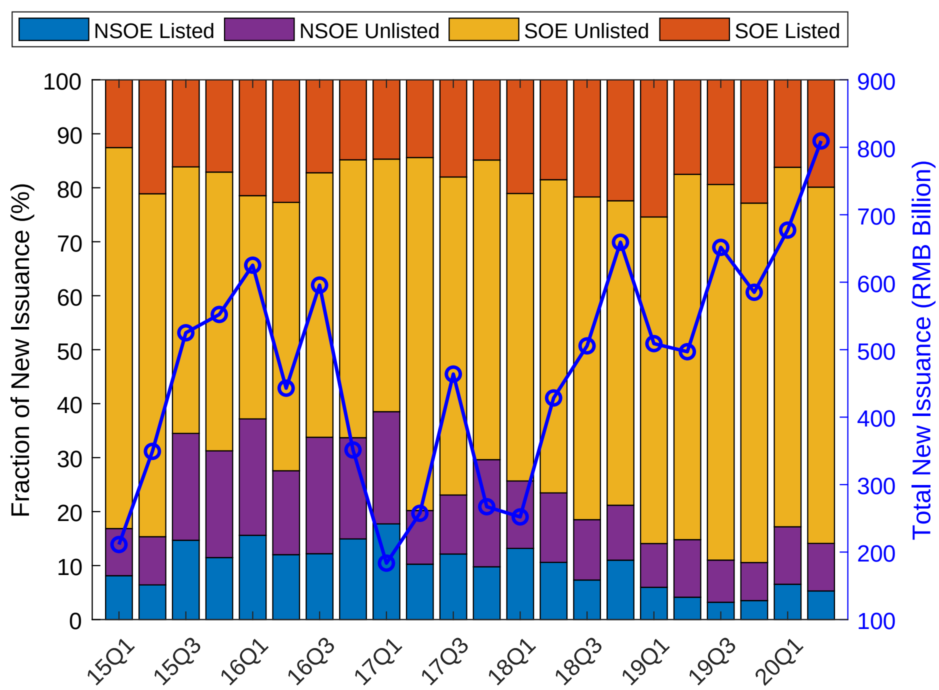


(b) **China's Corporate Bond Market**

Figure 1: The top panel plots the total amount outstanding of the Chinese credit market (right axis) and the fraction by instrument type (left axis). The bottom panel plots the total amount outstanding of the corporate bond market (right axis) and the fraction by issuer type (left axis). Data for 2020 is as of end of the second quarter.

