Intra-industry spill-over: Evidence from Chinese bond default

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Abstract

We investigate the intra-industry spill-over effect of bond defaults on the price of stocks, outstanding bonds and new bond issuances in China, the largest emerging debt market. We use a sample of A-shares and public corporate debt securities from 2006 to 2018. In the stock market, we find significantly negative reactions from individual industry rivals to industry default while weak reaction from the industry portfolios. In the bond market, both individual firms and industry portfolios witness a strong contagion effect. This contagion effect further spreads to the primary bond market, triggering a surge in the financing cost of the default firm's competitors after the default. In addition, our study sheds lights on a rich pattern of correlations across default events, which is helpful in improving the understanding of security pricing models and the efficiency of information transfer across markets.

Key words: Intra-industry; Spill-over; Contagion; Chinese debt market; Default

JEL codes: G12; G15; G23; G24

1. Introduction

Firms are not independent entities in the economy but are linked to each other. One firm suffering from negative credit events might have valuation implications for other firms within various business networks such as industrial rivals, supply chain partners, geographical neighbours, capital lenders, et cetera. Some anecdotal evidences support the spill-over of information among industrial competitors in financial markets. For example, the bankruptcy of Lehman Brothers on September 15, 2008 precipitated a widespread turmoil in the markets for all major financial assets. Another example is the default of Enron which caused significant adverse changes in the spreads on several utility companies' corporate bonds and increased borrowing costs for its industry peers throughout the US in 2001.

In an attempt to further investigate the intra-industry spill-over of negative information, this paper aims at estimating the effects of bond market defaults on the price of stocks, outstanding bonds and new bond issuances in China, based on a sample of publicly listed companies and public corporate debt securities issued in the period 2006-2018.

We particularly focus on China's bond market as it represents an important setting to study the intra-industry spill-over effect. Since the milestone policy reforms in 2005, China's onshore bond market has fast grown to the world's second largest bond market with value mounting up to US$ 12.9 trillion at the end of 2018, ranking only below the US according to Bank for International Settlements (BIS) data (see Figure 1). Although its sheer size seems too big to be ignored in the global fixed income market, China has not seen bond defaults until recent years. The first corporate bond default happened in 2014, causing a crash of market's belief in government bailout. Since then, the default number and volume have been increasing rapidly (Amstad and He, 2018). The default wave is extending to 2019. In the first season alone there have been 46 defaulted bonds with total face value of 32.59 billion yuan (~USD 4.88 billion).

Consequently, the Chinese corporate bond defaults have caused a heated discussion recently (Olsen 2018, White 2019). Under such circumstance, it is natural and essential to question how these defaults influence the investors' perception of the industry peers and what the rippling effect of bond defaults could be. Specifically, we investigate two research questions: (1) How do competitors' stock price, outstanding bond price and new bond issuance cost react to the bond default events? (2) How do the characteristics of default industries, default events and affected firms influence the spill-over effect?

Different from previous literature (e.g. Lang and Stulz, 1992, Jorion and Zhang, 2007), we use defaults rather than bankruptcies as negative shocks for two reasons. First, utilizing bond defaults to estimate the stock market reaction allows us to investigate not only the intra-industry rippling effect but also the efficiency of information transfer across capital markets. Second, and more importantly, default usually takes place more frequently and is set in motion much in advance of bankruptcy. Bankruptcies are relatively rare events (especially in China) that are often anticipated and preceded by late payments, debt renegotiation and fire sales. A bankruptcy event is therefore a very late indicator of ripple effects (Bams *et al*, 2016).

Surrounding the ripple effects of defaults, our empirical tests reveal several intriguing findings from the perspectives of both industry portfolios and individual firms. On one hand, there are no supportive evidences of significant reactions from the industry portfolios of stocks, which is inconsistent with the prior literates on the US market (Lang and Stulz, 1992). Conventionally, capital market efficiency predicts that the markets of different securities would react simultaneously upon observing a signal, because the information about the future industry prospects flow freely between bond and stock market (Fleming *et al*., 1998). Therefore, the irresponsive result in the stock market may reflect the low effectiveness of information transmission in China across security markets (Wang and Pang, 2008).

However, at the individual firm level, we find that the abnormal stock return starts to be significantly negative from the third day preceded the default. The 11-day cumulative abnormal return (CAR) is also significant at 1%, as of -0.319% for a sample of 5,241 firm-event observations around 184 defaults. The difference between results of portfolio and firm levels could be due to the individual investors' information incompleteness (Merton, 1987) and limited attention (Pashler and Johnston, 1998; Peng and Xiong, 2006), which suggests that each investor knows about only a subset of the available securities while these subsets could differ across investors. As investors' learning processes are constrained by their capacity (Peng, 2005; Sims, 2003), their perceptions of the negative shocks would be more likely reflected in the response of individual firms rather than the portfolios of them.

Compared with the stock market, the bond market is more responsive to the bond default events. For the secondary market, in the month following defaults, the industry portfolios experience a significantly negative return as of -0.458% and individual firms with outstanding bonds experience an average return erosion of 0.446%. The 7-month CARs are -0.777% and -0.117% for industry portfolios and individual firms respectively, calculated on a sample of 22,459 issuer-event observations around 111 bond defaults. These results confirm the negative relationship between sector-wide bond returns and negative credit events (Chang *et al*., 2015; Collin-Dufresne *et* al, 2010). The different traits in reactions between the stock and the bond market suggests low information transmitting effectiveness and the structural differences in their participant types in China.

In addition, we find the stock market reaction more responsive in the later period of default from 2017-2018 than the earlier period 2014-2016, while the bond market is more responsive in the earlier period. This further confirms that the information transmission *within* bond market and *between* stock and bond markets are distinctive from each other.

We further investigate how the primary bond market would be affected by the industry default. Within the same industry, there are 3,013 new public corporate debt securities issued by the rivals three months before and after the default events. On average, the competitive issuers' financing cost increased by 8.2 bps per annual after the default event, indicating the possibility of funds fleeing to safety assets and hence the drying up of liquidity (Connolly *et a*l., 2005; Kyle and Xiong, 2001; Vayanos, 2004). The increasing financing cost also reflects the updated belief from investors on the default probability of the issuers (Collin-Dufresne *et al*. 2010).

These results lead us to conclude that the contagion effect is dominating both the stock and bond intra-industry reactions to the bond default events. In other words, an event specific to one entity in the first place may have an immediate economic or perceived impact on other entities, which finds its expression in a cascade of subsequent price changes.

Furthermore, as predicted by Lang and Stulz (1992) and Bolton and Scharfstein (1990), the aforementioned-contagion effect is stronger for high-leverage or low-competition industries. More interestingly, this stronger effect is also observed in the regulated industries[1], which may stem from the nature of these industries of fundamental importance in Chinese economy that lead investors to have more faith in them (Yu *et al*., 2015). Therefore, the defaults of these industries are more unexpected. From the cross-sectional analysis, we also find that the information transparency and accessibility play an important role in attenuating the contagion effect. Specifically, less negative reaction is associated with publicly listed or SOE default firms, as well as affected firms that are publicly listed or rated by more reputable credit rating agencies (CRAs). This result confirms that information asymmetry aggravates to the industry peer-firms investors' concerns over the influence of negative credit event (Cespa and

[1] The regulated industries include Agriculture, Mining, Petroleum and Chemicals, Electric Power, Steam and Water Generation and Supply or Transportation and Communication.

Foucault, 2014; Garcia-Appendini, 2018; King and Wadhwani, 1990; Kodres and Pritsker, 2002). Additionally, the results from the stock market show that individuals invest more in more transparent firms with clear and concise financial disclosures (Lawrence, 2013).

Although the default events can be treated as exogenous shocks (Giesecke 2004), we still try to mitigate the potential endogeneity issue in robustness test. First, to avoid event clustering or similar occurrences that dilute the impact of previous events, we keep only the first event in each industry. Second, our results survive the inclusion of industry fixed effect and year fixed effects, indicating that we are not picking up unobserved differences in securities performance across industries or years. We also control for firm fixed effects which effectively alleviates the endogeneity problem assuming unobservable firm characteristics are time constant. Moreover, using alternative estimation windows or excluding the China stock market collapse period between June 2015 and January 2016 does not alter the results.

Our work relates most directly to a broad literature that studies the intra-industry spill-over effect[2]. A large body of literature focuses on the intra-industry spill-over effect in stock market associated with various negative credit events such as bankruptcy announcements (Lang and Stulz, 1992), rating announcements (Akhigbe, Madura and Whyte, 1997), bond downgrade announcements (Jorion and Zhang, 2010) and corporate scandals (Yu *et al.*, 2015). Studies also show that the feature of contagion can vary with institution (Slovin *et al*., 1999) and market condition (Adams *et al.*, 2014). We extent the research in the sense of adding new evidence from developing market by examining corporate bond default events.

Our study also contributes to explaining how the intra-industry rippling effect work in the bond market. Although a number of studies focus on how bond price reacts to rating

[2] Except the intra-industry spill-over, spill-over effect is well studies for firms with various relationships. See Bams *et al*. (2016), Boone and Ivanov (2012), Du and Lai (2018), Hertzel and Officer (2012), Hertzel *et al*. (2008), Joe and Oh (2017), Kedia and Rajgopal (2009).

changes[3], few are studying the intra-industry spill-over. Several articles investigate the default contagion effect in bond market as a whole, but none of them give a touch on intra-industry influence. For instance, Collin-Dufresne *et al.* (2010) analyse the impact of individual credit events on the broad corporate bond market. Berndt *et al.* (2010) develop a bond pricing model that allows for contagion and empirically show that the default of one firm can have a sizable impact on credit spreads of other firms. Bams *et al.* (2016) use major industry default event and find the spill-over effect to small firms' default rate along the supply chain. More in the spirit of our findings are the work of Jorion and Zhang (2007) and Chang *et al.* (2015) that both use CDS data. Jorion and Zhang (2007) find negative industry spill-over effect of bankruptcy, while Chang *et al*. (2015) find that bond rating downgrades negatively affect bondholders of the rival companies. To our best knowledge, we are the first to anticipate the bond return reactions from industry rival issuers to bond defaults. Moreover, our research enriches the literature by adding empirical evidence from primary bond market reactions. We document that investors' belief update on the competitive issuers' risk apply to not only outstanding bonds but also newly issued bonds. By testing the extension of default rippling within industry, we add evidence to the bond pricing models in Berndt *et al.* (2010) and Bai *et al.* (2015).

