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Pledgeability and Asset Prices: Evidence from the Chinese Corporate Bond Markets

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ABSTRACT

We provide causal evidence on the value of asset pledgeability by exploiting a unique feature of Chinese corporate bond markets: bonds with identical fundamentals are traded on two segmented markets with different rules for repo transactions. Using a policy shock that rendered AA+ and AA bonds ineligible for repo on one market only, we compare how bond prices changed across markets and rating classes around this event. When the haircut increases from 0% to 100%, bond yields increase by 39 bps to 85 bps. These estimates help us infer the magnitude of the shadow cost of capital in China.

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IT HAS LONG BEEN RECOGNIZED THAT ASSET prices depend not only on fundamental cash flows, but also on liquidity factors that are broadly related to the frictions prevalent in modern financial markets (Duffie (2010)). Among these liquidity considerations, asset pledgeability, or the ability of an asset to serve as collateral and help reduce financing costs, has arguably received the most attention because of its central role in the research of borrowing constraints in macroeconomics and finance (see, e.g., Kiyotaki and Moore (1997), Gromb and Vayanos (2002)).

In a setting in which collateral helps reduce the costs of borrowing for financially constrained investors, Gârleanu and Pedersen (2011) show that pledgeable assets carry a convenience yield. We refer to this convenience yield as the *pledgeability premium*. This premium is the product of asset pledgeability, which is inversely related to the haircut that an asset faces, and the per-unit value of pledgeability (or simply the value of pledgeability for brevity), which is the shadow value of relaxing marginal investors' collateral constraints. The goal of our paper is to offer an empirical estimate of the value of pledgeability.

We focus on bonds, which, besides their involvement in spot transactions, are often used in repurchase agreements, or repos. Repos are essentially collateralized loans—except repos are exempt from an automatic stay in the event of bankruptcy (Adrian et al. (2013))—with the assets in the transaction serving as the collateral. Lenders often set a *haircut* over the market price of the collateral bond to determine the amount of credit extended; the smaller the haircut, the greater the pledgeability of the bond.

Although the theoretical mechanisms through which pledgeability boosts asset values are relatively clear, it is difficult to measure this effect empirically. Asset pledgeability is endogenous and thus, in general, depends on asset fundamentals, market frictions, and the interactions between the two.

We overcome this endogeneity issue by exploiting a policy shock on asset pledgeability together with a set of unique institutional features in the Chinese bond markets. Two bond markets co-exist in China, namely, the over-the-counter (OTC) interbank market and the centralized exchange market. While commercial banks can trade only in the interbank market and retail investors only in the exchange market, nonbank financial institutions (NBFIs), which include mutual funds, insurance companies, and securities firms, are active investors in both markets. Our study focuses on dual-listed enterprise bonds, an important category of corporate bonds that are traded simultaneously on both markets. Trading frictions such as lengthy settlement delays can cause the two markets to be segmented to a large degree.

The two bond markets also differ significantly in their rules for repos. Interbank repos essentially follow the standard tri-party repo system in the United States; key transaction terms such as collateral, haircut, and repo rate are negotiated bilaterally. In contrast, the exchange acts as the central clearing counterparty (CCP) for all repo buyers and sellers and unilaterally determines the list of eligible collateral bonds as well as their respective haircuts, which are based largely on bond ratings. The differences in pledgeability and market segmentation imply that the prices of a given bond can differ between the two markets.

Our main empirical strategy is to exploit these cross-market valuation differences for dual-listed bonds. Specifically, for the same bond with simultaneous transactions on the two markets, we define the "exchange premium" as the yield on the interbank market minus that on the exchange market. Given NBFIs are common marginal investors who apply the same pricing kernel in the two markets, any (unobservable) fundamentals should affect the pricing of the bond on the two markets in the same way. As a result, the exchange premium isolates the pricing effects of the remaining nonfundamental factors, including cross-market differences in pledgeability and potentially other liquidity factors.

To further isolate the value of pledgeability, we exploit a policy shock that significantly changed the pledgeability for a set of bonds on the exchange market. After hours on December 8, 2014, the exchange suddenly announced that enterprise bonds with ratings below AAA would no longer be accepted as repo collateral; in Section I we provide further institutional background on this shock. Particularly relevant to our study, this policy applied to the exchange market only. However, it only changed the pledgeability of bonds rated AA+ and AA on the exchange, with AAA bonds unaffected and AA− bonds already ineligible for repo before the policy shock. AA+ and AA bonds' haircuts on the interbank market, however, were largely unchanged. These factors, together with the fact that the exchange sets haircuts based largely on ratings before the policy shock, makes the rating-based policy shock a strong instrument for haircut changes and allows us to identify the value of pledgeability.