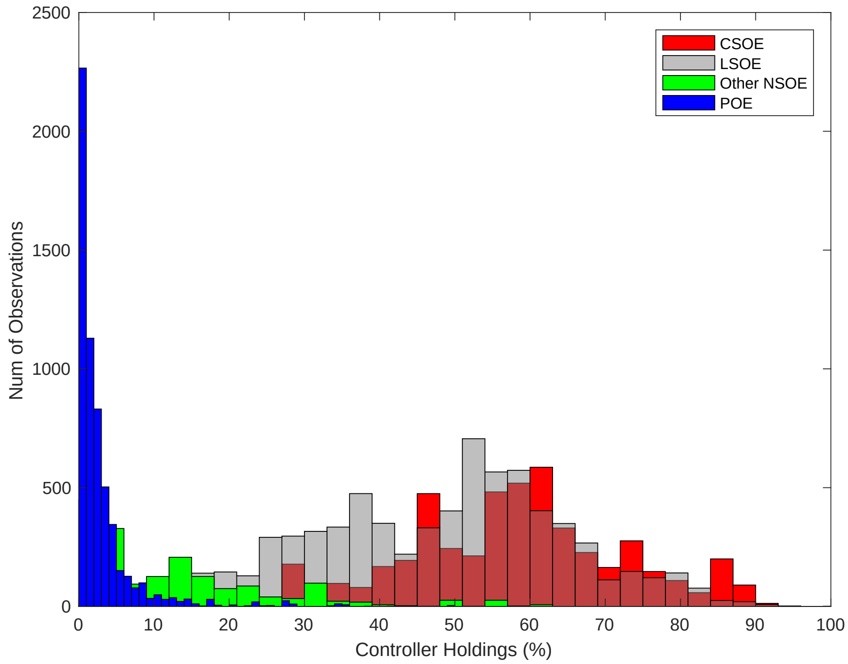


(a) **Quarterly Default in China's Credit Market**

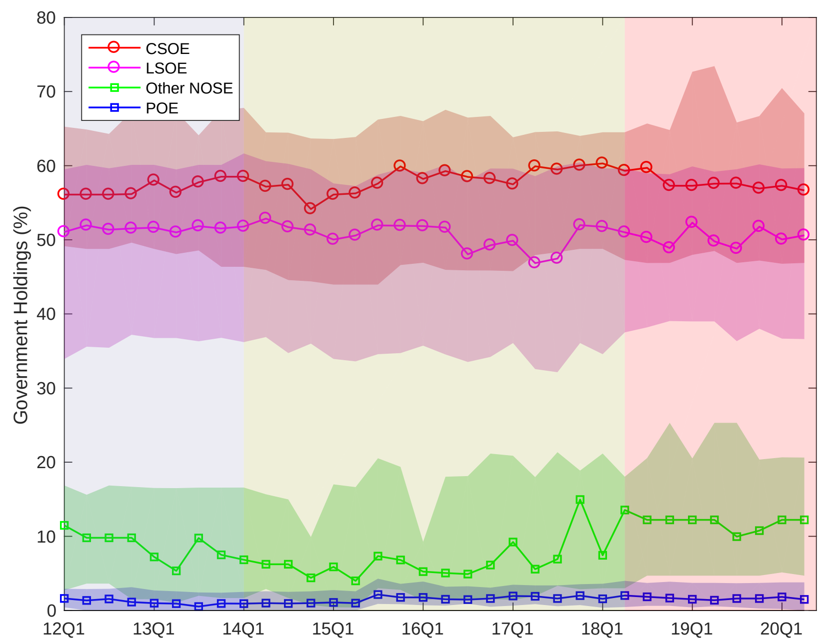


(b) **Quarterly New Issuance of Coporate Bonds**

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

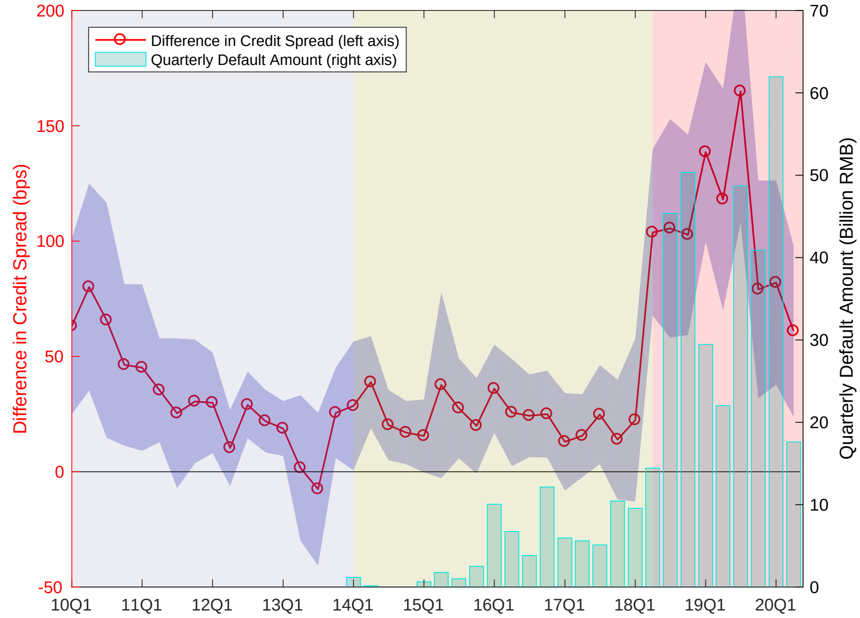


(a) **Distribution of Government Holdings**

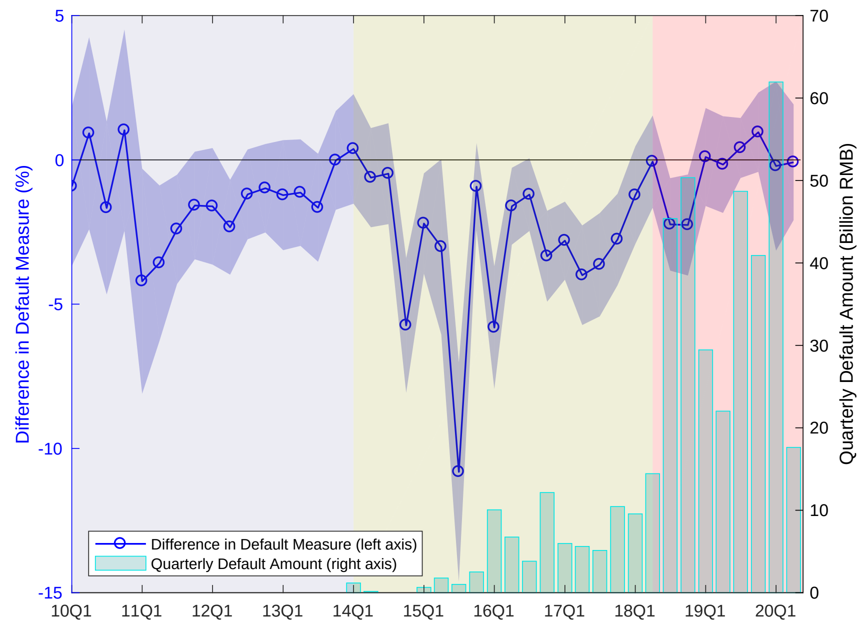


(b) **Government Holdings: P25, Median and P75**

Figure 3: This figure plots the distribution of the government holdings for four types of firms, namely central SOEs (CSOE), local SOEs (LSOE), other non-SOE firms (Mainly Public and Foreign Companies) and privately-owned enterprises (POE). Panel (a) plots the histogram of the government holdings for the full sample. Panel (b) plots the dynamic dispersion of government holdings. The doted line refers to the median and the shaded area indicates the 25 percentile and 75 percentile.

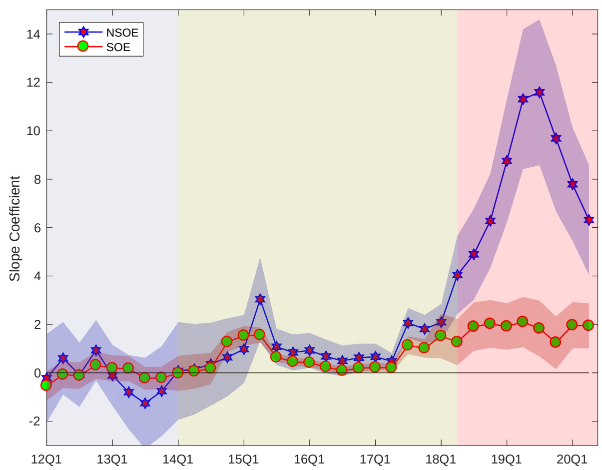


(a) **The SOE Premium: Difference in Credit Spread**

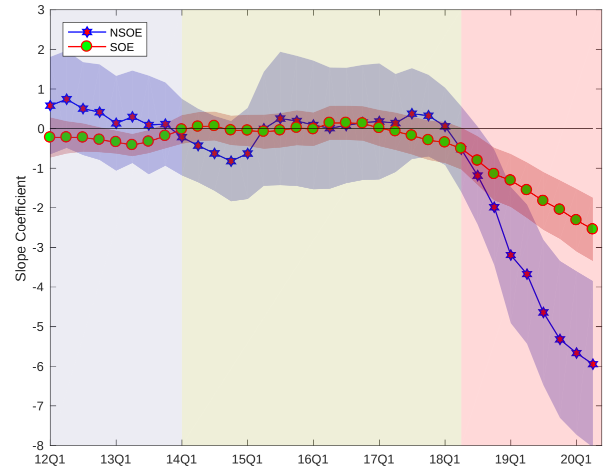


(b) **Difference in Default Measure**

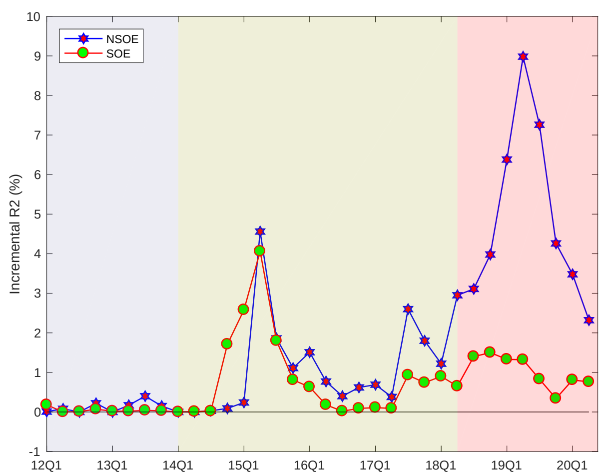
Figure 4: This figure plots the difference between listed non-SOEs and listed SOEs in credit spread (top panel, left axis) and in default measure (bottom panel, left axis), estimated using quarterly regressions, controlling for credit ratings and other bond and firm characteristics. The shaded area indicates the 95% confidence intervals. Also reported are the total quarterly default amounts in the credit market (right axis).



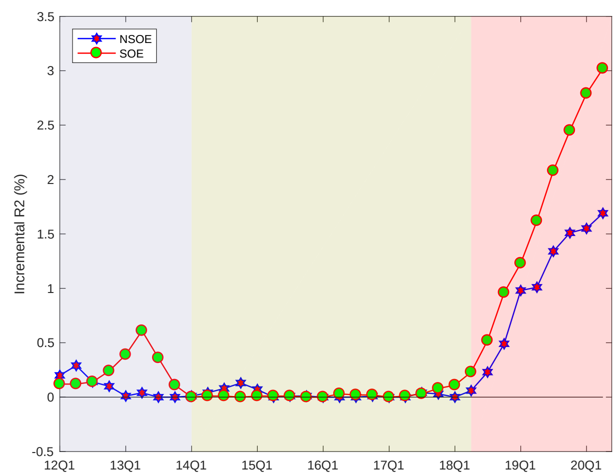
(a) **Credit Spreads on DM**



(b) **Credit Spreads on GovtHoldings**

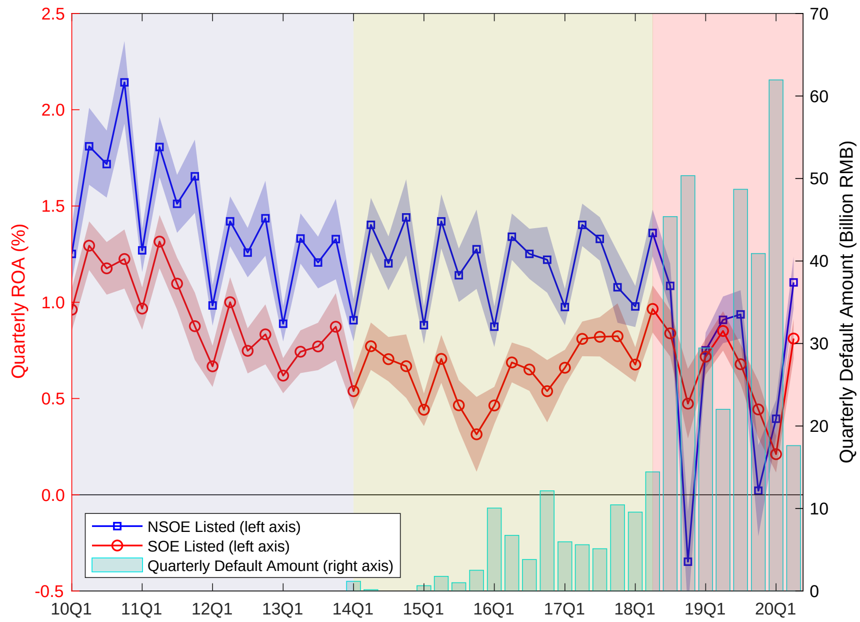


(c) **Incremental $\mathbf{R}^2$ by DM**

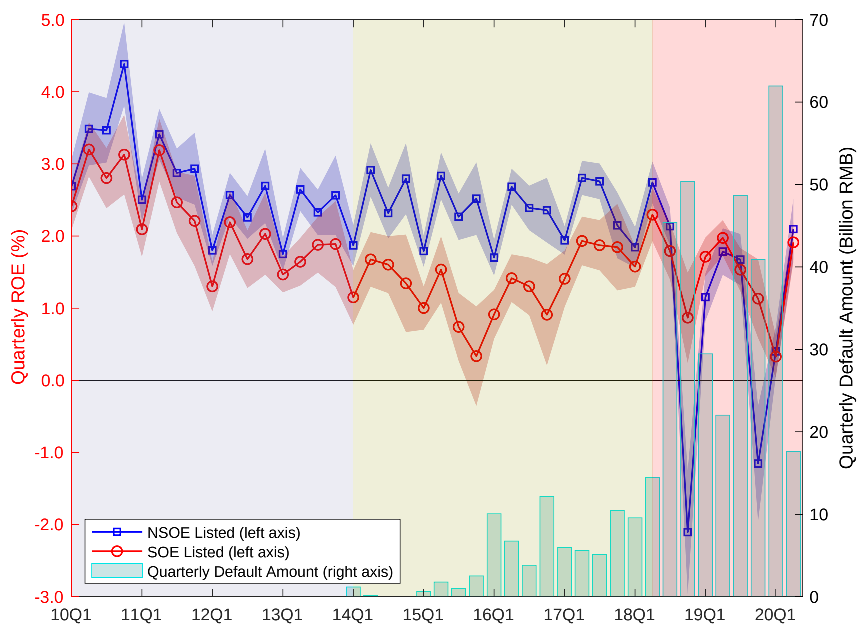


(d) **Incremental $\mathbf{R}^2$ by GovtHoldings**

Figure 5: This figure plots the slope coefficient (top two panels) and the additional adjusted R-squared (bottom two panels) from the regression of credit spreads on default measure and government holdings, respectively, controlling for credit ratings and other bond and firm characteristics. The additional adjusted R-squared is the difference in adjusted R-squared between the regression with and without default measure (or government holdings). The shaded area indicates the 95% confidence intervals.