We also add to the literature on the role of information asymmetry in exaggerating the contagion effect. A considerable amount of literature propose that public announcements of costly financial distress reveal negative information to outsiders about the true value of the firm as well as other firms in the industry that share similar cash flow characteristics with the distress firm (e.g. Collin-Dufresne *et al*., 2003; Giesecke, 2004; Lang and Stulz, 1992). If this story is true, one should expect the contagion effect to be particularly strong in the industries with poor

[3] Previous studies focus on how negative credit events such as downgrades impact bond price. Downgrades have strong negative influence on bond price (Hand *et al*., 1992; Hite and Warga, 1997; Wansley *et al*., 1992), and this effect is more pronounced for highly leveraged firms (Kliger and Sarig, 2000). Additionally, Steiner and Heinke (2001) find bond markets tend to over-react to the negative rating news and reverse strongly in the following weeks.

information transparency. Our results confirm that the contagion effect is stronger for default events with less transparent information and firms with less accessible information.

The rest of this paper proceeds as follows. We discuss the institutional background of China's bond market and bond defaults in Section 2 before we outline the data source and summary statistics in Section 3. We then present the empirical results and robustness test in Section 4 and conclude in Section 5.

2. Institutional background and hypothesis development

2.1 Institutional background

China's bond market

Growing from virtually non-existence in the 1990s, the Chinese bond market is now the second-largest bond market in the world since 2017 as shown in Figure 1. While government-related bond issues account for the largest total amount outstanding, the non-governmental, non-financial bond market grew from 5.98% to 38.54% of GDP from 2006 to 2016. The non-governmental, non-financial debt instruments include enterprise bonds, non-financial enterprise debt financing instruments (e.g., short-term commercial papers and medium-term notes), corporate bonds, convertible corporate bonds, and asset-backed securities (China Central Depository & Clearing Co., Ltd, 2017). These debt instruments are mainly traded on three markets that primarily differ by their regulatory authorities: the commercial bank over-the-counter market (OTC), the exchange-based market, and the interbank market.

We briefly discuss three types of bonds: corporate bonds, enterprise bonds and financial bonds. Corporate bonds issued by public firms are traded on exchange-based market (i.e., Shanghai or Shenzhen Stock Exchange) and are governed by the Chinese Securities Regulatory Commission (CSRC). Enterprise bonds include bonds issued mainly by SOEs are regulated by the National Development and Reform Commission (NDRC)[4]. They can be traded on either the interbank market or the exchange-based market. Another difference between corporate and enterprise bonds is the issuer type: more than half of the corporate bonds are issued by publicly listed companies, whereas less than 1% of enterprise bonds are issued by public firms (Livingston, *et al*., 2018). Financial bonds are issued by banks and other financial institutions. These bonds, together with short-term commercial papers and medium-term notes are traded on the interbank market and governed by the People's Bank of China (PBoC) (Hu, *et al*., 2019).

Bond default in China

Not one single corporate debt securities default event has ever happened before the default of "11 Chaori Bond" on March 5th, 2014. Following this unprecedented default was the deterioration of investors' belief on implicit government guarantee on corporate debt securities.

Up till the end of 2018, there have been 243 defaulted bonds, involving 105 issuers, with the total value of the default bonds being 193.20 billion yuan (~ USD 28.79 billion), and the average coupon rate at issuance for these bonds being 7.274%. Table 1 illustrates the summary statistics of these bonds. From Panel A and B, we observe that the number of defaults reached its highest in 2018 (126 out of 243) with the majority of them issued before 2016 (78%). One thing worth notice is the high ratings held by the bond issuers at issuance. Panel C of Table 1 shows the distribution of bond issuers at issuance, with 81.481% of which had ratings equal or above AA. This also reflects the rating inflation problem in China (Jiang and Packer, 2019). Panel D of Table 1 shows other characteristics of the default bonds. For example, 142 out of 243 defaulted bonds are publicly traded corporate debt securities, the other 101 are private issued bonds; 47 bonds are issued by state-owned enterprises (SOE) and 196 by non-SOEs. Finally, the percentage of total amount of defaulted bonds remains low: only 0.3% in the peak

[4] More detail about the regulatory structure can be found from Amstad and He (2018).

year 2018[5], which is miniscule compared with the global counterpart of 1.8% during 2008-2017 according to a recent Moody's[6] report.

2.2 Hypothesis development

2.2.1 Spill-over effect

We want to test whether the stock and bond market react to the default events at both industry and individual firm levels, and through what channels this spill-over effect transmitted from one distressed firm to its peers provided that companies are closely connected by various relationships in the economy, such as business partnership, supply chain and industry rivals.

The literature on spill-over effects associated with negative credit events typically centres around two possible effects that are of opposite directions. *Contagion effect* implies positive correlation between a negative credit event such as a default and other firms in the same industry. Three reasons might cause a contagion effect. First, firms in the same industry share similar cash flows, thus, default reflects new negative information for all firms across the industry[7]. Second, counterparty risk may exist for firms with close business ties in the same industry. Third, investors may update their beliefs on required return when they observe default (Collin-Dufresne *et al*., 2010). Furthermore, investor behavior will result in mimetic contagion (Topol, 1991). Thus, it is reasonable to expect firms within the same industry may suffer value damage when a member firm fails.

On the contrary, *Competition effect* indicates a negative correlation between reaction of the rival companies and the negative default events (e.g. Jorion and Zhang, 2007). Survivor firms can capture the market share of the defaulted firms thus increasing their sales and profit.

[5] Calculated based on 42,851 new corporate debt securities issued between 2006 and 2018.
[6] This estimation is derived from "Annual Default Study: Corporate Default and Recovery Rates, 1920 – 2017" by Moody's, which covers the credit histories of more than 25,000 corporate issuers that had long-term rated bonds between 1920 and 2017.
[7] Specifically, Shleifer and Vishny (1992) posit that default risk can propagate amongst firms in a given industry as the liquidity of the industrial assets dries up endogenously.

Alternatively, defaulted firms with financial distress may find it difficult to raise funds or invest more in new projects, where the rivals can prey on.

Motivated by the purpose of identifying the dominating effect, we develop our first Hypothesis based on previous studies that negative credit events will bring ripple effect to the industry rivals, and we take bond default as our events.

Hypothesis 1: Bond default events have spill-over effect on intra-industry competitors

Efficient market hypothesis implies that different security markets should not be segmented because security prices fully reflect all available information in a rapid and unbiased fashion (e.g. Basu,1977). Prior studies also confirm the relationship between stock and bond markets [8]. Despite its rapid economic growth and business expansion, the efficiency of information transfer in China's market is still under debate (Kang, *et al.*, 2002). In addition, Chinese stock market is still dominated by individual investors (Bohl, *et al*., 2010). In 2018, individual investors in the Shanghai A-share markets held over 99% of the accounts, with less than 1 % held by institutional investors. Meanwhile, 21.17% market share are held by individual investors. The trading volume contributed by individual investors accounts for 80% of the total trading volume[9]. The large fluctuation caused by individual investors in China's stock market (Bailey *et al*., 2009; Lee *et al*., 2010; Yao *et al*., 2014) might lead to less effective and distorted information transmission between bond market and stock market. In addition, individual investors tend to pay attention to only a subset of securities because of constrained information accessibility and limited attention. Due to these reasons, in the stock market, we may not observe strong reaction from the industry portfolio but significant reaction from individual firms to the bond default events.

Therefore, we develop Hypothesis 1A that:

[8] See Chordia *et al*. (2004), Ferreira and Gama (2007), Fleming *et al*. (1998), Keim and Stambaugh (1986), Kwan (1996).

[9] Shanghai Stock Exchange Statistical Annual, 2018.

Hypothesis 1Aa: Industry portfolios' stock return does not react to bond default

Hypothesis 1Ab: Individual industry rivals' stock return reacts to bond default

There are rare clues about how and how strong the bond market industry rivals will react to bond default. Previous studies focus on how negative credit events such as downgrades impact bond price. We conjecture that a contagion effect dominates the rivals' bond return to negative credit event through two mechanisms. First, the financial, legal, or business relationships between firms may act as conduit in spreading risk, i.e. the default by one firm can have a direct impact on the conditional default rates of other firms (Azizpour *et al*., 2018; Das *et al*., 2007). This is consistent with the network models of Acemoglu *et al*. (2015), Eisenberg and Noe (2001), and Elliott *et al*. (2014). In the sense of this potential default clustering (Bai *et al*., 2015; Berndt *et al*., 2010; Shleifer and Vishny, 1992), the firm-specific negative credit event in an industry sends out a signal about the default probability of the firm's industry peers. The second mechanism is that the fund managers will respond to negative shock by seeking a safe haven for their asset where a flight-to-quality (FTQ) takes place (Collin-Dufresne *et al*., 2004; Connolly *et al*., 2005; Gulko, 2002). This in turn will reduce the demand in the potentially problematic industry where the default happened, leading to return reduction. Because of the above two mechanisms and considering 99% of the participants in China's bond market are institutional investors., we develop Hypothesis 1B that:

Hypothesis 1B: Competitors bond return (both portfolio and individual firm level) negatively reacts to bond default

Default will further affect the rivals' bond issuance prices on the primary market. An initial credit shock may dry up the liquidity in the bond market (Kyle and Xiong, 2001; Vayanos, 2004). Together with the FTO and belief updating on competitors' default probability, investors need to reassess the value of newly issued bonds after the industry default. Therefore, we develop the Hypothesis 1C that:

Hypothesis 1C: Competitors new bond issuance cost increase after bond default

2.2.2 Cross-sectional predictions

Previous studies suggest that high-leverage industries are considered to have limited access to funds and are more financially stressed. Their competitors, on the other hand, may lose less or even gain in industries with less competition (e.g. Lang and Stulz, 1992). Thus, we develop the Hypothesis 2A that:

Hypothesis 2Aa: Contagion effect is stronger for higher-leverage industries

Hypothesis 2Ab: Competition effect is stronger for lower-competition industries

Since the highly regulated industries in China are less likely to be out of favour with the government due to their economic importance (Yu *et al*., 2015), people might have more faith in firms within these industries, we conjecture that the market would react more significantly to defaults in regulated industries as they are unexpected. Hence, we develop the Hypothesis 2B that:

Hypothesis 2B: Competition effect is stronger for regulated industries

As discussed in the previous hypothesis, one channel of default contagion is the learning effect through which investors learn from default events and update their beliefs on the default probabilities of other firms in the same industry. This learning about new information stems from the information asymmetry between firms and outside investors, which should be particularly strong in firms where information asymmetry is high because defaults reveal more previously unknown information to the market about the default firm comparing to their counterparts who are more transparent to the public. Investors who have access to more complete, more detailed and more frequently updated information about both the default firm and the competitor firms are able to make comparisons between the former and the later based on a larger information set after observing a default. Therefore, we develop the Hypothesis 2C that:

Hypothesis 2C: Contagion effect is more significant when information asymmetry is stronger

3. Data and variable construction

In this section, we give a detailed description of our sample selection and the definition of variables we construct in our study.

3.1 Sample selection

We compile our data from two sources. We obtain data on accounting information of firms, on major announcements of firms, and on defaults within public-traded bond market in China from Wind Information Co. Ltd (Wind), as well as data on daily returns of public-traded stocks from the China Stock Market & Accounting Research (CSMAR).