One potential concern with our identification strategy is that the policy shock could induce fire sales of the treated bonds on the exchange market, which would reduce their exchange premia. We emphasize two features of our empirical setting that help address this concern. First, this policy only applied to bonds that had not been used as collateral at the time of its announcement. In other words, there was no forced deleveraging pressure for investors who had taken a levered position in the affected bonds, as regulators wanted to minimize the policy's impact on market stability. This unique institutional feature makes our policy shock well-suited to studying the value of pledgeability by limiting any temporary price pressure due to forced fire sales.

Second, our empirical design is robust to potential panic selling by retail investors in the exchange market. As shown in the theoretical framework developed in Section II.B, NBFIs would respond to such behavior from retail investors by adjusting their holdings to restore their Euler equations in both markets. Therefore, the difference in prices across the two markets in equilibrium only reflects the value of pledgeability to the common marginal investors.

We show that the treatment group (AA+ and AA bonds) shared a similar trend in exchange premia as the control group (AAA and AA− bonds) before the December 2014 shock. After the policy shock, the raw exchange premia of the treatment group fell, while that of the control group did not change. This pattern suggests that the rating-dependent pledgeability shock adversely affected the exchange market prices of bonds with AA+ and AA ratings only. We highlight that our control group consists of both higher- (AAA) and lower-rated (AA−) bonds, a structure that further helps rule out many alternative fundamental-based explanations; typically, these alternative mechanisms lead to asset pricing reactions that are monotonic in asset quality, which is captured by credit ratings in our setting.

Using the rating-dependent policy shock as an instrument in a two-stage least squares (2SLS) regression, we find that raising the haircut from 0% to 100% leads to a 39 bps (0.39%) increase in the bond yield. This result provides an estimate of the value of pledgeability, that is, the shadow value in relaxing the financial constraints of NBFIs.

Although the exchange premia–based estimate helps address the issue of unobservable bond fundamentals, it could still underestimate the value of pledgeability. One leading concern is cross-market arbitrage; despite significant trading frictions, arbitrage forces will prevent the exchange premia of any dual-listed bond from drifting too far from zero, which could potentially bias the estimate of the value of pledgeability downward. The reason is that, in the absence of any arbitrage frictions, the exchange premium will always be zero regardless of haircut changes, resulting in an estimate of zero for the value of pledgeability. In addition, to the extent that the policy shock triggered a "flight-to-quality" event in the interbank market, such "flight-to-quality" would push up the interbank prices of AAA bonds relative to other bonds and hence reduce the exchange premia of AAA bonds following the shock. This economic force could also bias downward the estimate of the value of pledgeability when we use AAA-rated bonds as part of the control group.

We address this concern by providing an alternative instrumental variable (IV) estimate that likely overstates the price impact of changes in pledgeability; in this way, our two sets of IV estimates plausibly bound the magnitude of λ. Specifically, we compare the price changes of the treated bonds against those of the matched AAA bonds on the exchange market. These matched AAA bonds have similar haircuts and credit spreads in the pre-event sample as the treated AA+/AA bonds, but their pledgeability is not affected by the policy shock. The alternative IV estimate is likely to be upward biased, as these matched AAA bonds may have better unobservable fundamentals relative to the treated bonds, for example, the regulator has unfavorable private information on AA+/AA bonds. The resulting IV (over)estimate suggests that raising the haircut from 0% to 100% leads to a 85 bps increase in yield, compared to the exchange premia–based estimate of 39 bps. The range for the value of pledgeability provided by our two estimates is admittedly large. We provide preliminary evidence suggesting that the true value is likely closer to the exchange premia–based estimate of 39 bps, as the negative bias induced by cross-market arbitrage is likely small.

In our framework, the value of pledgeability reflects the shadow value of relaxing financial constraints for NBFIs. Equating shadow value with shadow cost faced by NBFIs, and accounting for the fact that financial constraints may not be always binding, we find that our estimates of λ ranging between 39 bps and 85 bps correspond to a shadow cost of capital of 1.1% to 2.4%. We discuss the economic magnitude in the broad context of the international financial market in the literature review.