(a) **ROA: SOEs vs Non-SOEs**



(b) **ROE: SOEs vs Non-SOEs**

Figure 6: This figure plots the quarterly ROA (top panel, left axis) and ROE (bottom panel, left axis) for non-SOEs and SOEs. ROA is net profit divided by lagged book asset, and ROE is net profit divided by lagged book equity. The shaded area indicates the 95% confidence intervals. Also reported are the total quarterly default amounts in the credit market (right axis).

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

	Non-SOE Listed			**SOE Listed**		
	mean	med	std	mean	med	std
NumIssuers	367			403		
NumBonds	923			1,477		
CreditSpread (%)	2.47	1.94	2.39	1.39	0.99	1.41
Rating	2.43	3.00	0.85	1.69	1.00	0.84
Maturity (yr)	2.97	2.79	1.25	3.33	2.95	1.70
IssueSize (billion)	1.03	0.80	0.89	2.00	1.20	2.56
Age (yr)	1.75	1.53	1.26	2.01	1.61	1.67
Coupon (%)	5.91	5.90	1.24	5.13	5.10	1.09
Embed	0.63	1.00	0.48	0.39	0.00	0.49
Exch	0.69	1.00	0.46	0.53	1.00	0.50
ZeroDays (%)	77	88	26	86	93	18
Turnover (%)	31	13	62	35	10	80
TradingDays (day)	15	8	18	10	5	12
	Non-SOE Unlisted			**SOE Unlisted**		
	mean	med	std	mean	med	std
NumIssuers	403			1,795		
NumBonds	1,518			7,061		
CreditSpread (%)	2.82	2.48	1.85	1.58	1.31	1.18
Rating	2.33	2.00	0.81	1.98	2.00	0.86
Maturity (yr)	3.11	2.81	1.47	3.59	3.23	1.86
IssueSize (billion)	1.09	1.00	0.92	1.67	1.00	2.18
Age (yr)	1.66	1.38	1.31	2.29	1.86	1.86
Coupon (%)	6.11	6.20	1.31	5.79	5.80	1.25
Embed	0.56	1.00	0.50	0.26	0.00	0.44
Exch	0.48	0.00	0.50	0.21	0.00	0.41
ZeroDays (%)	85	93	20	88	94	16
Turnover (%)	48	15	117	63	21	144
TradingDays (day)	10	5	13	8	4	11

The sample extends from January 2010 through June 2020. CreditSpread is the difference in yield between corporate bond and CDB bond of the same maturity. Rating is a numerical number: 1=AAA, 2=AA+, 3=AA, 4=AA-, etc. Embed is 1 for bonds issued with emdedded option. Exch is 1 for exchange-traded bonds. ZeroDays is the percent of non-trading days per quarter. Turnover is the ratio of quarterly trading volume to issuance size. TradingDays is the number of trading days per quarter.

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

	Non-SOE Listed						**SOE Listed**					
	Phase I		Phase II		Phase III		Phase I		Phase II		Phase III	
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
NumIssuers	178		315		227		256		340		252	
NumBonds	221		643		570		458		824		884	
CreditSpread (%)	2.03	1.25	2.06	1.39	3.57	3.78	1.21	0.79	1.32	1.31	1.70	1.89
Rating	2.73	0.75	2.60	0.73	1.91	0.91	1.85	0.86	1.80	0.89	1.34	0.61
Maturity (yr)	3.89	1.38	2.94	1.16	2.42	0.94	4.16	2.01	3.22	1.55	2.76	1.31
IssueSize (billion)	0.94	0.80	1.01	0.94	1.14	0.85	2.31	3.16	1.89	2.49	1.91	2.01
Age (yr)	1.25	1.04	1.81	1.30	1.94	1.21	1.54	1.36	2.26	1.69	1.98	1.77
Coupon (%)	6.45	0.99	5.96	1.23	5.46	1.25	5.44	0.97	5.24	1.09	4.65	1.05
Embed	0.52	0.50	0.65	0.48	0.65	0.48	0.28	0.45	0.43	0.50	0.43	0.49
Exch	0.77	0.42	0.70	0.46	0.63	0.48	0.56	0.50	0.56	0.50	0.45	0.50
ZeroDays (%)	62	30	76	26	88	16	79	21	85	19	92	10
Turnover (%)	44	91	32	56	20	47	54	118	31	70	26	46
TradingDays (day)	25	20	16	18	8	11	14	14	10	13	5	6
	Non-SOE Unlisted						**SOE Unlisted**					
	Phase I		Phase II		Phase III		Phase I		Phase II		Phase III	
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
NumIssuers	152		360		271		1,225		1,626		1,158	
NumBonds	309		1,073		897		3,024		4,758		3,534	
CreditSpread (%)	2.04	0.87	2.54	1.54	3.68	2.29	1.65	0.94	1.45	1.06	1.84	1.68
Rating	2.75	0.68	2.45	0.77	1.94	0.76	2.08	0.86	2.09	0.84	1.55	0.77
Maturity (yr)	4.03	1.83	3.20	1.40	2.51	1.06	4.75	1.95	3.32	1.62	2.61	1.51
IssueSize (billion)	1.04	0.69	1.08	0.88	1.14	1.06	1.84	2.51	1.56	2.09	1.72	1.88
Age (yr)	1.09	0.97	1.59	1.30	2.05	1.34	1.59	1.51	2.67	1.82	2.34	2.13
Coupon (%)	6.31	1.01	6.19	1.31	5.90	1.36	5.88	1.19	6.02	1.21	5.09	1.13
Embed	0.38	0.49	0.53	0.50	0.71	0.46	0.27	0.45	0.23	0.42	0.34	0.47
Exch	0.18	0.38	0.46	0.50	0.65	0.48	0.20	0.40	0.21	0.41	0.24	0.42
ZeroDays (%)	80	22	85	21	88	16	80	22	90	14	93	8
Turnover (%)	125	215	43	96	22	55	121	221	44	100	33	59
TradingDays (day)	13	15	10	14	8	11	13	15	7	9	5	6

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. See Table 1 for variable definitions.

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

	Non-SOE Listed											
	All			Phase I			Phase II			Phase III		
	mean	med	std	mean	med	std	mean	med	std	mean	med	std
NumFirms	367			178			315			227		
EquitySize (log)	23.30	23.26	1.02	22.57	22.48	0.93	23.31	23.28	0.88	23.77	23.70	1.08
EquityVolatility (%)	40.38	36.53	17.98	37.56	35.98	10.04	42.27	36.74	21.46	38.45	36.64	13.35
Leverage (%)	58.55	59.06	15.29	55.76	56.43	12.84	57.39	57.89	15.27	62.67	62.47	15.97
AssetGrowth (%)	24.96	20.91	19.42	28.69	24.45	21.24	24.69	20.65	19.64	23.08	19.50	17.28
AssetValue (log)	24.01	23.86	1.24	23.19	23.11	0.98	23.90	23.82	1.05	24.77	24.68	1.31
AssetVolatility (%)	22.95	19.72	15.50	22.13	21.19	10.34	26.04	21.61	17.44	17.33	14.59	12.21
DM (%)	21.18	18.07	12.78	18.70	17.87	6.59	22.48	18.45	14.97	20.21	17.50	10.60
GovtHoldings (%)	5.07	2.03	8.36	4.97	1.59	8.72	4.51	1.93	7.50	6.23	2.99	9.55
CtrlHoldings (%)	36.41	32.81	17.43	36.55	33.18	18.83	36.90	33.32	16.78	35.35	32.05	17.69
	SOE Listed											
	All			Phase I			Phase II			Phase III		
	mean	med	std	mean	med	std	mean	med	std	mean	med	std
NumFirms	403			256			340			252		
EquitySize (log)	23.71	23.56	1.34	23.31	23.05	1.40	23.71	23.52	1.28	24.05	23.98	1.28
EquityVolatility (%)	36.37	32.06	18.35	32.48	31.24	10.82	41.56	35.81	22.32	30.51	28.74	12.17
Leverage (%)	61.67	64.05	14.90	61.18	62.99	14.61	61.19	63.51	15.70	63.00	65.96	13.56
AssetGrowth (%)	14.32	12.11	13.04	19.69	17.01	14.23	12.82	11.15	12.99	12.11	10.38	10.37
AssetValue (log)	24.65	24.42	1.46	24.24	23.96	1.45	24.53	24.28	1.40	25.23	25.33	1.40
AssetVolatility (%)	17.18	13.31	13.83	15.07	12.89	9.54	21.41	16.69	16.24	11.46	8.51	9.07
DM (%)	22.56	18.79	15.12	18.39	17.70	7.83	26.78	21.33	18.91	18.71	17.10	9.26
GovtHoldings (%)	51.93	53.86	16.76	52.08	53.85	17.34	51.22	53.60	16.71	53.08	54.65	16.26
CtrlHoldings (%)	45.50	46.00	16.39	47.19	48.81	17.20	45.26	45.54	16.45	44.41	44.92	15.40