The information of defaults on bonds is our focal dataset, which originally contains 312 events in total between 2014 and 2018 for 243 bonds issued by 105 issuers. The earliest record of default in bond market is on 5th March 2014, followed by 311 events across 50 industries[10] by the end of 2018. Following the literature (Lang and Stulz, 1992), we keep the first default in each industry within a 11-day window for the investigation of stock market reaction, and within a 90-day window for that of bond market reaction. After this screening, there are 207 events and 116 events for the stock and the bond market analysis respectively.

Firstly, to study the stock market reaction to bond defaults, we merge the above 207-default-event dataset with the stock trading dataset and impose further restrictions to form our final sample on stocks. Specifically, there are 6 defaults in 5 industries deleted after being

[10] Industries are categorized by China Securities Regulatory Commission (CSRC).

merged due to the absence of trading stocks in these industries. To mitigate the impact on stock prices from the significant events of firms themselves other than defaults, we then exclude firms with announcements of earnings, restructuring, or divestments that are made within the 11-day window around defaults and are left with about three-fourth of stocks. To estimate the abnormal return based on the market model, we further restrict our sample to stocks with trading records from -250 days to -51 days before the first default in that particular industry and with records within the 11-day event window as well. After the above screening, our final sample on stocks contains 184 defaults between March 2014 and the end of 2018 and 1,616 unique stocks affected by these defaults across 42 industries, consisting of 5,241 firm-event observations. Among this sample, 16 defaults happened on publicly listed companies.

Secondly, in order to investigate the secondary bond market reaction to bond default, we merge the 116-default-event dataset with the 29,202 publicly traded corporate debt securities issued between 2006 and 2018 which includes super commercial papers, commercial papers, medium-term notes, enterprise bonds, and corporate bonds. We delete bonds out of the default industries and with severe problems of missing data on returns (we require price records for at least 8 months to calculate the 7-month return around the default event). We also calculate the volume-weighted average return for each issuer with outstanding bonds when defaults happen, leaving us with 22,459 firm-event observations for 3,621 issuers around 111 default events in 45 industries.

Finally, to estimate the impact of default on the financing cost of the competitors in the bond primary market, we collect the bond issuance data for public corporate debt securities between 2013 and 2018, consisting of 14,974 public corporate debt securities issued by non-financial issuers. We then merge it with the 116 default events and keep the bond issuance observations three months surrounding the event date, imposing a further restriction that issuers are industry peers of the default firm. Next, we delete observations with missing values of firm fundamental variables. For each default event, we also screen the sample to make sure there are at least one observation before and after the event respectively. Eventually, we are left with 3,013 issues for 1,570 issuers in 27 industries around 53 default events.

3.2 Main variables

To estimate the stock and bond market reaction to the bond defaults, our central variables are abnormal return and cumulative abnormal return for stock and bond market respectively. In addition, we use yield spread to test how the primary bond market reacts.

The measurement of stock market reactions around default events follows a standard event study approach. We first estimate the following market model in the estimation window [-250, -51] relative to the announcement date of the default

$$R_{i,t} = \alpha_i + \beta_i \times R_{m,t} + \varepsilon_i, \qquad (1)$$

where $R_{i,t}$ denotes the log stock return for firm i on day t and $R_{m,t}$ is the log stock market return aggregated across all the stocks that are listed on the two domestic stock exchanges: the Shanghai and Shenzhen stock exchanges). The cumulative abnormal return (CAR) for firm i is then calculated as the sum of the difference between the actual log stock return and the predicted log return from equation (1) over a specific event window surrounding the announcement date of a default. Then, we follow the methodology in Lang and Stulz (1992) to compute the abnormal industry portfolio returns[11] for each default in a certain industry for the 11-day window around the defaults.

For bond market reaction, following Bessembinder *et al*. (2009) (hereafter BKMX, 2009) we construct the abnormal bond return (ABR) based on a matching portfolio. First, ending price for each of the eight months surrounding the defaults is collected from Wind for

[11] Both equal-weighted and value-weighted portfolio returns are computed. For brevity, we only report the value-weighted portfolio results as there is no significant different between these two portfolios.

each outstanding bond within the same industry, and observed bond return (OBR) is calculated as

$$OBR_{i,t} = \frac{P_{i,t} - P_{i,t-1} + C_{i,t}}{P_{i,t-1}} \tag{2}$$

where $P_{i,t}$ is the dirty price which is the sum of clean price and the accrued interest, and $C_{i,t}$ is the coupon paid in month *t*, following Tsai and Wu (2015). Then we construct various matching portfolios and use them as the expected return/benchmark return (BBR) for the bond in our sample. That is, the abnormal bond return for bond *i* in month *t* is calculated as the difference between OBR and BBR

$$ABR_{i,t} = OBR_{i,t} - BBR_{i,t} \tag{3}$$

where $BBR_{i,t}$ is the value-weighted average return on a benchmark rating/time to maturity matched portfolio corresponding to bond *i* in month *t*. We use 30 benchmark portfolios: five rating classes (AAA, AA+, AA, AA-, and below AA-) and six time to maturity groupings (shorter than 1 year, 1 to 3 years, 3 to 5 years, 5 to 7 years, 7 to 10 years and over 10 years). Bond issuer's concurrent rating is used to assign issuer's bonds to portfolios. If the issuer has multiple ratings on the market, we choose the lowest one to define its portfolio.

For firms with multiple outstanding bonds, we employ the Firm Level Approach (BKMX, 2009) which treats the firm as a portfolio. The above AR is calculated for each bond and the firm's AR is the volume-weighted average of the AR to the different bond issues. Therefore, the weighted average abnormal bond return (ABR) for firm *k* at each date point is calculated as

$$ABR_{k,t} = \sum_{i=1}^{J} ABR_{i,t}\, w_{i,t} \tag{4}$$

where *J* is the number of bonds outstanding for firm *k* and *w* is the volume weight of bond *i* relative to the total volume of bonds outstanding for firm *k*. This approach does not suffer from a cross-correlation problem and accurately represents the change in firm value.

Finally, for each default, we construct an industry portfolio as a value-weighted portfolio where the weight is the total asset of each competitive issuer in the event industry.

We also analyze how the at-issue bond yield spread vary around the bond default in the same industry, where *Bond Yield* is defined as the percentage difference between the bond issue's offering yield and the yield on a comparable Treasury note. Holding all other bond characteristics constant, this yield spread primarily represents the credit risk of the underlying bond issue.

3.3 Control variables

Our control variables account for the characteristics of the default industry, affected companies, and bond issues (Blume *et al*., 1998; Campbell and Taksler, 2003; Ziebart and Reiter, 1992). Specifically, for default industries' characteristics, we control for industry leverage ratio (*Leverage_Industry*) which is computed based on the asset-weighted leverage of firms for each default. We also control for the industry competition level (*HHI*), which is proxied by the Herfindahl Index as a proxy, that defined as the squared sum of the fractions of industry sales by the non-defaulted firms. The regulation status of the industry is considered as well. We define *Regulated Industry* as a dummy variable which equals one if the industry belongs to Agriculture, Mining, Petroleum and Chemicals, Electric Power, Steam and Water Generation and Supply or Transportation and Communication, zero otherwise (Yu *et al*., 2015).

For default events, we define *Private bond* as a dummy variable to indicate the public traded status of the default bonds; *Private default issuer* as a dummy variable to indicate whether the default issuer is a public listed company; *Non-SOE default* as a dummy variable which equals one if the default issuer is state-owned and zero otherwise.

To control the credit risk for listed companies, we construct *z-score* based on Altman *et al* (1995) that

$$Z = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \quad (5)$$

where X_1 is working capital scaled by total assets, X_2 is retained earnings scaled by total assets, X_3 is operating income scaled by total assets, and X_4 is book value of equity scaled by total liability. A higher value of *z-score* indicates lower credit risk. For bond issuers, we control for *Current Rating_High* that equals one if the most recent rating for the affected firm before the default is AA+ or above, zero otherwise. We also control for financial variables shown to have a material impact on a firm's default risk including the firm size (natural logarithm of total asset in RMB 100 million, denoted as *Size*), financial leverage ratio (total liability divided by total assets, denoted as *Leverage*), *Sales* (sales to asset), earnings (earnings before interest and tax divided by total assets; denoted as *ROA*). We further control the daily stock return volatility in previous twelve months for the competitive publicly listed firms (*VOL*), whether the listed company issued public bonds in previous period (*Bond issue*) and the listed status (*Listed*) of bond issuer. To proxy the information quality of the firms, we also control the auditor's reputation (*Big 4*) and the credit rating agencies' reputation (*Global CRA*).

For the primary bond market analysis, we further consider four important issue attributes: years to maturity (*Maturity*), issue size measured by the natural log of the par value of debt in RMB 100 million (*ISize)*, whether the issue has credit enhancement terms such as collateral or guarantees from a third party (*Enhancement*) and whether the bond is callable (*Callable*). Apart from this, we control the bond issuer's long-term credit rating at issuance, which is defined as *High Rating* (equals one if the issuer's rating is AA+ or above, zero otherwise). All the variables are defined in detail in Appendix 1. To mitigate the outlier concern, we winsorize the continuous variables at the top and bottom 0.5% of the sample distribution.

3.4 Descriptive statistics

Table 2 summarizes the characteristics of sample default events for stock and bond markets respectively. For the 184 default events for stock market, the average industry leverage ratio is 56.021% compared with 64.570% for the 111 events for bond market. The HHI is around 20% for both sample; more than 20% of the default industries feature as the regulated industries. The ratio of privately issued bonds in the default bonds are 38.6% and 45.0% respectively. More than 80% of the default bonds are issued by non-publicly listed firms and more than 75% of the defaults happened on non-SOE firms.

Table 3 provides the descriptive statistics of our key variables for the secondary markets, while Table 4 summarizes the characteristics of both issuers and issues for primary bond market. All statistics are at the firm-event level. While both secondary markets respond negatively to the defaults (indicated by negative sample CARs) in the firm level, the stock market differs from the bond market sample from many aspects as shown in Table 3. For instance, *Size* and *Leverage* of the sample firms under bond market analysis are larger on average, whereas sample firms under stock market analysis enjoy higher *ROA* and tend to be older indicated by *Firm age*. With respect to the third-party certification of the information, only 7.3% of the stock market sample are audited by the Big 4 auditing firms and 38.4% of the bond market sample are rated by global CRAs. Around 50% of the sample bond issuers have a high rating above AA+, reflecting the well documented rating inflation issue in China's bond market (Hu *et al*., 2019; Livingston *et al*., 2018).