Literature review. Equilibrium asset pricing with financial constraints is an active research field. Gârleanu and Pedersen (2011) consider a general equilibrium model with two assets that have identical cash flows but may differ in their margins/haircuts, and tie their equilibrium pricing differences (bases) to margin differences modulated by the shadow cost of capital. Their model provides the closest theoretical framework to our empirical study.[1]

There is no doubt that margin constraints or haircuts are endogenously determined by aggregate conditions in financial markets as well as by asset characteristics. Influential theoretical contributions include Fostel and Geanakoplos (2008) and Geanakoplos (2010), who show that riskless lending arises endogenously due to heterogeneous beliefs; extensions include Simsek (2013) and He and Xiong (2012), among others. Brunnermeier and Pedersen (2009) relate the haircut of assets to a value-at-risk constraint and highlight the downward spiral in a general equilibrium model with endogenous leverage constraints.

Our paper contributes to the literature that connects pledgeability to asset prices. Related empirical studies include Gorton and Metrick (2012), Copeland, Martin, and Walker (2014), and Krishnamurthy, Nagel, and Orlov (2014), among others, with a focus on the failure of the law of one price and its connections to margin constraints and liquidity.[2] Using a policy shock that hits different dealers in a heterogeneous way, Macchiavelli and Zhou (2022) demonstrate

[1] An early theoretical contribution includes Detemple and Murthy (1997), who study the role of the short-sale constraint, which is intrinsically linked to margin requirements or haircuts in equilibrium. Other general equilibrium models with financial constraints include Basak and Cuoco (1998), Gromb and Vayanos (2002), Danielsson, Shin, and Zigrand (2001), He and Krishnamurthy (2013), Chabakauri (2015), and Rampini and Viswanathan (2019). For recent empirical studies on intermediary asset pricing, see Adrian, Etula, and Muir (2014), He, Kelly, and Manela (2017), and He, Khorrami, and Song (2022). More generally, equilibrium asset pricing terms can also be endogenously determined in a framework with OTC search markets (Duffie, Gârleanu, and Pedersen (2005), He and Milbradt (2014), Chen et al. (2018), among others), of which the Chinese interbank market is one. Based on this framework, Vayanos and Wang (2007) and Vayanos and Weill (2008) study the premia of on-the-run Treasuries as a symptom of the failure of the law of one price. Previous studies also document empirically how price dispersion arises in OTC municipal and corporate bond markets due to dealers' market power (Green, Hollifield, and Schürhoff (2007a, 2007b)), bond characteristics (Harris and Piwowar (2006)), selling pressure (Feldhütter (2012)), and more recently, trading networks (Di Maggio, Kermani, and Song (2017), Hendershott et al. (2020), Li and Schürhoff (2019)).

[2] Examples include Longstaff (2004) and Lewis, Longstaff, and Petrasek (2021), who document the premium of Treasury securities over agency or corporate bonds that are guaranteed by the U.S. government; Krishnamurthy (2002), who documents the on-the-run Treasury premium; and Bai and Collin-Dufresne (2019), Choi, Shachar, and Shin (2019), and Siriwardane (2019), who study the credit default swap (CDS)-bond basis, which is the pricing difference between a corporate bond and its synthetic replicate (buying Treasury and selling CDS). In a recent study, Ai et al. (2020) examine the link between pledgeability and asset pricing in the U.S. equity market. Zevelev (2021) exploits a constitutional amendment in Texas to identify the impact of collateral service flows on house prices.

that a dealer's funding liquidity causally affects the liquidity that the dealer provides to the market. Our identification strategy of exploiting price variations across two markets has a similar flavor to theirs.

The value of pledgeability that we estimate in the Chinese bond markets, which ranges from 39 bps to 85 bps, is somewhat higher than the value found in other major markets. We take these comparisons with caution since the value of pledgeability depends on the shadow value of relaxing the funding constraint, which can vary over time and across countries. Ashcraft, Gârleanu, and Pedersen (2011) empirically examine the price impact of reducing the haircuts of some eligible mortgage-backed securities by exploring one of the Term Asset-Backed Securities Loan Facility (TALF) programs in March 2009, arguably the worst time during the Great Financial Crisis. Based on market reactions of bonds that were rejected by the program (which may carry additional information beyond pledgeability), they find that an increase in the haircut from 0% to 100% would result in an increase in bond yields of 28 bps to 52 bps. Pelizzon et al. (2019) also find a somewhat smaller estimate—13 bps to 59 bps decrease in yields for a 100% drop in haircut—by exploiting the haircut reduction resulting from a corporate bond's inclusion in the European Central Bank's eligible list of collateral for its open market operations.[3] Our paper is distinct because the Chinese enterprise bonds that we consider are dual listed and our setting has two control groups, one with higher credit quality than the treatment group and another with lower credit quality. These features allow us to identify the causal effect of asset pledgeability on asset prices by ruling out the impact of changes in (unobservable) asset fundamentals that are often correlated with changes in asset pledgeability.