DM is the default measure, the inverse of Merton's distance-to-default. GovtHoldings is the total government equity holdings within firm's top 10 shareholders. CtrlHoldings is the total equity holdings by the end-controller within firm's top 10 shareholders. EquitySize and AssetValue are the log of the firm's equity size and model-implied asset value, respectively. EquityVolatility and AssetVolatility are the annualized equity and asset volatility, respectively. 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. The sample period is from January 2010 to June 2020.

Table 4: **Difference in Credit Spreads and Default Measures**

	Listed Sample						**UnListed Sample**		
	CreditSpread (%)			**DM (%)**			**CreditSpread (%)**		
	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III
NSOE	0.20***	0.21***	1.06***	-1.50***	-3.08***	-0.55	0.16***	0.79***	1.54***
	[3.08]	[3.58]	[7.78]	[-2.95]	[-4.23]	[-0.91]	[3.47]	[12.92]	[17.28]
Rating	0.51***	0.53***	1.24***	0.79*	-0.18	1.60***	0.54***	0.41***	0.46***
	[6.39]	[10.96]	[4.84]	[1.94]	[-0.51]	[3.13]	[14.11]	[16.89]	[14.58]
Maturity	0.04***	0.00	-0.22***	-0.08	0.18	0.06	0.08***	-0.03*	-0.25***
	[2.61]	[0.16]	[-4.38]	[-0.52]	[0.83]	[0.35]	[9.00]	[-1.85]	[-13.98]
Age	0.02	-0.00	0.00	-0.06	0.59***	0.14	0.01	-0.09***	-0.02
	[1.17]	[-0.16]	[0.04]	[-0.28]	[2.85]	[1.45]	[0.95]	[-9.51]	[-1.39]
IssueSize	-0.00	-0.05***	-0.08**	-0.53***	0.02	-0.01	-4.60***	-8.39***	-15.64***
	[-0.25]	[-3.41]	[-2.03]	[-3.23]	[0.10]	[-0.07]	[-9.26]	[-9.98]	[-9.80]
ZeroDays	-0.91***	-2.07***	-4.57***	-0.34	-4.60***	-1.45	-0.54***	-1.53***	-2.92***
	[-3.98]	[-9.10]	[-5.93]	[-0.40]	[-3.28]	[-1.23]	[-3.95]	[-9.02]	[-8.49]
Embed	-0.05	1.74***	2.22***	-1.21	1.22	-0.67	0.07	0.90***	2.37***
	[-0.33]	[8.90]	[10.10]	[-0.79]	[1.20]	[-1.12]	[1.19]	[7.22]	[17.88]
Exch	0.01	-0.17***	0.90***	-0.37	-0.54	-0.38	-0.06	0.04	0.49***
	[0.12]	[-2.65]	[3.62]	[-0.66]	[-0.84]	[-0.78]	[-0.99]	[0.96]	[5.08]
Embed_Exch	-0.07	-2.03***	-3.42***	0.94	-2.00	0.44	-0.10	-0.97***	-2.21***
	[-0.38]	[-10.78]	[-11.94]	[0.56]	[-1.52]	[0.55]	[-1.64]	[-6.69]	[-14.81]
EquitySize	-0.15***	-0.20***	-0.23***	-0.46	-1.41***	-1.55***			
	[-4.84]	[-5.04]	[-4.16]	[-1.36]	[-2.58]	[-5.39]			
Constant	4.19***	6.48***	9.36***	32.23***	63.03***	50.62***	0.90***	1.81***	3.42***
	[4.24]	[6.97]	[4.90]	[2.76]	[4.60]	[7.02]	[4.86]	[8.84]	[9.53]
Obs	4,344	10,072	5,348	4,344	10,072	5,350	21,525	45,315	16,999
Adj R^2	0.543	0.468	0.385	0.151	0.660	0.331	0.544	0.382	0.457

Quarterly panel regressions with credit spreads and default measures (DM) as the dependent variables, respectively, with quarter and industry fixed effects. NSOE is one for bonds issued by NSOEs and zero for SOEs. DM is the default measure, the inverse of Merton's distance-to-default. 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 5: **Explaining the SOE Premium**

	Phase I			Phase II			Phase III		
NSOE	0.20***	0.20***	0.20**	0.21***	0.25***	0.18*	1.06***	1.09***	-0.09
	[3.08]	[2.95]	[2.46]	[3.58]	[4.32]	[1.68]	[7.78]	[7.76]	[-0.48]
DM		-0.13			1.26***			4.78***	
		[-0.40]			[4.52]			[5.24]	
GovtHoldings			0.00			-0.08			-2.81***
			[0.01]			[-0.37]			[-7.82]
Rating	0.51***	0.51***	0.51***	0.53***	0.53***	0.52***	1.24***	1.16***	1.20***
	[6.39]	[6.29]	[6.23]	[10.96]	[11.23]	[11.01]	[4.84]	[4.73]	[4.66]
Maturity	0.04***	0.04***	0.04***	0.00	0.00	0.00	-0.22***	-0.22***	-0.20***
	[2.61]	[2.63]	[2.60]	[0.16]	[0.07]	[0.16]	[-4.38]	[-4.45]	[-4.20]
Age	0.02	0.02	0.02	-0.00	-0.01	-0.00	0.00	-0.00	0.01
	[1.17]	[1.17]	[1.17]	[-0.16]	[-0.52]	[-0.16]	[0.04]	[-0.11]	[0.31]
IssueSize	-0.00	-0.00	-0.00	-0.05***	-0.05***	-0.05***	-0.08**	-0.08**	-0.05
	[-0.25]	[-0.33]	[-0.26]	[-3.41]	[-3.43]	[-3.32]	[-2.03]	[-2.10]	[-1.28]
ZeroDays	-0.91***	-0.92***	-0.91***	-2.07***	-2.01***	-2.07***	-4.57***	-4.50***	-4.39***
	[-3.98]	[-3.99]	[-3.98]	[-9.10]	[-9.08]	[-9.08]	[-5.93]	[-5.94]	[-5.72]
Embed	-0.05	-0.05	-0.05	1.74***	1.73***	1.74***	2.22***	2.25***	2.24***
	[-0.33]	[-0.34]	[-0.33]	[8.90]	[8.88]	[8.89]	[10.10]	[10.39]	[10.54]
Exch	0.01	0.01	0.01	-0.17***	-0.16**	-0.17***	0.90***	0.92***	0.91***
	[0.12]	[0.12]	[0.12]	[-2.65]	[-2.52]	[-2.64]	[3.62]	[3.70]	[3.80]
Embed_Exch	-0.07	-0.06	-0.07	-2.03***	-2.00***	-2.03***	-3.42***	-3.44***	-3.46***
	[-0.38]	[-0.37]	[-0.38]	[-10.78]	[-10.76]	[-10.74]	[-11.94]	[-11.64]	[-12.43]
EquitySize	-0.15***	-0.15***	-0.15***	-0.20***	-0.18***	-0.20***	-0.23***	-0.16***	-0.18***
	[-4.84]	[-4.95]	[-4.79]	[-5.04]	[-4.76]	[-4.84]	[-4.16]	[-2.62]	[-3.08]
Constant	4.19***	4.23***	4.19***	6.48***	5.69***	6.50***	9.36***	6.94***	9.16***
	[4.24]	[4.51]	[4.24]	[6.97]	[6.14]	[7.10]	[4.90]	[3.64]	[4.75]
Obs	4,344	4,344	4,344	10,072	10,072	10,072	5,348	5,348	5,348
Adj R^2	0.543	0.543	0.543	0.468	0.476	0.468	0.385	0.402	0.398