In Table 4, we present the characteristics of bonds and issuers in the primary bond market and track the change in them between the pre- and post-default period. *Post* is a dummy variable equals one if the bond is issued within three months after the default in the same industry, zero if it is within three months before the default. Specifically, in Panel A, we document 2.251% of *Bond yield*. The average issue size is RMB 8.688 in 100 million. Few

(10.4%) among them have credit enhancement and 11.5% of them are publicly listed companies. Some of these characteristics are significantly different in the periods before and after defaults, as recorded in Panel B of Table 4. The cost of issuance increases from 2.220% to 2.285% in the post period, which is also illustrated by the Graph C in Figure 2. In addition, we find that the bonds issued in the post period tend to have larger issuance size, lower sales to assets, higher ratings and more SOEs.

4. Empirical results

4.1 Stock market reaction

In this section, we report our findings for stock market reactions to bond defaults. Before examining the spill-over effects within the industry, we report the estimates of the stock market reaction to default firms themselves (who are publicly listed). In Panel A of Table 5, we observe a significant decrease in the abnormal return one day after the announcement of default. The market reaction remains negative until the last day of the 11-day window, which is further corroborated by the estimates of the cumulative returns. To better illustrate the market reactions, we plot the average abnormal returns (AR) in the Graph A of Figure 2 (denoted in blue).

We then show the stock market reactions to the default events at portfolio level in Panel B of Table 5, which represents the industry portfolio (cumulative) abnormal returns to stock across the 11-day window around 184 defaults. In general, competitor portfolios exhibit negligible reactions to defaults. Specifically, the average abnormal return to stock on event dates is insignificantly positive. It does not turn to significantly negative until the last day of the event window. In addition, evidence from the average cumulative abnormal returns across event window, denoted by CAR [-5,5], further support that the overall industry seems to be unaffected by defaults.

We further extend our investigation of the market reactions to individual firms, which is shown in Panel C of Table 5. Across the 11-day window, the overall reaction of individual competitors to defaults tends to be stronger than that of portfolios. In particular, the average abnormal returns exhibit significantly positive reaction prior to the event while turning significantly negative during the post-event period. As a result, the average cumulative abnormal returns turn out to be also negative by the end of the 11-day window. Furthermore, if we plot the average abnormal returns at firm level in Graph A of Figure 2, it would be obvious that the returns in the last a few days of the event window tends to be negative. In general, the individual competitor's stock tends to exhibit negative – although slightly postponed – reaction to defaults, indicated by significantly negative AR (3) to AR (5) and CAR [-5,4] to CAR [-5,5].

The above results are consistent with our Hypothesis 1Aa and 1Ab that the industry portfolio is insensitive to the industry default while the individual firms are responsive. The investor structure can provide some explanations that individual investors have limited attention on the stocks they are interested in. The reason for the different degree of reactions between portfolios and firms could be that we construct our portfolio by value weighting, while the overall result for individual firms comes from simple average. This implies that firms with different characteristics may react to their peers' defaults differently. Following this intuition, we conduct several empirical tests along with further discussion later in this paper.

4.2 Secondary bond market reaction

In this section, we report our findings for reactions of secondary bond market at both the industry portfolio level and the individual firm level. We document significantly negative reaction in the secondary bond market both at the portfolio level and at individual firm level.

The bond market reactions to the default events are illustrated in Table 6, which shows the (cumulative) abnormal returns to bond across the 7-month window around 111 defaults.

Note that due to the way we construct the bond abnormal return [refer to equation (3) for computing ABR], the AR of interest in Table 6 is the one on Month 1, i.e. AR (1), instead of the one on Month 0, within which the defaults occur.

Panel A of Table 6 suggests a negative market reaction to the industry defaults at portfolio level. The significantly negative value of AR (1) provides evidence in support of that the competitors' bond price has been affected by defaults, which is further corroborated by the results of cumulative abnormal return across the event window (CAR [-3,3]). In fact, the CAR in bond market has remained negative at 1% significance level from the event month onwards. In line with the numerical results, we observe a sharp decrease in average abnormal return in the month preceded by events in bond market at the portfolio level (denoted by the blue line) in Graph B of Figure 2.

With respect to the individual firm level, we document a similarly strong reaction to that at the industry portfolio level. Specifically, the significant negative AR (1) in Panel B of Table 6 suggests that the competitors have experienced salient contagion effects, supported by the evidences as cumulative abnormal return across the event window (i.e. CAR [-3,3]). The negative impacts from defaults, represented by CARs, have remained significant at 5% level during the post-event period. The consistency in reactions between different levels suggests that in the bond market, the contagion effect tends to penetrate among firms with distinct characteristics. One noteworthy result is that for both bond portfolio and individual firms, we observe significantly negative returns two months before the default [AR (-1)] while significantly positive returns one month before the default [AR (0)]. Overall, the bond market reactions confirm our Hypothesis 1B that the contagion effect dominates the bond market.

To track the market reaction overtime, we further compare the stock and the bond market reactions by splitting the sample period as shown in Table 7. For the stock market, the industry portfolios remain irresponsive to the defaults in both periods (see Panel A) while the individual firms are more reactive in the period 2017-2018. This confirms our conjecture that the information transmission from the bond market to the stock market is less efficient in China. What is interesting is that contrary to stock market, the bond market exhibits a more significantly negative reaction in the period 2014-2016 than in 2017-2018 although there are more events happening and thus more firms affected in the later period (see, e.g. -1.353 % vs. -0.287% in CAR [-3, 3] for portfolio and -0.160% vs. -0.092% for individual firms). This might be due to the more shocked effects brought by default in the early stage, which broke investors' belief in the government bailout.

4.3 Primary bond market reaction

As shown in Panel B of Table 4, *Bond yield* experiences a significant increase following defaults, reflecting higher costs of issuance. In this section, we present the empirical results in further details with respect to the regression on *Bond yield*, following Eq. (6).

$$Bond\ yield_{i,t} = \beta_0 + \beta_1 Post_i + \beta_2 X_{i,t} + \varepsilon_{i,t} \tag{6}$$

where *Post* is indicating the bond issuance time and $X_{i,t}$ denotes the aforementioned controls on issuer and bond in Section 3.3.

Column (1) of Table 8 shows the result for full sample. In general, the bond yield has significantly increased by 0.082% on average after the events took place. This change is also economically significant in the sense that the financing cost for those firms who made issuance after peers' defaults has increased by RMB 0.712 million per year on average. This finding is in line with previous studies which show that firms in distress would impose indirect costs to non-distressed competitors by increasing costs of credit and restricting credit access (Benmelech and Bergman, 2011; Garcia-Appendini, 2018; Hertzel and Officer, 2012; Jorion and Zhang, 2007; Lang and Stulz, 1992). Other control variables are as expected. Specifically, longer maturity of bond, callable feature of bond or higher leverage taken by issuers contribute to higher costs of issuance while larger issuance sizes are correlated with lower bond yields.

4.4 Cross-sectional analysis

One possible explanation for the mild response of the stock market to defaults could be that the reactions from industries with different characteristics cancel out each other and thus the sample as a whole tends to exhibit less reactive. Therefore, in this section, we construct some cross-sectional predictions based on the characteristics of default industry, default events and affected firms.

Fist, we conduct a set of univariate tests for the industry stock and bond portfolios in Table 9, categorised by the industry and default events' characteristics. Lang and Stulz (1992) argue that all else being equal, the intra-industry spill-over effects would be negative in industries with high leverage and intense competition, while zero or even positive in less competitive industries with low leverage. Following this insight, we look into these industry characteristics by dividing the sample based on *Leverage_Industry* and *HHI*, respectively.

Panel A and Panel B in Table 9 provide the comparison between the CARS of subsamples – high-leverage vs. low-leverage industries, and high-competition vs. low-competition industries, in both the stock market and the bond market. As one would expect, the cumulative abnormal return to stock for the high-leverage group is -0.094%, meanwhile that of low-leverage group is 0.173%, higher than that of its counterpart. While neither of these values is statistically significant, the result is still consistent with what Lang and Stulz (1992) have suggested. Similar relative magnitudes could be found in the bond market, where the cumulative abnormal return to bond for the high-leverage group is -1.107%, lower than that of the low-leverage group (-0.441%). Furthermore, not only these two values but also the mean difference between them are statistically significant. These results indicate that the more one industry highly leveraged, the more likely it would be affected by defaults, especially in the bond market.

As for the degree of competition, consistent with the argument that competitors may lose less or even gain in industries with less competition (e.g. Lang and Stulz, 1992), we document that the cumulative abnormal returns to stock are positive for high-HHI industries, with an average abnormal return of 0.381, higher than that of the other group (-0.280). Contrary pattern is found for the bond market. However, the mean difference between groups is not significantly different from zero for both markets.

We further categorize our sample by the regulation status of the industries. Since the highly regulated industries in China are less likely to be out of favour with the government due to their importance (Yu *et al*., 2015) and people tend to have more faith in firms within these industries, we conjecture that the market would react more significantly to defaults in regulated industries as they are unexpected. Consistent with our expectation, we document negative stock market reaction for regulated industries and significant mean difference in CAR between two subsamples in Panel C of Table 9. Meanwhile, the bond market reacts indifferently to defaults in both regulated and non-regulated industries (the reaction for each subsample is significant though), implying that debtholders perceive defaults as negative signals regardless of the regulation status of industries.

We then turn to the investigation of the influence categorized by characteristics of default events. As Yu *et al.* (2015) suggests, when the bad news is about SOE firms, peer firms may suffer from more negative influence, i.e. more extensive contagion effect. However, we record results contrary to their conclusion. Specifically, the stock market reacts positively to SOE defaults, while the bond market reacts less negatively to SOE defaults (see Panel D of Table 9). One plausible explanation is that, capital market seems to be optimistic about the SOE defaults as they might conceive this as an improvement in market competition. An alternative interpretation could be that when non-SOEs default, as less information about these firms has been disclosed before comparing to their SOE counterparts, investors would be more likely to be pessimistic about what the default events have revealed about the industry. In other words, the contagion effect seems propagate through an information channel.

The information channel could also explain the results for the subgroups by the listed status of the default bond and the default issuer. As suggested by the results in Panel E and F of Table 9, stockholders and bond holders tend to conceive the defaults of privately traded bonds or non-publicly listed issuers as bad news for other competitors, since the information about these bonds is less accessible.

We further conduct the multivariate regression analysis by employing Eq. (7)

$$CAR = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon_{i,t} \quad (7)$$

where *CAR* is the 11-day CAR (7-month CAR) for stock (bond) market; X_1, X_2 and X_3 denote control variables of default industry, default events and the affected firms. Table 10 show the regression results. We observe consistent results with our conjecture that the negative market reactions tend to be stronger for industries with higher leverage ratio, regulated industries, default firms who are not publicly listed or non-SOEs. The above results are more significant for stock market. We also find that affected firms with certain characteristics respond differently to the peer defaults. For example, in the stock market, lower stock price volatility and larger sales would attenuate the negative influence from the default (see Column (2)). In the bond market, rated by global rating agencies or having a listed status, which convey more transparent information to the investors, could alleviate the negative reaction to the default. It is also worth to point out that bondholders have a more negative attitude to the industry competitors with a higher credit rating before the default events (see Column (4)). One plausible explanation is that bondholders might adjust their beliefs more for high-rating firms (Collin-Dufresne *et al.*, 2010) when default happen in the same industry.