Finally, our paper also contributes to the burgeoning literature on the Chinese bond markets, which includes Fan and Zhang (2007), Ang, Bai, and Zhou (2023), Wang and Xu (2019), Chen, He, and Liu (2020), Geng and Pan (2021), and Ding, Xiong, and Zhang (2022). In a closely related paper, Fang, Wang, and Wu (2021) study the effect of nonconventional monetary policy, that is, the expansion of the collateral eligibility list from government bonds and AAA corporate bonds to corporate bonds with ratings above AA– for the Medium-term Lending Facility (MLF, a frequently used lending program by People's Bank of China, or PBoC) on June 1, 2018. Because the MLF haircuts of these newly eligible bonds are unobservable, we cannot directly compare their policy-induced price changes to our estimated value of pledgeability.[4]

[3] We have scaled the estimated effect by Ashcraft, Gârleanu, and Pedersen (2011) proportionally. For instance, the lower bound effect of rejection by the TALF is estimated to be around 20 bps, but because the TALF rejection essentially raised the bond haircut by 75% (from 25% to 100%), the effect of a 100% increase in haircut should be around 28 bps. Similarly, we have also scaled the lower and upper bounds of the estimates using the haircut schedule of assets eligible for use as collateral in Eurosystem market operations in Pelizzon et al. (2019), who find that the average yield reaction is 11 bps to 24 bps for lendable bonds and 30 bps to 50 bps for nonlendable bonds.

[4] Asset pledgeability also matters for the stock market in China, for example, Bian et al. (2021) document the role of leveraged margin trading in the 2015 crash of the Chinese stock market. Complementary to our angle of rating-dependent pledgeability, Liu et al. (2019) find that retail

The rest of the paper is organized as follows. Section I describes the institutional details relevant to our empirical investigations. In Section II, we outline the data utilized and the economic framework that underpins our estimations. Market responses to the policy shock are documented in Section III. Our 2SLS estimation results, estimations using an alternative matched control group, and additional discussions are presented in Section IV. Section V concludes.

I. Institutional Background

This section Chinese bond markets that are relevant for our study. For more details on the history of the Chinese bond markets, see Amstad and He (2020).

A. Chinese Bond Markets and Dual-Listed Enterprise Bonds

Over the past decade, China has taken enormous strides to develop its bond markets as an integral part of financial reforms. Chinese bond market capitalization scaled by GDP rose from 35% in 2008 to almost 100% in 2019; in comparison, the U.S. bond market has remained slightly above 200% of U.S. GDP during the same period (Appendix Figure A1).

Enterprise bonds. There are three major categories of fixed-income securities in the Chinese bond markets based on issuing entities: government bonds, financial bonds, and nonfinancial corporate bonds.[5] Our paper focuses on enterprise bonds, a type of corporate bond that is issued mainly by nonlisted state-owned enterprises (SOEs) and regulated by the National Development and Reform Commission (NDRC). Enterprise bonds accounted for 25% of total corporate bonds outstanding by 2014 when the policy shock in question occurred.

Exchange and interbank markets and dual-listed enterprise bonds. Two distinct and largely segmented markets co-exist in contemporary Chinese bond markets: the OTC interbank market and the centralized exchange market. Our study focuses on dual-listed enterprise bonds, which are traded on both the exchange and interbank bond markets.

After its establishment in 1997, the interbank market was the only market in which enterprise bonds were issued and traded. In 2005, the NDRC granted

investors play a significant role in explaining the pricing wedge between the interbank and exchange markets for the dual-listed bonds. Several papers also look at the implicit government guarantee in the Chinese bond markets. Among them, Liu, Lyu, and Yu (2017) investigate the role of implicit local government guarantees for municipal corporate bonds (MCBs), Jin, Wang, and Zhang (2023) study the first bond default by a central SOE in 2015 to estimate the real effects of implicit guarantees, and Huang, Huang, and Shao (2023) study the same question by looking at financial bonds issued by commercial banks.