Quarterly panel regressions of credit spreads on NSOE, default measures (DM) and government holdings (GovtHoldings), respectively, with quarter and industry fixed effects. NSOE is one for bonds issued by NSOEs and zero for SOEs. DM is the default measure, the inverse of Merton's distance-to-default. 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 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 6: **Price Discovery: Credit Spreads on Default Measures and Government Holdings**

NSOE	Phase I				Phase II				Phase III			
DM		-0.03		-0.01		1.63***		1.62***		7.89***		8.01***
		[-0.03]		[-0.02]		[2.88]		[2.89]		[3.83]		[3.94]
GovtHoldings			0.45	0.45			0.24	0.12			-5.52***	-5.69***
			[1.06]	[1.05]			[0.52]	[0.27]			[-4.56]	[-5.14]
Rating	0.74***	0.74***	0.75***	0.75***	0.41***	0.41***	0.41***	0.42***	1.64***	1.44***	1.58***	1.37***
	[2.99]	[2.99]	[3.05]	[3.05]	[4.65]	[4.82]	[4.77]	[4.88]	[4.34]	[4.06]	[4.24]	[3.85]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	7.88***	7.88***	7.86***	7.86***	10.83***	9.99***	10.85***	10.00***	15.07***	12.97***	11.64***	9.40***
	[3.97]	[4.11]	[3.99]	[4.13]	[6.94]	[6.55]	[6.92]	[6.52]	[4.77]	[4.23]	[3.49]	[2.94]
Obs	1,372	1,372	1,372	1,372	4,182	4,182	4,182	4,182	2,095	2,095	2,095	2,095
Adj R^2	0.484	0.483	0.484	0.484	0.376	0.386	0.376	0.386	0.367	0.397	0.382	0.413
SOE	Phase I				Phase II				Phase III			
DM		0.09		0.08		1.04***		1.04***		2.09***		1.47*
		[0.65]		[0.58]		[3.84]		[3.83]		[2.65]		[1.87]
GovtHoldings			-0.17	-0.17			-0.11	-0.12			-2.32***	-2.18***
			[-1.26]	[-1.25]			[-0.52]	[-0.57]			[-6.05]	[-6.02]
Rating	0.39***	0.39***	0.39***	0.38***	0.55***	0.55***	0.54***	0.55***	0.58***	0.56***	0.53***	0.52***
	[11.23]	[11.20]	[11.01]	[10.97]	[9.50]	[9.83]	[9.76]	[10.06]	[4.88]	[4.72]	[4.70]	[4.61]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.25***	3.22***	3.32***	3.29***	5.22***	4.50***	5.24***	4.51***	7.45***	6.12***	7.83***	6.87***
	[3.63]	[3.65]	[3.82]	[3.85]	[5.68]	[4.87]	[5.75]	[4.93]	[4.77]	[3.95]	[5.22]	[4.60]
Obs	2,972	2,972	2,972	2,972	5,890	5,890	5,890	5,890	3,253	3,253	3,253	3,253
Adj R^2	0.542	0.542	0.543	0.543	0.500	0.508	0.500	0.508	0.386	0.393	0.412	0.415

Quarterly panel regressions of credit spreads on default measures (DM) and government holdings (GovtHoldings) and other Controls with quarter and industry fixed effects. DM is the default measure, the inverse of Merton's distance-to-default. GovtHoldings is the total government equity holdings within firm's top 10 shareholders. Other Controls include bond maturity, issuance size, age, exchange market dummy, optionality, liquidity and equity size. The detailed results are given in Tables A.2 and A.3. 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 7: **The Real Impact of the Credit-Market Segmentation**

	Panel A: NSOE Dummy								
	ROA (%)			**ROE (%)**			**DM (%)**		
	Phase I	Phase II	Phase III	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	-2.21***	-3.49***	-0.41
	[7.80]	[8.94]	[1.09]	[6.70]	[8.00]	[-0.03]	[-6.65]	[-4.44]	[-0.65]
EquitySize	0.19***	0.19***	0.35***	0.78***	0.74***	1.09***	-0.67***	-1.49***	-2.60***
	[6.08]	[6.34]	[8.68]	[10.86]	[11.05]	[7.58]	[-2.93]	[-4.11]	[-9.12]
Constant	-3.56***	-4.05***	-7.03***	-16.25***	-16.66***	-21.40***	30.78***	59.66***	78.79***
	[-4.86]	[-4.95]	[-8.51]	[-9.75]	[-9.43]	[-7.94]	[5.08]	[6.30]	[12.08]
Obs	15,677	18,487	10,844	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	0.093	0.589	0.181

	Panel B: Government Holdings								
	ROA (%)			**ROE (%)**			**DM (%)**		
	Phase I	Phase II	Phase III	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	2.55***	6.49***	-0.05
	[-6.46]	[-7.93]	[-1.03]	[-5.77]	[-6.77]	[0.10]	[3.68]	[4.31]	[-0.03]
EquitySize	0.17***	0.21***	0.36***	0.76***	0.78***	1.09***	-0.55**	-1.63***	-2.56***
	[5.74]	[6.84]	[9.14]	[10.99]	[11.64]	[8.20]	[-2.45]	[-4.30]	[-9.19]
Constant	-2.73***	-3.84***	-7.01***	-14.73***	-16.17***	-21.35***	26.44***	58.66***	77.78***
	[-3.76]	[-4.61]	[-8.34]	[-9.40]	[-9.09]	[-7.85]	[4.45]	[6.17]	[12.17]
Obs	15,677	18,487	10,844	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	0.082	0.588	0.180

Quarterly panel regressions with ROA, ROE, Default Measures as the dependent variables on Non-SOE Dummy (NSOE) and government holdings (GovtHoldings), respectively, with quarter and industry fixed effect. ROA is the ratio of the net profit to the lag book asset. ROE is the net profit to the lag book equity. DM is the default measure, the inverse of Merton's distance-to-default. 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. 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 8: **The Real Impact of the Credit-Market Segmentation and the US-China Trade War**

	Panel A: Trade-War-Less-Affected Industries								
	ROA (%)			**ROE (%)**			**DM (%)**		
	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III
NSOE	0.53***	0.53***	0.08	0.93***	1.19***	-0.26	-2.46***	-4.16***	-0.46
	[5.98]	[6.81]	[0.59]	[4.28]	[5.68]	[-0.59]	[-5.77]	[-4.45]	[-0.54]
EquitySize	0.19***	0.20***	0.32***	0.73***	0.78***	1.07***	-0.70***	-1.55***	-2.64***
	[4.77]	[5.18]	[8.01]	[8.53]	[8.66]	[8.76]	[-3.00]	[-3.84]	[-7.96]
Constant	-3.62***	-4.21***	-6.20***	-15.18***	-17.54***	-20.54***	31.38***	60.81***	80.15***
	[-3.92]	[-4.28]	[-6.99]	[-7.85]	[-7.81]	[-8.17]	[4.91]	[5.72]	[10.47]
Obs	9,615	11,074	6,402	9,615	11,074	6,402	9,615	11,074	6,402
Adj R^2	0.065	0.069	0.089	0.041	0.045	0.083	0.098	0.574	0.184
	Panel B: Trade-War-Affected Industries								
	ROA (%)			**ROE (%)**			**DM (%)**		
	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III	Phase I	Phase II	Phase III
NSOE	0.60***	0.52***	0.20	1.26***	1.18***	0.34	-1.82***	-2.33***	-0.05
	[5.78]	[5.89]	[1.53]	[4.87]	[5.80]	[0.98]	[-3.25]	[-2.95]	[-0.07]
EquitySize	0.18***	0.18***	0.39***	0.81***	0.65***	1.11***	-0.62*	-1.39***	-2.55***
	[4.02]	[4.05]	[5.63]	[6.60]	[7.25]	[5.18]	[-1.89]	[-3.04]	[-6.88]
Constant	-3.10***	-3.34***	-7.88***	-16.22***	-13.70***	-23.03***	32.68***	52.77***	80.61***
	[-3.15]	[-3.36]	[-4.90]	[-5.88]	[-6.61]	[-4.82]	[4.49]	[5.12]	[9.44]
Obs	6,062	7,413	4,442	6,062	7,413	4,442	6,062	7,413	4,442
Adj R^2	0.066	0.050	0.107	0.071	0.042	0.090	0.086	0.618	0.186

Quarterly panel regressions with ROA, ROE, Default Measures as the dependent variables on Non-SOE Dummy (NSOE) and government holdings (GovtHoldings), respectively, with quarter and industry fixed effect. ROA is the ratio of the net profit to the lag book asset. ROE is the net profit to the lag book equity. DM is the default measure, the inverse of Merton's distance-to-default. 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. Panel A reports the result for Trade-War-Less-Affected industries. Panel C reports the result for Trade-War-Affected industries. The most affected industries by trade war are summarized in Table A.2 by Benguria et al. (2020). 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.