We further conduct the cross-sectional estimation on primary bond market by adding interaction terms between *Post* and some controls to Eq. (6). The results are shown in Column (2) – (5) in Table 8. Specifically, the negative influence of default on financing cost is weaker for issuers who are rated by global CRAs or publicly listed, or for events where the default firms is publicly listed[12]. Whether the default firms are SOEs or not does not affect the reaction from the primary bond market. These results could be explained by theories built on asymmetric information, which suggests that investors might have difficulties in obtaining the information about the financial distressed firms and thus the distresses would be propagated through the information channel (Cespa and Foucault, 2014; Garcia-Appendini, 2018; King and Wadhwani, 1990; Kodres and Pritsker, 2002).

4.4 Robustness test

We conduct several robustness checks to alleviate some concerns about our main findings. The results for these tests are available upon request. To start with, we shorten the event window from 11 days to 7 days for the stock market and from 7 months to 3 months for the bond market. In parallel, as a robustness to test the primary bond market reaction, we restrict the estimation window from 3 months around the event date to 2 months. The results remain qualitatively the same.

Next, as has been documented that clustering of defaults or similar occurrences can dilute the impact of previous events, we keep only the first default of each industry, the results are qualitatively unchanged.

We also consider excluding the China stock market collapse during mid-June 2015 to late January 2016 (Sornette *et al*., 2015; Zeng *et al*., 2016), as investors might be more likely

[12] We also conduct the regression of Bond yield on the interaction term between *Post* and *Private bond*. Because all the default events in this sample are privately issued bonds, we eliminate this regression.

to react to the frequent bad news from the stock market rather than to the defaults in the bond market. Our main findings still hold.

Finally, we examine whether the cross-sectional prediction show different patterns for SOEs versus non-SOEs. It is often assumed that the Chinese government could bail an SOE out should it become financially distressed. Therefore, we conduct the analysis as in Table 8 and Table 10 for the SOE group and the non-SOE group respectively. Our conclusion still holds for the secondary market reactions. As for the primary bond market, investors are more responsive to the bonds issued by SOEs after the default, indicating that they are requesting higher compensation after the belief updating.

5. Conclusion

In this paper, we investigate the intra-industry spill-over effects of bond default events in China. Event study and cross-sectional analysis are employed to estimate both the stock and bond market reactions to such negative credit events.

We find the stock market negatively reacts to the default events, significantly at the individual firm level while insignificantly at the portfolio level. The distinct results for these two levels could be due to the individual investor-dominated structure of Chinese stock market, in which individuals could only pay attention to the limited stocks they are concerned about rather than to the portfolios. In contrast, on the secondary bond market, both individual firms and industry portfolios show significantly negative reactions to the peers' defaults. Meanwhile, the peers who issue bonds after the default events experience a significant increase in financing cost on the primary bond market. These results suggest that the negative information on bond defaults transmits more effectively within bond market than across security markets. Moreover, we find that the contagion effect is stronger for high-leveraged industries, regulated industries, default events with less transparent information and firms with less accessible information.

Our paper provides new evidences and insights on the study of spill-over effects from negative credit events. We provide the detailed analysis of the extent and drivers of the contagion effects for bond defaults. This study could also improve our understanding of the role played by information asymmetry in the spill-over effects.

Appendix Table 1 Variable definition

Variable name	Variable definition	Data source
Bond Yield	Percentage difference between the bond issue offering yield and the yield on a treasury note of comparable maturity	Wind
Leverage_Industry	Asset-weighted leverage of firms for each default	Wind, Calculation
HHI	The squared sum of the fractions of industry sales by the non-defaulted firms	Wind, Calculation
Regulated industry	A dummy variable equals one if the industry is one of the following: Agriculture, Mining, Petroleum and Chemicals, Electric Power, Steam and Water Generation and Supply or Transportation and Communication, and zero otherwise	Wind
Private bond	A dummy variable equals one if the default bond is a publicly listed bond, and zero otherwise	Wind
Private default issuer	A dummy variable to indicate whether the default issuer is a public listed company	Wind
Non-SOE default	A dummy variable equals one if the default firm is a non-SOE, and zero otherwise	Wind
z-score	Modified Z score for manufacturing and non-manufacturing public listed firms in a given year, derived from Altman et al (1995)	CSMAR
Current Rating_High	A dummy variable equals one if the most recent rating for the affected firm before the default is AA+ or above, and zero otherwise	Wind
Size	Natural logarithm of total asset in RMB 100 million	Wind
Leverage	Total liability scaled by total assets, expressed in percentage	Wind, CSMAR
Sales	Total sales scaled by total assets	Wind, CSMAR
ROA	Operating income scaled by total assets, expressed in percentage	Wind, CSMAR
VOL	Daily stock return volatility in previous twelve months for the competitive firms, expressed in percentage	CSMAR
Firm age	Number of years since the establishment of the competitive firm to the default event year, representing the history of the affect firms	Wind
Bond issue	A dummy variable indicating whether the affected firm has bond issuance history	Wind
SOE	A dummy variable equals one if the affected firm is a state-owned enterprise, and zero otherwise	Wind
Listed	A dummy variable equals one if the affected bond issuer is a publicly listed company, and zero otherwise	Wind
Big 4	A dummy variable equals one if the firms is audited by big four auditors, and zero otherwise	CSMAR
Global CRA	A dummy variable equals one if the issuer is rated by a global CRA, and zero otherwise	Wind
High Rating	A dummy variable equals one if the long-term rating for the bond issuer at issuance is AA+ or above, and zero otherwise	Wind
Maturity	Number of years to the maturity date of a certain debt issue	Wind
ISize	Natural logarithm of the par value of a certain issue in RMB 100 million	Wind
Enhancement	A dummy variable indicating whether the issue has credit enhancements	Wind
Callable	A dummy variable equals one if the bond is callable, and zero otherwise	Wind
Post	A dummy variable equals one if the new bond is issued after the default event, and zero otherwise	Wind

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Table 1
Description of default bonds

This table presents the descriptive statistics of default bonds between 2014 and 2018. There are 243 unique bonds experiencing defaults during the sample period 2014-2018. Panel A shows the distribution of default years. Panel B shows the distribution of issuance year for default bonds. Panel C presents the rating distribution for bond issuers at bond issuance. Panel D shows some characteristics of the default bonds. Public bonds group include default bond that are publicly issued and traded. SOE group includes default bonds are issued by state-owned companies. Listed firm group includes default bonds issued by publicly listed companies.

Panel A: Default distribution

		2014	**2015**	**2016**	**2017**	**2018**
Observation		6	23	57	31	126

Panel B: Issuance year of default bonds

	2010-2013	**2014**	**2015**	**2016**	**2017**	**2018**
Observation	59	28	54	50	36	16

Panel C: Distribution of issuer's rating at issuance

	AAA	**AA+**	**AA**	**AA-**	**Below A+**	**N/A**
Observation	10	52	136	27	6	12

Panel D: Other characteristics

	Listed status of bond		**Ownership of issuer**		**Listed status of issuer**	
	Public bonds	Private bonds	SOE	non-SOE	Listed firm	Private firm
Observation	142	101	47	196	47	196

Table 2

Summary statistics of default samples

This table summarizes the characteristics of the default industry and default events in the samples for the stock and bond market reaction analysis during our sample period 2014-2018. Panel A and Panel B present the summary statistics for the stock and the bond markets respectively. *Leverage_Industry* is the asset-weighted leverage of firms for each default; *HHI* is the squared sum of the fractions of industry sales by the non-defaulted firms; *Regulated industry* is a dummy variable which equals one if the industry falls into the regulated group that consists of Agriculture, Mining, Petroleum and Chemicals, Electric Power, Steam and Water Generation and Supply or Transportation and Communication, zero otherwise; *Private bond* is a dummy variable equals one if the default bond is a publicly listed bond and zero otherwise; *Private default* issuer is a dummy variable to indicate whether the default issuer is a public listed company; *Non-SOE default* is a dummy variable equals one if the default firm is a non-SOE, otherwise zero.

Panel A: Summary statistics of default event sample – stock market analysis

	Mean	**Std.dev**	**Median**	**N**
Leverage_Industry	56.021	13.544	53.957	184
HHI	0.243	0.214	0.173	184
Regulated industry	0.228	0.421	0.000	184
Private bond	0.386	0.488	0.000	184
Private default issuer	0.848	0.360	1.000	184
Non-SOE default	0.766	0.424	1.000	184

Panel B: Summary statistics of default event sample – bond market analysis

	Mean	**Std.dev**	**Median**	**N**
Leverage_Industry	64.570	6.621	65.521	111
HHI	0.199	0.232	0.121	111
Regulated industry	0.272	0.446	0.000	111
Private bond	0.450	0.500	0.000	111
Private default issuer	0.865	0.343	1.000	111
Non-SOE default	0.784	0.414	1.000	111

Table 3
Summary statistics of secondary market reaction
This table summarizes the characteristics of affected listed companies and bond issuers by bond default events. Panel A presents the mean, median and standard deviation values of various firm characteristics for 5,241 firm-event observations affected by 184 bond defaults between 2014 and 2018. Panel B presents the mean, median and standard deviation values of various firm characteristics for 25,459 firm-event observations affected by 111 bond defaults between 2014 and 2018. *CAR* for stock market is calculated as the sum of the difference between the actual log stock return and the predicted log return over a 11-day window surrounding the announcement date of a default, for each affected listed firm. *CAR* for bond market is the sum of the difference between the actual bond return and the benchmark portfolio return over a 7-month window surrounding the announcement date of a default, for each affected bond issuer. *Size* is the natural logarithm of total asset in RMB 100 million. *Sales* is the total sales scaled by total assets. *Leverage* is the total liability scaled by total assets, expressed in percentage. *z-score* is the modified Z score for manufacturing and non-manufacturing public listed firms in a given year, derived from Altman et al (1995). *ROA* is the operating income scaled by total assets, expressed in percentage. *VOL* is the stock price volatility in previous twelve months for the competitive firms, expressed in percentage. *SOE* is a dummy variable that equals one if the affected firm is a state-owned enterprise, and zero otherwise. *Big 4* is a dummy variable that equals one if the firm is audited by big four auditors and zero otherwise. *Current Rating_High* is a dummy variable that equals one if the most recent rating for the affected firm before the default is AA+ or above, and zero otherwise. *Bond issue* is a dummy variable indicating whether the affected firm has bond issuance history in previous years. *Listed* is a dummy variable that equals one if the affected bond issuer is a publicly listed company and zero otherwise. *Global CRA* is dummy variable that equals one if the issuer is rated by a global CRA and zero otherwise All the continuous variables are winsorized at the top and bottom 0.5% of the sample distribution. All the variables are defined in detail in Appendix 1. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Summary statistics of stock market reaction