[5] This classification follows Amstad and He (2020). Government bonds, which account for 55% of bonds outstanding in 2019, are issued by formal government agencies. Financial bonds (18% of bonds outstanding in 2019) are issued by financial institutions, and corporate bonds (25% of bonds outstanding in 2019) are issued by nonfinancial firms. Another widely used classification among practitioners in China groups financial bonds and corporate bonds together as “credit bonds,” as opposed to “interest rate” bonds, which are government bonds in the classification we use.

nonlisted SOEs access to the exchange market to expand the potential investor base. About 78% of enterprise bonds outstanding were dual-listed by the end of 2014 when the policy shock in question took place. At the same time, the interbank market, as opposed to the exchange market where the policy shock occurred, was still the "home" market for dual-listed enterprise bonds, with almost all enterprise bond issuances still initially placed in the interbank market: in 2014, 562 out of 568 newly issued dual-listed enterprise bonds were first listed on the interbank market (see Figure IA.1 in the Internet Appendix for the depository amount and issuance of dual-listed enterprise bonds by market).[6]

Default risk. During our mid-2014 to mid-2015 sample period, default risk for Chinese enterprise bonds as a whole was negligible, simply because enterprise bonds are issued predominantly by SOEs with either larger size or stronger government guarantees. As we explain below in Section I.D, this fact implies that it is unlikely that the policy shock on December 8, 2014 was due to rising regulatory concerns about the default risk of enterprise bonds.

Although the first corporate bond default in China (by publicly traded non-SOE Shanghai Chaori Solar Engergy) took place in March 2014, credit spreads of enterprise bonds in our sample period remained at a level that is similar to that in 2010 when the practice of "rigid payment" was still widely expected in Chinese bond markets (Zhu (2016)). There was no dual-listed enterprise bond default until May 2016, almost one year after our sample period, when non-SOE Inner Mongolia Nailun failed to deliver its interest payment that month. Across both exchange and interbank markets, reactions to the first default of dual-listed enterprise bonds were largely muted. It was not until the U.S.-China trade war and Beijing's New Asset Management Rules hit the market in 2018 that default incidents and credit spreads started to climb in a noticeable way (see, e.g., Geng and Pan (2021), J.P. Morgan Asset Management (2018)).[7]

B. Exchange and Interbank Bond Markets in China

We now discuss institutional features of the two bond markets that are relevant to our study.

Trading protocols and liquidity. The Chinese interbank bond market, similar to those in developed economies like the United States, employs a quote-driven OTC trading protocol in which the terms of trade are finalized through

[6] The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

[7] The RMB value of defaulted corporate bonds in China is RMB 1.3, 13.4, 39.5, and 38 billion from 2014 to 2017; it soared to RMB 127.8 and 147.8 billion in 2018 and 2019. Nevertheless, most defaults do not relate to enterprise bonds; during 2018 and 2019 the annualized default rate is only around 0.1% for enterprise bonds while this rate is much higher at 0.7% for all other types of corporate bonds. For comparison, the global counterpart during 2008 to 2017 is 1.8%, according to a 2017 report by Moody's (see Section 6.1 in Amstad and He (2020)). In a recent paper, Li and Ponticelli (2022) study the role of "specialized bankruptcy court," which sheds light on how China is addressing the recent increase in corporate defaults following a decade-long debt boom.

bilateral bargaining between relevant parties. In contrast, the trading protocol on the exchange market, which resides on the Shanghai and Shenzhen stock exchanges, is facilitated by an order-driven mechanism, with electronic order books aggregating orders from all participants who observe all these orders publicly. Matched trades are settled via the China Securities Depository & Clearing Corporation (CSDC), which provides depository and settlement services for the exchange market.

Both bond markets in China are quite active (see, e.g., Figure A2 in the Appendix). They differ in that the interbank market satisfies infrequent but large transaction needs (wholesale) while the exchange market accommodates frequent but small trades (retail). This feature is in sharp contrast to bond markets in the United States, where the exchange market attracts limited trading in corporate bonds (Biais and Green, 2019).[8]

Market participants and common institutional investors. The interbank market mainly serves institutional players, with participants including commercial banks, policy banks, pensions, and NBFIs such as mutual funds, insurance companies, and securities firms. In contrast, the exchange market hosts NBFIs, corporate investors, and high-net-worth retail investors with ample investment experience.