A Appendix

A.1 Construction of Government-Holdings Measure

In this subsection, we provide a detailed construction of our measure of government holdings. As described in Section 3.2, we build the measure from ground up by piecing together three separate datasets detailing, for each listed firm in China, information on the top ten shareholders and their state affiliations.

In addition to this initial construction, 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 top ten shareholders. Their approach is effectively the same as our construction. Comparing their measures against ours, we find 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 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 their 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 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 on 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.[20]

To better assess the data quality across different sources, we use two measures to compared 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

[20]For example, Cong, Gao, Ponticelli, and Yang (2019) use the the share of registered capital effectively owned by the government as the measure of state-ownership from Annual Survey of Industrial Firms (ASIF) of the 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 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.

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.1 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 period, 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 on 2015Q3, driven mainly by the stock crash in July 2015 amid governments' 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.1 reports the mean error for the three data sources. We see 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 mean error of our raw estimation, as the addition information from Wind and CSMAR becomes more valuable in helping us construct the robust measure. Moreover, our initial construction (labeled as Raw) tends to have high error rates but relatively low mean errors because our inability to identify those small shareholders with low holdings among top ten shareholders. Indeed, this is where professional data services such as Wind and CSMAR can add value.

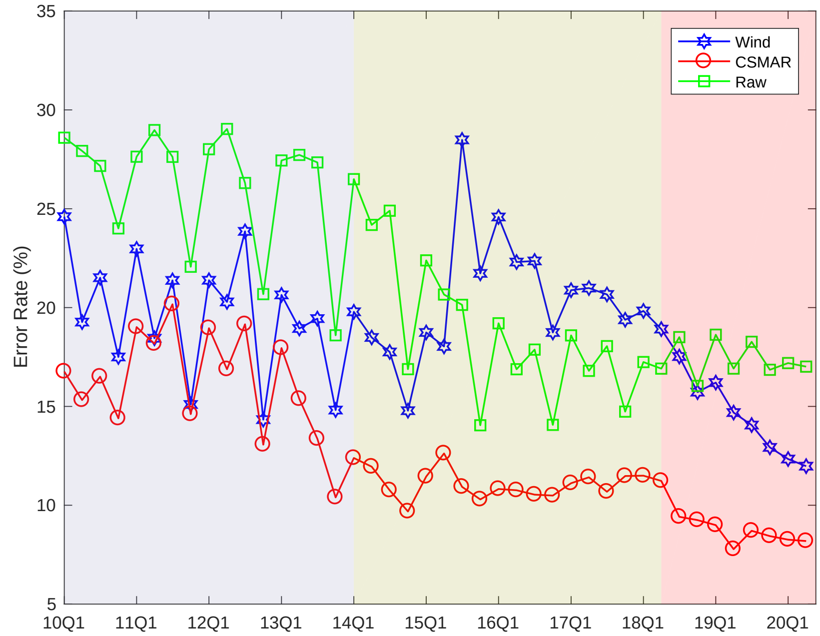
Overall, by compiling the information from the three data sources with varying degrees of information and imperfection, the robust version of our government holdings measure is so far the most comprehensive when it comes to proxies for government support. It could be useful for other research settings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

A.2 Credit Spreads and End-Controller Holdings

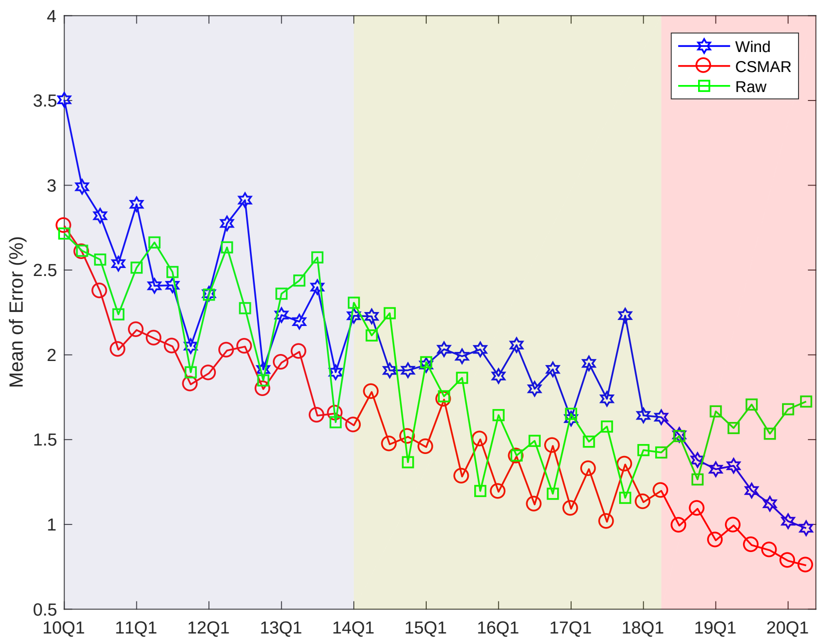
Next we use our end-controller holdings to proxy for government support as a robustness check. Let's first look at the summary statistics from Table 3, for the SOE sample, the average end-controller holdings (Ctrlholdings) are 45.5% with a standard deviation of 16.4% and there is a slight decrease from Phase I to III. Decomposing the SOE group into central SOE (CSOE) and local SOE (LSOE), as shown in Figure A.2, we find that the CSOE group on average has higher end-controller holdings than LSOE group, consistent with the patterns shown in panel (b) of Figure 3 for government holdings. Moving to the non-SOE sample, the average end-controller holdings are 36.4% with a standard deviation of 17.4%, also exhibit a downward trend from Phase I through Phase III. Decomposing the NSOE group into POEs and other NSOEs, we find that the end-controller holdings are more concentrated for the POE sample. As the other NSOE group mainly consists of public firms without a definitive end-controller, they are expected to have the lowest end-controller holdings with least concentrated ownership. Different from the small variations in government holdings for POE group, the end-controller holdings exhibit large variations in all periods.

For SOEs, the expectation is such that end-controllers with more at stake are more likely to extent government support. By contrast, there is no such expectation for the NSOE group as their end-controllers are unrelated to governments. We test this hypothesis in the quarterly panel regression as in Regression (4) by replacing Govtholdings with CtrlHoldings. The coefficient b captures the connection between credit spreads and controller holdings (CtrlHoldings). The main results are summarized in Table A.1. In the SOE panel, we see a similar result as in the Table 6. Prior to 2018Q2, there is no significant relation between credit spreads and government support proxy. The coefficients are -0.15 (t-stat=-1.12) in Phase I and 0.15 (t-stat=0.75) in Phase II. Moving to the Phase III, the government support proxy becomes important in explaining the credit spreads. The estimate is -2.03 and also highly significant with a t-stat of -4.74, implying that one standard deviation increase in controller holdings is associated with a reduction of 33 bps in credit spreads, comparable to the 38 bps reduction for the government holdings.

In the NSOE panel, we do not find any statistically significant connection between credit spreads and controller holdings (CtrlHoldings) in phase II and III. The insignificant result in phase III confirms our hypothesis that the information content of the end-controller holdings measure for NSOE group is unrelated to government support. Instead, it measures the ownership concentration for NSOEs. The coefficients are -0.55 (t-stat=-2.22) in Phase I, 0.16 (t-stat=0.71) in Phase II and -0.11 (t-stat=-0.17) in Phase III. Thus CtrlHoldings do not provide any explanatory power on the credit spreads.



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



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

Figure A.1: This figure plots the quarterly error rates in 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.

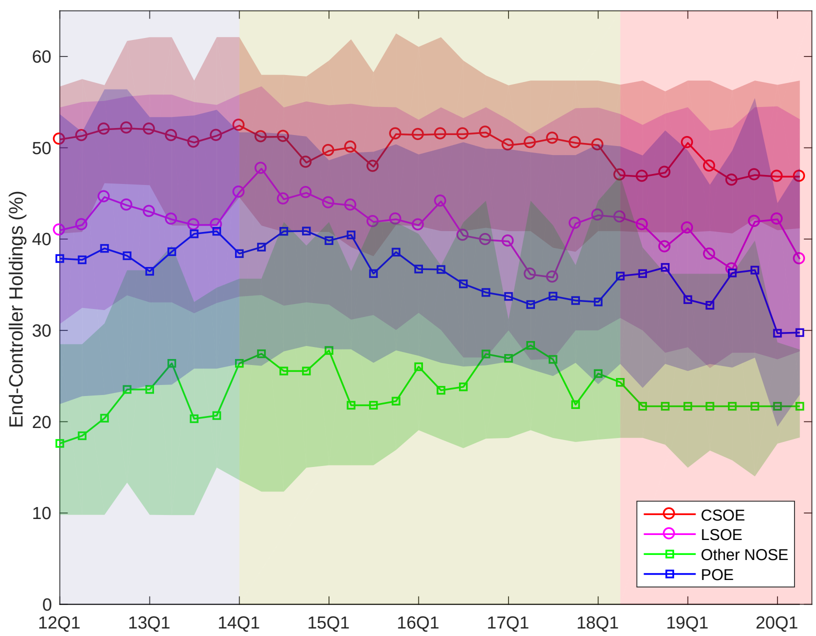


Figure A.2: This figure plots the dynamic dispersion of the end-controller holdings for four types of firms, namely central SOEs (CSOE), local SOEs (LSOE), privately-owned enterprises (POE) and other non-SOE firms (Mainly Public and Foreign Companies). The doted line refers to the median and the shaded area indicates the 25 percentile and 75 percentile.