	Mean	**Std.dev**	**Median**	**N**
CAR [-5, 5]	-0.301	7.100	-0.595	5,241
Size	4.111	1.522	3.904	5,241
Sales	0.642	0.518	0.503	5,241
Leverage	45.500	21.190	45.520	5,241
z-score	7.744	4.355	6.786	5,241
ROA	5.543	5.172	4.885	5,241
VOL	2.682	0.847	2.535	5,241
SOE	0.472	0.499	0.000	5,241
Big 4	0.073	0.260	0.000	5,241
Bond issue	0.446	0.497	0.000	5,241

Panel B: Summary statistics of bond market reaction

	Mean	**Std.dev**	**Median**	**N**
CAR [-3, 3]	-0.118	6.745	0.922	22,459
Size	5.949	1.267	5.765	22,459
Sales	1.065	3.671	0.130	22,459
Leverage	58.960	14.740	60.350	22,459
Current Rating_High	0.496	0.500	0.000	22,459
ROA	3.333	3.001	2.590	22,459
Listed	0.161	0.368	0.000	22,459
Global CRA	0.384	0.486	0.000	22,459

Table 4
Summary statistics of primary bond market

This table presents the mean, median and standard deviation values of various bond and firm characteristics for 3,013 bonds issued by 1,570 competitive firms three months before and after 53 bond default events. Panel A summarizes the descriptive statistics for the full sample, whereas Panels B outlines the sample distributions by *Post*, which is a dummy variable that equals one if the bond issued after default event and zero otherwise. We also conduct *t*-tests on the difference-in-means for the comparison between bonds issued before and after defaults. *Bond Yield* is the percentage difference between the issuance offering yield and the yield on a treasury security of comparable maturity. *Maturity* is the number of years to maturity date of a debt security. *ISize* represents the debt issue size, calculated as the natural log of the par value of debt initially issued in RMB 100 million. *Enhancement* is a dummy variable indicating whether the debt issue has credit enhancements. *Callable* is dummy variable that equals one if the bond is callable, and zero otherwise. *Rating* is the long-term rating for the bond issuer at issuance. *High Rating* is a dummy variable if the issuer's long-term credit rating is AA+ or above, and zero otherwise. All the continuous variables are winsorized at the top and bottom 0.5% of the sample distribution. The remaining variables are defined as in Table 3. All the variables are defined in detail in Appendix 1. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Summary statistics of bond issuance around default event

	Mean	Std. Dev	Median	N
Bond yield	2.251	1.077	2.037	3,013
Post	0.477	0.500	0.000	3,013
iSize	2.162	0.766	2.303	3,013
Maturity	3.865	2.079	3.000	3,013
Enhancement	0.104	0.305	0.000	3,013
Callable	0.096	0.295	0.000	3,013
Size	6.270	1.364	6.156	3,013
Sales	0.342	0.413	0.188	3,013
Leverage	61.650	14.672	63.513	3,013
High Rating	0.653	0.476	1.000	3,013
ROA	3.800	2.978	3.140	3,013
Listed	0.115	0.320	0.000	3,013
Global CRA	0.429	0.495	0.000	3,013

Panel B: Characteristics before and after default

	Pre-default		**Post-default**		**Mean diff**
	Mean (1)	Std. Dev	Mean (2)	Std. Dev	(2) – (1)
Bond yield	2.220	1.064	2.285	1.090	0.065**
iSize	2.134	0.745	2.193	0.786	0.059**
Maturity	3.837	2.053	3.896	2.107	0.059
Enhancement	0.098	0.297	0.111	0.314	0.013
Callable	0.092	0.289	0.100	0.300	0.008
Size	6.182	1.306	6.367	1.418	0.185***
Sales	0.359	0.434	0.322	0.387	-0.037**
Leverage	61.362	14.401	61.966	14.961	0.604
High Rating	0.644	0.479	0.663	0.473	0.019
ROA	3.852	3.026	3.743	2.923	-0.109
Listed	0.107	0.309	0.125	0.331	0.018
Global CRA	0.427	0.495	0.431	0.495	0.004
# of observation	1,576		1,437		

Table 5
Stock market reaction

This table presents the stock market reaction to default events for default firms, industry portfolios and individual firms between 2014 and 2018. Panel A shows the market reaction to 16 default companies who are publicly listed firms. Panel B presents the stock market reaction for industry portfolios. The abnormal return (daily) is computed based on the market model. The sample includes 184 defaults with 1,616 presumably affected firms in 42 industries. An industry portfolio return is a value-weighted portfolio of firms with the same CSRC industry code that is composed of a capital letter followed by two digits. The value is the market value of the stock at the end of year *t-1* where *t* is the event year. Panel C shows the stock market reaction from individual firms. The sample includes 5,241 affected firm-event observations for 184 defaults in 42 industries. # denotes the number of abnormal returns of portfolios available for computing the average abnormal returns or cumulative average abnormal returns. T-statistics are used to evaluate the significance, while the associated p-values are reported.

Panel A: Stock market reaction – default firms

	#	AR	p-value		#	CAR	p-value
-5	16	0.199	0.880	[-5, -5]	16	0.199	0.880
-4	16	-1.914	0.162	[-5, -4]	16	-1.716	0.445
-3	16	-0.556	0.677	[-5, -3]	16	-2.271	0.467
-2	16	-1.474	0.194	[-5, -2]	16	-3.745	0.343
-1	16	-0.470	0.733	[-5, -1]	16	-4.215	0.421
0	16	0.530	0.626	[-5, 0]	16	-3.684	0.519
1	16	-2.608	0.015	[-5, 1]	16	-6.293	0.294
2	16	-0.611	0.523	[-5, 2]	16	-6.904	0.210
3	16	-0.719	0.505	[-5, 3]	16	-7.622	0.185
4	16	-0.501	0.600	[-5, 4]	16	-8.123	0.185
5	16	1.466	0.269	[-5, 5]	16	-6.657	0.283

Panel B: Stock market reaction – industry portfolios

	#	AR	p-value		#	CAR	p-value
-5	184	0.035	0.688	[-5, -5]	184	0.035	0.688
-4	184	-0.155	0.103	[-5, -4]	184	-0.120	0.370
-3	184	0.140	0.112	[-5, -3]	184	0.019	0.912
-2	184	0.083	0.316	[-5, -2]	184	0.102	0.620
-1	184	-0.018	0.845	[-5, -1]	184	0.086	0.705
0	184	0.066	0.520	[-5, 0]	184	0.151	0.518
1	184	0.024	0.796	[-5, 1]	184	0.174	0.475
2	184	-0.042	0.618	[-5, 2]	184	0.133	0.607
3	184	-0.034	0.689	[-5, 3]	184	0.099	0.709
4	184	0.097	0.293	[-5, 4]	184	0.196	0.502
5	184	-0.157	0.090	[-5, 5]	184	0.040	0.897

Panel C: Stock market reaction – individual firms

	#	AR	p-value		#	CAR	p-value
-5	5,241	0.006	0.834	[-5, -5]	5,241	0.006	0.834
-4	5,241	-0.143	0.000	[-5, -4]	5,241	-0.137	0.002
-3	5,241	0.058	0.045	[-5, -3]	5,241	-0.079	0.139
-2	5,241	0.144	0.000	[-5, -2]	5,241	0.066	0.303
-1	5,241	-0.098	0.002	[-5, -1]	5,241	-0.033	0.641
0	5,241	0.026	0.382	[-5, 0]	5,241	-0.006	0.933
1	5,241	0.031	0.286	[-5, 1]	5,241	0.025	0.759
2	5,241	-0.011	0.691	[-5, 2]	5,241	0.013	0.879
3	5,241	-0.101	0.001	[-5, 3]	5,241	-0.087	0.338
4	5,241	-0.135	0.000	[-5, 4]	5,241	-0.223	0.022
5	5,241	-0.096	0.001	[-5, 5]	5,241	-0.319	0.002

Table 6
Bond market reaction
This table presents the bond market reaction to default events for both industry portfolios and individual firm levels. Panel A outlines the bond market industry portfolio's reaction. The sample includes 22,459 firm-event observations for 111 default events in 45 industries. The AR (monthly) is calculated as the difference between the actual return and the return of a benchmark portfolio. For firms with multiple outstanding bonds, the AR for the firm-event observation is a value-weighted average of AR across all outstanding bonds where the value is the bond size. An industry portfolio return is a value-weighted portfolio of firms with the same CSRC industry code, and the value is the total outstanding bond size of each firm. Panel B outlines the firm-level bond market reaction. The sample includes 22,459 firm-event observations for 3,621 issuers for 111 default events. # denotes the number of abnormal returns of observations available for computing the average abnormal return or cumulative average abnormal return. T-statistics are used to evaluate the significance, while the associated p-values are reported.

Panel A: Bond market reaction – industry portfolios							
	#	**AR**	**p-value**		**#**	**CAR**	**p-value**
-3	111	0.023	0.535	[-3, -3]	111	0.023	0.535
-2	111	0.004	0.931	[-3, -2]	111	0.027	0.607
-1	111	-0.412	0.000	[-3, -1]	111	-0.385	0.000
0	111	0.365	0.000	[-3, 0]	111	-0.020	0.792
1	111	-0.458	0.000	[-3, 1]	111	-0.478	0.000
2	111	-0.177	0.322	[-3, 2]	111	-0.655	0.002
3	111	-0.122	0.473	[-3, 3]	111	-0.777	0.002

Panel B: Bond market reaction - individual firms							
	#	**AR**	**p-value**		**#**	**CAR**	**p-value**
-3	22,459	0.074	0.000	[-3, -3]	22,459	0.074	0.000
-2	22,459	0.052	0.009	[-3, -2]	22,459	0.126	0.000
-1	22,459	-0.365	0.000	[-3, -1]	22,459	-0.239	0.000
0	22,459	0.503	0.000	[-3, 0]	22,459	0.264	0.000
1	22,459	-0.449	0.000	[-3, 1]	22,459	-0.185	0.000
2	22,459	0.039	0.131	[-3, 2]	22,459	-0.146	0.002
3	22,459	0.028	0.165	[-3, 3]	22,459	-0.118	0.009

Table 7

Market reaction in different periods

This table presents the stock and bond market reactions to default events in the periods 2014-2016 and 2017-2018. Panel A presents the stock market reaction for industry portfolios. The abnormal return (daily) is computed based on market model. The sample includes 184 defaults in 42 industries. An industry portfolio return is a value-weighted portfolio of firms with the same CSRC industry code that is composed of a capital letter followed by two digits. The value is the market value of the stock at the end of year *t-1* where *t* is the event year. Panel B shows the stock market reaction from individual firms. The sample includes 5,241 affected firm-event observations for 184 defaults. Panel C outlines the bond market industry portfolio's reaction. The sample includes 111 default events in 45 industries. The AR (monthly) is calculated as the difference between the actual return and the return of a benchmark portfolio. For firms with multiple outstanding bonds, the AR for the firm-event observation is a value-weighted average of AR across all outstanding bonds where the value is the bond size. An industry portfolio return is a value-weighted portfolio of firms with the same CSRC industry code, and the value is the total outstanding bond size of each firm. Panel D outlines the firm-level bond market reaction. The sample includes 22,459 firm-event observations for 3,621 issuers for 111 default events. # denotes the number of abnormal returns of observations available for computing the average abnormal return or cumulative average abnormal return. T-statistics are used to evaluate the significance, while the associated p-values are reported.