We emphasize that NBFIs, a group of sophisticated institutional investors, have access to and are marginal investors in both markets in China. For instance, almost all securities firms, one key set of NBFI investors, are active in both markets in terms of both trading and market making. There are many reasons for them to be active in both markets, an obvious one being their need to participate in the primary market distribution of different bonds in these two markets. We formalize this premise in Section II.B, where we discuss the theoretical framework for our study.

By the end of 2014, the aggregate holdings of NBFIs accounted for 76% and 57% of the enterprise bonds deposited on the exchange and interbank markets, respectively. These numbers are quite similar by mid-2014 and mid-2015 (see, e.g., Panel A of Figure IA.2 in the Internet Appendix). In contrast, retail investors hold about 0.6% of enterprise bonds on the exchange market, while commercial banks hold about 35% on the interbank market.

Limits to arbitrage. Despite having identical fundamentals, the two market prices of a dual-listed bond can differ, due to market frictions that prevent "textbook" cross-market arbitrage. The most significant friction relates to settlement delays. Suppose an investor wants to sell interbank market–acquired bonds on the exchange or use it in a repurchase agreement on the exchange. To do so, she needs to apply for a transfer of custody from the interbank market to the exchange market, which took more than five working days in 2014. A

[8] Appendix Table AI provides a more detailed comparison of the secondary market liquidity in the two Chinese bond markets and in the U.S. corporate bond market. Market (il)liquidity is comparable between the interbank market and the exchange market in China based on the fraction of bonds that do not trade on a given day. Compared to the U.S. corporate bond market, China's bond markets are slightly less liquid based on nontrading days, but are more liquid in terms of turnover.

transfer in the opposite direction was slightly faster at two to three working days. Such delays expose an arbitrageur to significant price risk. Moreover, simultaneously buying and selling a large quantity of the same bond on the two markets is difficult due to market illiquidity.

Limits to arbitrage explain why the prices of the same bond may differ across the two markets. We argue that the differences in pledgeability on the two "repo" markets are a major factor causing the prices to differ in the first place, which we explain in more detail in Section III.B.

C. Repos on the Exchange and the Interbank Market

As a form of collateralized borrowing with the security serving as collateral, repurchase agreements—or simply repos—are quite active on both the exchange and interbank markets. We now explain different repo transactions mechanisms on these two markets.

Repos on the interbank market. In a repo transaction on the Chinese interbank market, a seller (the borrower) contacts a buyer (the lender) and the two parties reach an agreement on the terms of trade based on bilateral bargaining.[9] As explained in Section I.B, the interbank market is dominated by large institutions with institution-specific funding needs and constraints, and hence each repo contract tends to be highly customized, including the specification of collateral, the repo rate, and the method of delivery. These terms reflect the risks of the underlying securities and that of the counterparty, and large state-owned commercial banks are typically in an advantageous position.

The China Foreign Exchange Trade System (CFETS) reports daily aggregate transaction volume and volume-weighted repo rates for the interbank market, but there is no such aggregate information on haircuts. While lacking access to trade-level repo data on the interbank market, we obtain proprietary information on average interbank haircuts for enterprise bonds before and after the policy shock in question based on transactions conducted by an anonymous major financial institution in China (see Section III.A).

Repos on the exchange market. For repos on the exchange market, the exchange not only facilitates transactions, but also acts as the CCP for all repo buyers and sellers. Unlike the third-party agent in tri-party repos in the United States, the CCP guarantees that obligations are met to all nondefaulting parties regardless of whether obligations to the CCP have been met. This market mechanism is similar to some CCP-based European electronic platforms (see, e.g., Mancini, Ronaldo, and Wrampelmeyer (2016)).

[9] Two types of repo transactions are available for China's interbank market participants: pledged repo, where bonds are used as a pledge of rights, and outright repo, where bonds are sold to a reverse repo party. Unlike the United States where outright repos are more popular, in China pledged repos account for the majority of interbank repo transactions (94.2% in our one-year sample period), so that the collateral takers cannot reuse the collateral for another repo transaction. In the context of our paper, if collateral cannot be reused (rehypothecated), this should effectively decrease the supply of collateral and raise the premium earned by pledgeable assets in equilibrium, as shown by the theoretical analysis in Bottazzi, Luque, and Páscoa (2012).

On a daily basis, the CSDC unilaterally sets the collateral pool, that is, the list of securities eligible as collateral, and their conversion rates (CR), which is the borrowed amount quoted as a fraction of the face value of the security. As an example, imagine that the CSDC sets the conversion rates for Treasuries and AAA corporate bonds to be 1 and 0.9, respectively. Then an investor posting one unit of each bond as collateral, each with face value of 100 RMB, will be able to borrow $190 = 100 \times 1 + 100 \times 0.9$ RMB from the exchange.