Table A.1: **Price Discovery: Using End-Controller Holdings as a Proxy for Government Support**

NSOE	Phase I				Phase II				Phase III			
DM		-0.03		0.03		1.63***		1.64***		7.89***		8.00***
		[-0.03]		[0.03]		[2.88]		[2.92]		[3.83]		[3.78]
CtrlHoldings			-0.55**	-0.55**			0.16	0.20			-0.11	0.46
			[-2.22]	[-2.28]			[0.71]	[0.91]			[-0.17]	[0.69]
Rating	0.74***	0.74***	0.76***	0.76***	0.41***	0.41***	0.41***	0.41***	1.64***	1.44***	1.64***	1.43***
	[2.99]	[2.99]	[3.07]	[3.07]	[4.65]	[4.82]	[4.61]	[4.76]	[4.34]	[4.06]	[4.36]	[4.03]
Constant	7.88***	7.88***	8.56***	8.55***	10.83***	9.99***	10.80***	9.94***	15.07***	12.97***	15.20***	12.41***
	[3.97]	[4.11]	[4.40]	[4.54]	[6.94]	[6.55]	[6.88]	[6.50]	[4.77]	[4.23]	[4.69]	[3.78]
Obs	1,372	1,372	1,372	1,372	4,182	4,182	4,182	4,182	2,095	2,095	2,095	2,095
Adj R^2	0.484	0.483	0.489	0.489	0.376	0.386	0.376	0.386	0.367	0.397	0.367	0.397
SOE	Phase I				Phase II				Phase III			
DM		0.09		0.09		1.04***		1.03***		2.09***		1.57**
		[0.65]		[0.61]		[3.84]		[3.82]		[2.65]		[2.01]
CtrlHoldings			-0.15	-0.15			0.15	0.13			-2.03***	-1.87***
			[-1.12]	[-1.11]			[0.75]	[0.66]			[-4.74]	[-4.55]
Rating	0.39***	0.39***	0.39***	0.39***	0.55***	0.55***	0.55***	0.55***	0.58***	0.56***	0.55***	0.54***
	[11.23]	[11.20]	[11.12]	[11.08]	[9.50]	[9.83]	[9.63]	[9.93]	[4.88]	[4.72]	[4.75]	[4.64]
Constant	3.25***	3.22***	3.33***	3.30***	5.22***	4.50***	5.23***	4.51***	7.45***	6.12***	7.80***	6.77***
	[3.63]	[3.65]	[3.87]	[3.90]	[5.68]	[4.87]	[5.65]	[4.84]	[4.77]	[3.95]	[5.02]	[4.39]
Obs	2,972	2,972	2,972	2,972	5,890	5,890	5,890	5,890	3,253	3,253	3,253	3,253
Adj R^2	0.542	0.542	0.543	0.543	0.500	0.508	0.500	0.508	0.386	0.393	0.404	0.407

Quarterly panel regressions of credit spreads on default measures (DM) and controller holdings (CtrlHoldings) with quarter and industry fixed effects. DM is the default measure, the inverse of Merton's distance-to-default. CtrlHoldings is the total equity holdings by the end-controller within firm's top 10 shareholders. 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 A.2: **Price Discovery within the Non-SOE Sample**

	NSOE Listed											
	Phase I				Phase II				Phase III			
DM		-0.03		-0.01		1.63***		1.62***		7.89***		8.01***
		[-0.03]		[-0.02]		[2.88]		[2.89]		[3.83]		[3.94]
GovtHoldings			0.45	0.45			0.24	0.12			-5.52***	-5.69***
			[1.06]	[1.05]			[0.52]	[0.27]			[-4.56]	[-5.14]
Rating	0.74***	0.74***	0.75***	0.75***	0.41***	0.41***	0.41***	0.42***	1.64***	1.44***	1.58***	1.37***
	[2.99]	[2.99]	[3.05]	[3.05]	[4.65]	[4.82]	[4.77]	[4.88]	[4.34]	[4.06]	[4.24]	[3.85]
Maturity	0.08	0.08	0.09	0.09	-0.07	-0.08	-0.07	-0.08	0.02	-0.05	0.11	0.05
	[1.46]	[1.47]	[1.56]	[1.57]	[-1.35]	[-1.44]	[-1.37]	[-1.44]	[0.10]	[-0.33]	[0.72]	[0.36]
Age	-0.05	-0.05	-0.05	-0.05	-0.08*	-0.09**	-0.08*	-0.10**	0.24	0.21	0.36**	0.34*
	[-0.73]	[-0.75]	[-0.73]	[-0.75]	[-1.81]	[-2.10]	[-1.82]	[-2.08]	[1.37]	[1.22]	[2.06]	[1.92]
IssueSize	0.03	0.03	0.02	0.02	-0.11*	-0.12*	-0.11*	-0.12**	0.00	-0.06	0.02	-0.05
	[0.39]	[0.39]	[0.24]	[0.23]	[-1.85]	[-1.94]	[-1.91]	[-1.97]	[0.03]	[-0.40]	[0.12]	[-0.33]
ZeroDays	-1.31***	-1.31***	-1.33***	-1.33***	-2.19***	-2.12***	-2.20***	-2.13***	-5.74***	-5.52***	-5.43***	-5.20***
	[-4.31]	[-4.26]	[-4.35]	[-4.29]	[-7.51]	[-7.26]	[-7.52]	[-7.26]	[-6.85]	[-7.01]	[-6.37]	[-6.47]
Embed	-0.54***	-0.53***	-0.52***	-0.52***	1.49***	1.50***	1.49***	1.50***	1.16**	1.20***	0.90**	0.92**
	[-3.89]	[-2.94]	[-4.02]	[-3.01]	[6.08]	[6.17]	[6.12]	[6.18]	[2.56]	[2.65]	[2.00]	[2.15]
Exch	-0.07	-0.07	-0.07	-0.07	-0.30**	-0.27**	-0.30**	-0.27**	-0.24	-0.14	-0.41	-0.32
	[-0.35]	[-0.34]	[-0.34]	[-0.33]	[-2.40]	[-2.18]	[-2.34]	[-2.14]	[-0.68]	[-0.37]	[-1.14]	[-0.82]
Embed_Exch	0.35*	0.34*	0.33*	0.33*	-1.62***	-1.61***	-1.62***	-1.61***	-2.22***	-2.21***	-2.04***	-2.03***
	[1.88]	[1.75]	[1.84]	[1.73]	[-5.75]	[-5.86]	[-5.79]	[-5.88]	[-3.93]	[-3.80]	[-3.82]	[-3.70]
EquitySize	-0.29***	-0.29***	-0.29***	-0.29***	-0.31***	-0.29***	-0.32***	-0.29***	-0.44***	-0.38***	-0.30**	-0.24**
	[-5.05]	[-5.05]	[-5.00]	[-5.00]	[-4.94]	[-4.75]	[-4.93]	[-4.72]	[-3.74]	[-3.26]	[-2.52]	[-1.99]
Constant	7.88***	7.88***	7.86***	7.86***	10.83***	9.99***	10.85***	10.00***	15.07***	12.97***	11.64***	9.40***
	[3.97]	[4.11]	[3.99]	[4.13]	[6.94]	[6.55]	[6.92]	[6.52]	[4.77]	[4.23]	[3.49]	[2.94]
Obs	1,372	1,372	1,372	1,372	4,182	4,182	4,182	4,182	2,095	2,095	2,095	2,095
Adj R^2	0.484	0.483	0.484	0.484	0.376	0.386	0.376	0.386	0.367	0.397	0.382	0.413

Quarterly panel regressions of credit spreads on default measures (DM) and government holdings (GovtHoldings) for NSOE, with quarter and industry fixed effects. DM is the default measure, the inverse of Merton's distance-to-default. 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 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 A.3: **Price Discovery within the SOE Sample**