Panel A: Stock market reaction – industry portfolios

	2014-2016 (1)								**2017-2018 (2)**						
	#	**AR**	**p-value**		**#**	**CAR**	**p-value**		**#**	**AR**	**p-value**		**#**	**CAR**	**p-value**
-5	69	0.112	0.452	[-5, -5]	69	0.112	0.452	-5	115	-0.012	0.910	[-5, -5]	115	-0.012	0.910
-4	69	-0.176	0.224	[-5, -4]	69	-0.065	0.767	-4	115	-0.142	0.258	[-5, -4]	115	-0.154	0.370
-3	69	0.123	0.368	[-5, -3]	69	0.059	0.822	-3	115	0.150	0.193	[-5, -3]	115	-0.004	0.986
-2	69	0.149	0.337	[-5, -2]	69	0.208	0.538	-2	115	0.044	0.645	[-5, -2]	115	0.040	0.881
-1	69	-0.072	0.606	[-5, -1]	69	0.136	0.713	-1	115	0.015	0.894	[-5, -1]	115	0.055	0.847
0	69	-0.011	0.957	[-5, 0]	69	0.124	0.733	0	115	0.112	0.288	[-5, 0]	115	0.167	0.585
1	69	0.104	0.478	[-5, 1]	69	0.229	0.575	1	115	-0.025	0.835	[-5, 1]	115	0.142	0.643
2	69	-0.121	0.346	[-5, 2]	69	0.107	0.796	2	115	0.006	0.958	[-5, 2]	115	0.148	0.655
3	69	0.050	0.751	[-5, 3]	69	0.157	0.697	3	115	-0.084	0.379	[-5, 3]	115	0.065	0.855
4	69	0.309	0.021	[-5, 4]	69	0.467	0.305	4	115	-0.030	0.803	[-5, 4]	115	0.034	0.929
5	69	-0.008	0.961	[-5, 5]	69	0.459	0.319	5	115	-0.245	0.024	[-5, 5]	115	-0.212	0.606

Table 7 - Continued

Panel B: Stock market reaction - individual firms

	2014-2016 (1)							2017-2018 (2)						
	#	AR	p-value		#	CAR	p-value		#	AR	p-value		#	CAR	p-value
-5	1,414	-0.053	0.383	[-5, -5]	1,414	-0.053	0.383	-5	3,827	0.029	0.403	[-5, -5]	3,827	0.029	0.403
-4	1,414	-0.295	0.000	[-5, -4]	1,414	-0.349	0.000	-4	3,827	-0.087	0.009	[-5, -4]	3,827	-0.059	0.223
-3	1,414	-0.004	0.943	[-5, -3]	1,414	-0.353	0.002	-3	3,827	0.081	0.017	[-5, -3]	3,827	0.022	0.710
-2	1,414	0.154	0.010	[-5, -2]	1,414	-0.199	0.150	-2	3,827	0.141	0.000	[-5, -2]	3,827	0.163	0.021
-1	1,414	-0.214	0.001	[-5, -1]	1,414	-0.412	0.007	-1	3,827	-0.056	0.121	[-5, -1]	3,827	0.107	0.171
0	1,414	0.043	0.473	[-5, 0]	1,414	-0.369	0.019	0	3,827	0.021	0.560	[-5, 0]	3,827	0.128	0.127
1	1,414	0.149	0.005	[-5, 1]	1,414	-0.220	0.204	1	3,827	-0.013	0.717	[-5, 1]	3,827	0.116	0.204
2	1,414	0.018	0.751	[-5, 2]	1,414	-0.203	0.267	2	3,827	-0.022	0.519	[-5, 2]	3,827	0.093	0.342
3	1,414	-0.062	0.280	[-5, 3]	1,414	-0.265	0.159	3	3,827	-0.115	0.001	[-5, 3]	3,827	-0.022	0.832
4	1,414	-0.013	0.812	[-5, 4]	1,414	-0.279	0.158	4	3,827	-0.180	0.000	[-5, 4]	3,827	-0.202	0.070
5	1,414	-0.073	0.194	[-5, 5]	1,414	-0.351	0.091	5	3,827	-0.104	0.002	[-5, 5]	3,827	-0.306	0.010

Panel C: Bond market reaction – industry portfolios

	2014-2016 (1)							2017-2018 (2)						
	#	AR	p-value		#	CAR	p-value		#	AR	p-value		#	CAR	p-value
-3	51	0.087	0.048	[-3, -3]	51	0.087	0.048	-3	60	-0.032	0.585	[-3, -3]	60	-0.032	0.585
-2	51	-0.044	0.450	[-3, -2]	51	0.043	0.566	-2	60	0.044	0.444	[-3, -2]	60	0.013	0.863
-1	51	-0.402	0.000	[-3, -1]	51	-0.359	0.000	-1	60	-0.420	0.000	[-3, -1]	60	-0.407	0.000
0	51	0.293	0.001	[-3, 0]	51	-0.066	0.577	0	60	0.426	0.000	[-3, 0]	60	0.019	0.849
1	51	-0.512	0.007	[-3, 1]	51	-0.578	0.003	1	60	-0.412	0.000	[-3, 1]	60	-0.393	0.001
2	51	-0.457	0.237	[-3, 2]	51	-1.034	0.015	2	60	0.061	0.130	[-3, 2]	60	-0.332	0.011
3	51	-0.319	0.389	[-3, 3]	51	-1.353	0.011	3	60	0.044	0.294	[-3, 3]	60	-0.287	0.031

Panel D: Bond market reaction - individual firms

	2014-2016 (1)							2017-2018 (2)						
	#	AR	p-value		#	CAR	p-value		#	AR	p-value		#	CAR	p-value
-3	8,185	0.087	0.001	[-3, -3]	8,185	0.087	0.001	-3	14,274	0.067	0.009	[-3, -3]	14,274	0.067	0.009
-2	8,185	0.015	0.558	[-3, -2]	8,185	0.102	0.004	-2	14,274	0.073	0.009	[-3, -2]	14,274	0.140	0.000
-1	8,185	-0.397	0.000	[-3, -1]	8,185	-0.294	0.000	-1	14,274	-0.347	0.000	[-3, -1]	14,274	-0.207	0.000
0	8,185	0.416	0.000	[-3, 0]	8,185	0.121	0.020	0	14,274	0.553	0.000	[-3, 0]	14,274	0.345	0.000
1	8,185	-0.333	0.000	[-3, 1]	8,185	-0.211	0.000	1	14,274	-0.515	0.000	[-3, 1]	14,274	-0.170	0.003
2	8,185	-0.008	0.813	[-3, 2]	8,185	-0.219	0.001	2	14,274	0.067	0.067	[-3, 2]	14,274	-0.103	0.111
3	8,185	0.059	0.052	[-3, 3]	8,185	-0.160	0.020	3	14,274	0.011	0.686	[-3, 3]	14,274	-0.092	0.178

Table 8

Bond issuance around default events

This tables presents the OLS regression on *Bond yield* around the default event dates. The sample consists of 3,013 new bond issuances by 1,570 competitive companies in three months before and after 53 default events in 27 industries. Column (1) shows the result for the full sample. Column (2) – (5) illustrate the cross-sectional analysis. All the variables are the same as in Table 2 and 4. All the continuous variables are winsorized at the top and bottom 0.5% of the sample distribution. Robust standard errors clustered at the industry level are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Post	0.082**	-0.114*	-0.019	0.119***	0.115***
	(0.038)	(0.060)	(0.066)	(0.037)	(0.025)
Post×Private default issuer		0.228***			
		(0.060)			
Private default issuer		0.037			
		(0.081)			
Post×Non-SOE default			0.109		
			(0.076)		
Non-SOE default			0.046		
			(0.070)		
Post×Global CRA				-0.081*	
				(0.040)	
Global CRA				0.052	
				(0.056)	
Post×Listed					-0.264***
					(0.085)
Listed					0.204***
					(0.066)
iSize	-0.064**	-0.065**	-0.066**	-0.063**	-0.060**
	(0.028)	(0.030)	(0.028)	(0.027)	(0.028)
Maturity	0.038***	0.037***	0.037***	0.038***	0.037***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Enhancement	-0.291**	-0.290**	-0.286**	-0.286**	-0.290**
	(0.121)	(0.118)	(0.117)	(0.120)	(0.115)
Callable	0.741***	0.756***	0.744***	0.741***	0.747***
	(0.082)	(0.077)	(0.083)	(0.080)	(0.077)
Size	0.051	0.084	0.046	0.054	0.056
	(0.109)	(0.113)	(0.107)	(0.111)	(0.103)
Sales	-0.113	-0.099	-0.119	-0.125	-0.086
	(0.348)	(0.340)	(0.338)	(0.343)	(0.339)
Leverage	0.015***	0.014***	0.014**	0.014***	0.015***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
High Rating	-0.006	-0.009	-0.007	-0.011	-0.008
	(0.099)	(0.097)	(0.097)	(0.099)	(0.102)
ROA	-0.035**	-0.040***	-0.033**	-0.035**	-0.036**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Constant	1.935***	1.953***	1.972***	1.904***	1.862***
	(0.586)	(0.618)	(0.575)	(0.588)	(0.553)
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	3,013	3,013	3,013	3,013	3,013
Adjusted R2	0.796	0.798	0.797	0.796	0.798

Table 9

Industry portfolio reaction in stock and bond market reaction – Univariate analysis