Given a bond with face value FV and market price P, one can translate its conversion rate CR into the haircut using the formula

$$\left(1 - \text{haircut}\right) \cdot P = CR \cdot FV \Rightarrow \text{haircut} = 1 - \frac{FV \cdot CR}{P}. \tag{1}$$

The haircut is negatively correlated with the conversion rate; a haircut of 100% implies zero pledgeability for that security. Essentially, all eligible securities become completely fungible after adjusting for their respective conversion rates. This feature is necessary for the exchange market, which relies on standardization to function. Even though repo lenders and borrowers have limited information about each other and the actual composition of the collateral pool as the exchange does not publish such information, counterparty risk is negligible due to the exchange's implicit government backing. Finally, the repo rates at various maturities are set by the market via a central limit order book aggregating all bids and asks from repo sellers (borrowers) and buyers (lenders) in continuous double auctions. One-day repo transactions account for about 90% of total exchange market repo transactions.

D. The Policy Shock in the Exchange Market

To identify the effects of changes in pledgeability on bond pricing, we exploit a policy shock on the exchange market. In a nutshell, after market closing on December 8, 2014, the exchange suspended the repo eligibility of all enterprise bonds rated below AAA. In this section, we describe the background and nature of the policy shock.

The local government debt problem. The background of this policy shock is related to the local government debt problem in China (Chen, He, and Liu (2020)). In 2009, Beijing responded to the 2007/08 global financial crisis with a RMB four trillion stimulus package in which local government financing vehicles (LGFVs, which are local SOEs) funded heavy infrastructure investment mainly through loans extended by commercial banks. Three to five years later, the back-to-normal credit policy forced LGFVs to turn to the bond market and aggressively issue MCBs, mainly in the form of dual-listed enterprise bonds by that time.[10] As a result, the enterprise bond market became flooded with

[10] An MCB, also known as an Urban Construction Investment Bond or Chengtou Bond, is a perfect example of the mixture between planning and market in the contemporary Chinese economy. In a strictly legal sense, MCBs are issued by LGFVs, which are regular corporations, yet MCBs are viewed by the market as being implicitly backed by the corresponding local government. As shown

Table I

Sample Coverage

This table reports the sample coverage by rating. Panel A presents the number of bonds for the dual-listed enterprise bond sample, the simultaneous trading sample, and the simultaneous trading sample with MCB only. Panel B presents the dual-listed enterprise bond sample coverage over all enterprise bonds. Panel C presents the enterprise bond sample coverage over all corporate bonds. Sample coverage measures in Panels B and C include number of bonds, notional RMB value, number of nonzero trading days, and RMB trading volume.

Panel A: Dual-Listed Sample and Simultaneous-Trading Sample					
	All	AAA	AA+	AA	AA−
$N_{dual-listed}$	1,912	234	578	981	119
$N_{simultaneous}$	1,028	83	318	536	91
$N^{mcb}_{simultaneous}$	894	49	279	490	76
Panel B: Dual-Listed Sample Relative to All Enterprise Bonds					
	All	AAA	AA+	AA	AA−
Number of bonds	81.7%	60.5%	82.5%	87.8%	88.1%
Notional value	78.3%	59.2%	83.6%	88.5%	90.1%
Days with trades	92.1%	83.3%	92.2%	93.0%	97.2%
RMB trading volume	82.7%	55.1%	78.8%	90.9%	90.6%
Panel C: Enterprise Bonds Relative to All Corporate Bonds					
	All	AAA	AA+	AA	AA−
Number of bonds	28.0%	21.6%	38.8%	48.8%	5.5%
Notional value	26.5%	18.8%	37.6%	56.4%	5.5%
Days with trades	41.5%	25.5%	53.0%	57.9%	19.7%
RMB trading volume	26.7%	13.1%	29.8%	66.8%	4.6%

MCBs; the share of MCB-type enterprise bonds rose from 30% in 2010 to 67% by the end of 2014, and 87% of enterprise bonds that enter our final sample are MCBs (Panel A, Table I).