	SOE Listed											
	Phase I				Phase II				Phase III			
DM		0.09		0.08		1.04***		1.04***		2.09***		1.47*
		[0.65]		[0.58]		[3.84]		[3.83]		[2.65]		[1.87]
GovtHoldings			-0.17	-0.17			-0.11	-0.12			-2.32***	-2.18***
			[-1.26]	[-1.25]			[-0.52]	[-0.57]			[-6.05]	[-6.02]
Rating	0.39***	0.39***	0.39***	0.38***	0.55***	0.55***	0.54***	0.55***	0.58***	0.56***	0.53***	0.52***
	[11.23]	[11.20]	[11.01]	[10.97]	[9.50]	[9.83]	[9.76]	[10.06]	[4.88]	[4.72]	[4.70]	[4.61]
Maturity	0.03**	0.03**	0.03**	0.03**	0.02	0.02	0.02	0.02	-0.29***	-0.28***	-0.27***	-0.27***
	[2.37]	[2.37]	[2.33]	[2.33]	[1.14]	[1.11]	[1.12]	[1.08]	[-6.91]	[-6.94]	[-7.07]	[-7.06]
Age	0.03*	0.03*	0.03*	0.03*	0.02	0.01	0.02	0.01	-0.07*	-0.07*	-0.07*	-0.07**
	[1.67]	[1.68]	[1.67]	[1.67]	[0.85]	[0.62]	[0.85]	[0.61]	[-1.88]	[-1.90]	[-1.95]	[-1.96]
IssueSize	-0.02**	-0.02**	-0.02**	-0.02**	-0.05***	-0.05***	-0.05***	-0.05***	-0.05	-0.05	-0.02	-0.02
	[-2.24]	[-2.20]	[-2.09]	[-2.06]	[-3.06]	[-3.01]	[-3.00]	[-2.96]	[-1.22]	[-1.18]	[-0.59]	[-0.60]
ZeroDays	-0.65***	-0.65***	-0.66***	-0.66***	-1.89***	-1.84***	-1.90***	-1.84***	-1.86*	-1.83*	-1.73*	-1.72*
	[-2.77]	[-2.77]	[-2.79]	[-2.79]	[-6.97]	[-7.06]	[-7.01]	[-7.11]	[-1.71]	[-1.68]	[-1.67]	[-1.65]
Embed	-0.06	-0.05	-0.05	-0.05	1.83***	1.81***	1.83***	1.81***	2.58***	2.59***	2.62***	2.62***
	[-0.41]	[-0.39]	[-0.35]	[-0.34]	[8.23]	[8.16]	[8.23]	[8.16]	[13.17]	[13.21]	[13.96]	[13.91]
Exch	0.00	0.01	0.01	0.01	-0.16**	-0.16**	-0.16**	-0.16**	1.28***	1.27***	1.29***	1.29***
	[0.08]	[0.09]	[0.09]	[0.10]	[-2.18]	[-2.17]	[-2.16]	[-2.16]	[5.95]	[5.88]	[6.22]	[6.15]
Embed_Exch	0.03	0.03	0.03	0.03	-2.09***	-2.07***	-2.09***	-2.07***	-3.75***	-3.76***	-3.79***	-3.79***
	[0.20]	[0.18]	[0.19]	[0.18]	[-10.00]	[-9.89]	[-9.97]	[-9.85]	[-13.20]	[-13.41]	[-13.88]	[-13.98]
EquitySize	-0.10***	-0.10***	-0.10***	-0.10***	-0.16***	-0.14***	-0.16***	-0.14***	-0.21***	-0.16***	-0.18***	-0.15***
	[-3.44]	[-3.45]	[-3.31]	[-3.32]	[-4.21]	[-3.78]	[-4.01]	[-3.58]	[-4.17]	[-3.34]	[-3.92]	[-3.29]
CSOE	0.00	0.00	0.01	0.01	-0.05	-0.07	-0.05	-0.07	-0.26*	-0.29**	-0.20	-0.22*
	[0.06]	[0.05]	[0.14]	[0.14]	[-0.78]	[-1.26]	[-0.77]	[-1.26]	[-1.88]	[-2.22]	[-1.52]	[-1.79]
Constant	3.25***	3.22***	3.32***	3.29***	5.22***	4.50***	5.24***	4.51***	7.45***	6.12***	7.83***	6.87***
	[3.63]	[3.65]	[3.82]	[3.85]	[5.68]	[4.87]	[5.75]	[4.93]	[4.77]	[3.95]	[5.22]	[4.60]
Obs	2,972	2,972	2,972	2,972	5,890	5,890	5,890	5,890	3,253	3,253	3,253	3,253
Adj R^2	0.542	0.542	0.543	0.543	0.500	0.508	0.500	0.508	0.386	0.393	0.412	0.415

Quarterly panel regressions of credit spreads on default measures (DM) and government holdings (GovtHoldings) for SOE, with quarter and industry fixed effects. DM is the default measure, the inverse of Merton's distance-to-default. 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 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 A.4: **Summary Statistics: Listed Firms with Participation in Credit Market**

	NSOE Listed											
	All			Phase I			Phase II			Phase III		
	mean	med	std	mean	med	std	mean	med	std	mean	med	std
NumFirms	821			570			693			791		
EquitySize	22.35	22.34	1.06	21.73	21.63	0.98	22.71	22.67	0.89	22.52	22.39	1.06
EquityVolatility	44.27	40.80	18.00	41.83	40.75	10.89	47.05	40.75	22.94	42.70	41.00	14.94
Leverage	46.72	47.56	18.70	43.15	44.28	20.12	47.34	47.59	17.95	50.08	50.88	17.32
AssetGrowth	28.68	20.92	31.56	38.81	28.97	36.73	27.22	20.46	29.92	18.64	14.82	22.32
AssetValue	22.80	22.78	1.11	22.16	22.09	1.04	23.09	23.04	0.96	23.09	22.97	1.10
AssetVolatility	30.53	27.49	16.75	28.92	27.90	12.11	34.26	29.06	20.39	26.38	24.79	13.43
DefaultMeasure	21.88	18.83	12.76	18.58	17.58	6.94	22.92	18.83	14.84	24.21	20.98	13.76
ROA	1.13	0.92	1.88	1.41	1.13	1.77	1.18	0.90	1.74	0.69	0.70	2.14
ROE	2.11	1.92	5.01	2.71	2.13	4.35	2.35	1.94	4.18	0.98	1.61	6.60
GovtHoldings	3.60	0.89	7.59	3.77	0.68	7.79	3.51	1.08	7.39	3.52	0.79	7.65
CtrlHoldings	37.09	34.58	16.87	40.12	38.21	17.51	36.99	34.95	16.29	33.55	30.76	16.29
	SOE Listed											
	All			Phase I			Phase II			Phase III		
	mean	med	std	mean	med	std	mean	med	std	mean	med	std
NumFirms	623			544			543			562		
EquitySize	22.79	22.64	1.05	22.45	22.28	1.02	23.04	22.89	0.98	22.93	22.77	1.06
EquityVolatility	39.64	36.55	17.18	37.92	36.99	11.06	43.20	37.63	22.18	36.24	34.23	14.22
Leverage	56.46	57.89	18.00	56.65	58.45	18.01	57.08	58.29	18.05	55.02	56.18	17.79
AssetGrowth	16.18	11.69	23.14	22.33	16.32	26.51	13.46	10.22	21.06	10.39	7.50	17.25
AssetValue	23.48	23.33	1.15	23.12	22.97	1.12	23.69	23.53	1.09	23.73	23.62	1.17
AssetVolatility	22.71	19.69	14.61	21.85	20.35	11.48	25.65	21.17	17.64	18.90	16.22	12.21
DefaultMeasure	23.39	20.12	14.20	20.36	19.19	8.33	26.60	21.40	18.36	22.91	20.46	12.41
ROA	0.76	0.57	1.47	0.95	0.72	1.53	0.63	0.49	1.41	0.66	0.52	1.42
ROE	1.71	1.63	4.94	2.22	1.97	4.99	1.34	1.43	5.10	1.50	1.48	4.46
GovtHoldings	48.02	48.61	16.20	47.39	48.39	16.51	48.36	48.82	15.85	48.49	48.61	16.24
CtrlHoldings	42.48	42.36	15.67	42.80	43.00	16.10	42.93	42.59	15.47	41.11	41.04	15.22

DM is the default measure, the inverse of Merton's distance-to-default. GovtHoldings is the total government equity holdings within firm's top 10 shareholders. CtrlHoldings is the total equity holdings by the end-controller within firm's top 10 shareholders. EquitySize and AssetValue are the log of the firm's equity size and model-implied asset value, respectively. EquityVolatility and AssetVolatility are the annualized equity and asset volatility, respectively. 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. ROA and ROE are the net profit divided by lagged book asset and lagged book equity, respectively. The sample period is 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.