This table presents the stock and bond market reaction by default industries and default events characteristics. The stock market sample includes 184 defaults between 2014 and 2018 in 42 industries. We compute the cumulative average abnormal return of the industry portfolio for each default over the 11-day window surrounding events. The bond market sample includes 111 defaults between 2014 and 2018 in 45 industries. We compute the cumulative average abnormal return of the industry portfolio for each default over the 7-month window surrounding events. The industry characteristics are obtained from Wind for the fiscal year preceding the defaults. Panel A shows the results categorized by the industry leverage, which is computed based on the asset-weighted leverage of firms in each industry for each event. High leverage group includes industries whose industrial leverage ratio is higher than the sample median. Panel B shows the results categorized by Herfindahl index (*HHI*), which is defined as the squared sum of the fractions of industry sales by the affected firms. In general, a low HHI indicates high competition. High *HHI* group includes industries whose *HHI* is above the sample median. Panel C shows the results categorized by the regulation status of the industry, where regulated industries include the following: Agriculture, Mining, Petroleum and Chemicals, Electric Power, Steam and Water Generation and Supply, Transportation and Communication. Panel D shows the results categorized by ownership of default firm, where SOEs are state-owned enterprises. Panel E shows the results categorized by the public traded status of the default bond. Panel E shows the results categorized by the publicly listed status of the default firms. # denotes the number of abnormal returns of observations available for computing the average CAR and p-values are reported. We also conduct *t*-tests for the difference-in-means for the comparisons between groups. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Market reaction by industry portfolio characteristics – Industry Leverage

	Stock market		**Bond market**	
	High	Low	High	Low
CAR	-0.094	0.173	-1.107	-0.441
p-value	0.815	0.713	0.019	0.022
#	92	92	56	55
Mean difference	-0.267		-0.667*	

Panel B: Market reaction by industry portfolio characteristics - HHI

	Stock market		**Bond market**	
	High	Low	High	Low
CAR	0.381	-0.280	-1.014	-0.536
p-value	0.244	0.779	0.043	0.000
#	89	95	56	55
Mean difference	0.661		-0.478	

Panel C: Market reaction by industry portfolio characteristics – Regulated status

	Stock market		**Bond market**	
	Regulated	Non-regulated	Regulated	Non-regulated
CAR	-1.259	0.424	-0.569	-0.854
p-value	0.041	0.232	0.040	0.011
#	42	142	30	81
Mean difference	-1.683**		0.285	

Table 9 - Continued

Panel D: Market reaction by default event characteristics – Ownership of the default firm

	Stock market		**Bond market**	
	Non-SOE	SOE	Non-SOE	SOE
CAR	-0.327	1.242	-0.912	-0.287
p-value	0.356	0.044	0.004	0.058
#	141	43	87	24
Mean difference	-1.569**		-0.625	

Panel E: Market reaction by default event characteristics – Listed status of the default bond

	Stock market		**Bond market**	
	Private	Public	Private	Public
CAR	-0.188	0.182	-0.779	-0.775
p-value	0.706	0.645	0.059	0.016
#	71	113	50	61
Mean difference	-0.370		-0.004	

Panel F: Market reaction by default event characteristics – Listed status of the default firm

	Stock market		**Bond market**	
	Private	Public	Private	Public
CAR	0.009	0.212	-0.659	-1.531
p-value	0.979	0.822	0.005	0.201
#	156	28	96	15
Mean difference	-0.203		0.872	

Table 10
Cross-sectional analysis for market reaction
This table presents the cross-sectional analysis by OLS regression on the stock and bond market reaction between 2014 and 2018. The left-hand-side variable for Column (1) to (4) are the 11-day CAR around default events for the stock market. There are 5,241 firm-event observations affected by 184 bond defaults. The left-hand-side variable for Column (5) to (8) are the 7-month CAR around default events for the bond market. There are 25,459 firm-event observations affected by 111 bond defaults. All the continuous variables are winsorized at the top and bottom 0.5% of the sample distribution. All the variables are the same as in Table 2 and 4 and defined in detail in Appendix 1. Robust standard errors clustered at the industry level are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

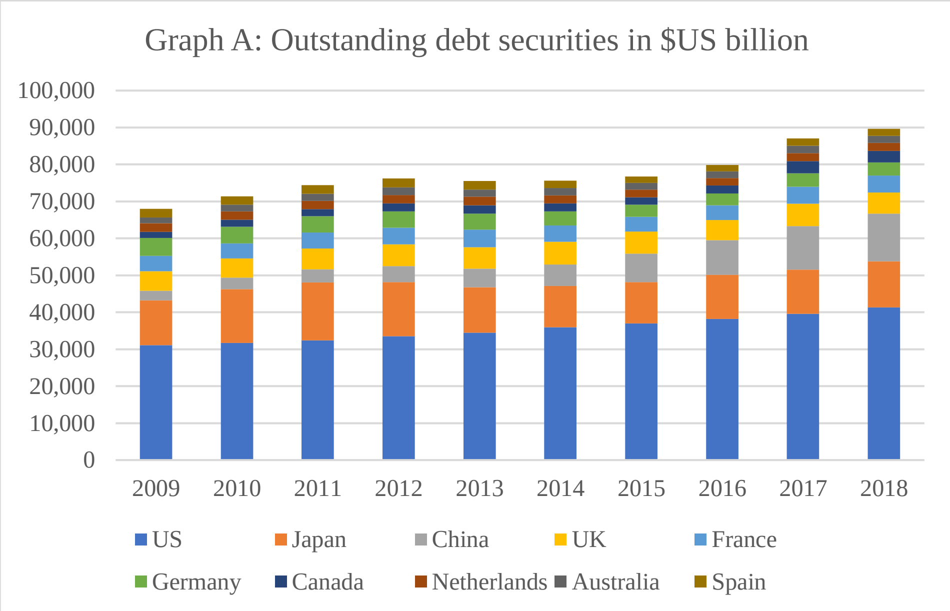
	Stock market				Bond market			
	Industry portfolios	Individual firms			Industry portfolios	Individual firms		
	Full sample	Full sample	2014-2016	2017-2018	Full sample	Full sample	2014-2016	2017-2018
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep.var	11-day CAR				7-month CAR			
Leverage_Industry	-0.101				-0.156			
	(0.071)				(0.137)			
HHI	1.771				-8.378			
	(4.037)				(6.351)			
Regulated Industry	-3.564**				-1.974			
	(1.581)				(3.977)			
Private bond	-1.003	-0.429	-1.070	-0.087	-0.813	-0.106	-0.014	-0.124
	(0.858)	(1.054)	(1.533)	(1.580)	(0.801)	(0.159)	(0.135)	(0.209)
Private default issuer	-0.622	-2.377***	-1.502	-1.959	-1.229	0.185	0.044	0.376
	(1.077)	(0.662)	(4.026)	(1.375)	(1.807)	(0.239)	(1.198)	(0.282)
Non-SOE default	-3.894***	-3.625***	-5.643***	-2.618*	-0.400	-0.046	0.072	-0.238
	(0.784)	(0.894)	(1.086)	(1.533)	(1.074)	(0.215)	(0.174)	(0.284)
Bond Issue		-0.672	10.423	-8.173***				
		(2.253)	(19.396)	(2.664)				
Big 4		1.791	8.899	4.783				
		(4.968)	(23.057)	(15.516)				
Global CRA						1.453***	1.213***	1.706***
						(0.154)	(0.390)	(0.190)
VOL		-1.556**	0.127	-3.349***				
		(0.688)	(0.951)	(0.862)				
Listed						0.276**	-0.080	0.556***
						(0.122)	(0.175)	(0.150)
z-score		-0.329**	-0.852**	0.087				
		(0.148)	(0.349)	(0.225)				

Table 10 - Continued

Current Rating_High						-1.335***	-0.100	-2.179***
						(0.259)	(0.445)	(0.316)
ROA		-0.112**	-0.061	-0.266**		0.054	-0.095	0.056
		(0.055)	(0.182)	(0.118)		(0.036)	(0.064)	(0.058)
Size		0.641	-3.046	1.642		0.175***	0.096	0.226***
		(0.902)	(8.266)	(2.422)		(0.036)	(0.063)	(0.051)
Sales		4.422**	7.503	3.789		0.028**	0.015	0.036**
		(1.887)	(8.671)	(5.100)		(0.011)	(0.019)	(0.014)
Leverage		-0.069	-0.213	-0.127*		-0.032***	-0.041**	0.020
		(0.044)	(0.229)	(0.063)		(0.011)	(0.017)	(0.023)
Constant	8.792*	7.611	20.839	10.558**	15.195	1.201	2.495	-2.447
	(4.782)	(6.214)	(15.304)	(5.139)	(14.430)	(1.095)	(1.810)	(1.576)
Firm fixed effect	No	Yes			No	Yes		
Industry fixed effect	Yes	No			Yes	No		
Year fixed effect	Yes	Yes			Yes	Yes		
Observations	184	5,241	1,414	3,827	111	22,459	8,185	14,274
Adjusted R2	0.060	0.088	0.191	0.050	0.317	0.183	0.190	0.203

Figure 1 Debt market in China as compared with other developed countries

Graph A charts the total outstanding debt securities in US$ billion for China and other developed countries. Graph B depicts the ratio of the outstanding debt securities in proportion to the country's GDP from 2009 to 2018.



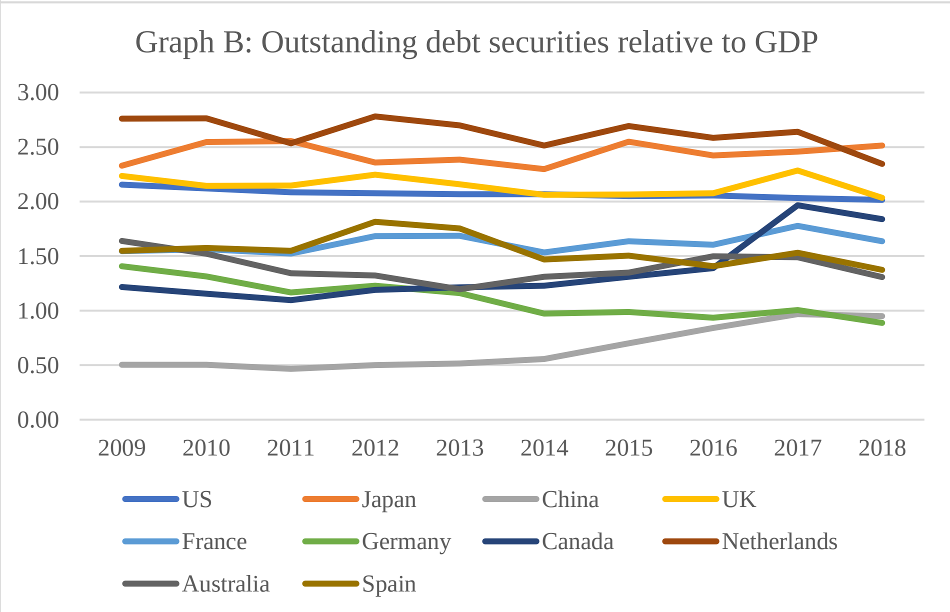


Figure 2 Market reaction around default events

Graph A shows the stock market reaction for 11 days around the default events. Graph B charts the secondary bond market reaction for 7 months around the default events. Graph C illustrates the bond issuance yield change for 6 months around the defaults.