Increasingly concerned about local government debt problems, the Central Economic Work Conference in 2014, China's highest-profile annual meeting that convenes in Beijing each January to set the national agenda for economic development, added "controlling local government debts" as one of its major agenda items for that year. This prompted many follow-up policies, such as a pilot program started in May 2014 that allowed a number of local governments to issue municipal bonds, and on October 2, 2014 the State Council of China promulgated the influential and directive guideline Document No. 43 (hereafter, Doc. 43). In a nutshell, Doc. 43 outlined the legal framework for local government debts, aiming to gradually replace MCBs with standard

in Chen, He, and Liu (2020), LGFVs issue MCBs to refinance maturing bank loans and continue ongoing infrastructure projects over the 2012 to 2015 period, fueling the shadow banking sector in China.

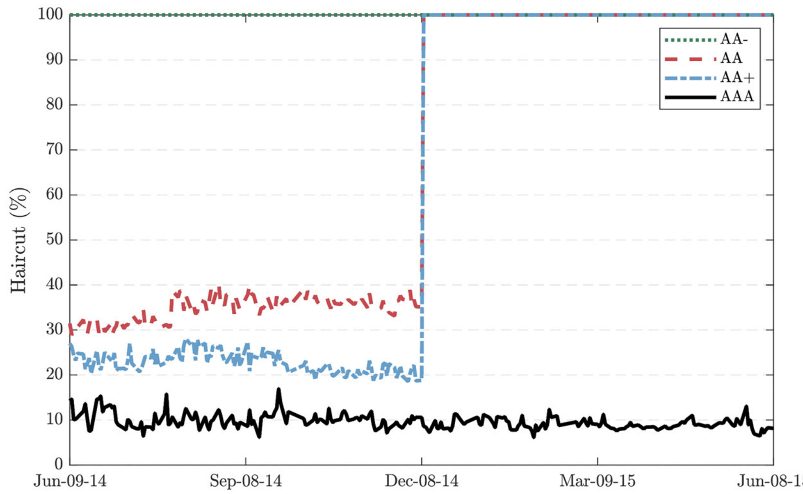

Figure 1. Average repo haircut on the exchange market. This figure plots the average daily haircut on the exchange market for dual-listed enterprise bonds in each of the four rating categories. The sample period is June 9, 2014 to June 8, 2015.

municipal bonds and to reclassify existing MCBs to bonds with/without full government support.

The CSDC and the policy shock. Under the broad agenda of "reining in local government debt," various layers of Chinese financial regulators, including the CSDC, had been coordinating to support Beijing even *before* the release of Doc. 43. MCBs were popular on the exchange market, due to their low perceived credit risk and relatively high pledgeability, due to transparent conversion rates published by the CSDC. Starting in May 2014, the CSDC disqualified a small list of AA+ and AA bonds as collateral for repo transactions on the exchange market; see Section II.A for details. It is important to note that the CSDC retained great discretion in deciding the exact composition of these blacklists. Not surprisingly, these small-scale and often idiosyncratic regulatory moves triggered little market-wide response from financial investors; see Section III.A for their market reactions.

To curb the demand of MCBs in a more effective way, the CSDC decided to slash the conversion rates for all enterprise bonds with ratings below AAA. After hours on December 8, 2014, the CSDC issued "Circular on Relevant Measures for Strengthening Risk Management of Enterprise Bond Repo" to immediately disqualify sub-AAA enterprise bonds from being used as collateral in repo transactions in both the Shanghai and Shenzhen exchanges. In this document, the CSDC raised concerns about the risk of enterprise bonds that were mainly issued by local governments, echoing Doc. 43 issued two months earlier by the State Council of China.

As shown in Figure 1, the policy change led to immediate and significant increases in the haircuts for AA+ and AA enterprise bonds on the exchange. In contrast, the average haircut for AAA bonds on the exchange remained steady. Since AA− bonds were already ineligible as repo collateral on the exchange six months before the event, their haircuts were also unaffected by the new policy.

This sudden move by the CSDC, which affected about 80% of enterprise bonds, surprised exchange market investors to a large extent. Widely known as the "Zhong-Zheng-Deng" event among Chinese investors, bond market participants viewed this policy tightening as a "black swan" event, as they had instead expected a tightening in the competing interbank market instead around that time.[11] We analyze market reactions in Section III.A, but as an initial piece of preliminary supporting evidence, we do not observe any bond rating changes in our sample during the [−1, 0] month window, suggesting that market participants did not "expect" this policy shock that targeted on rating directly.

Another unique feature of this policy is worth emphasizing. To minimize the potential negative market impact, regulators drafted the policy change on December 8, 2014 in such a way that it only applied to bonds that had not been used as collateral yet; roughly one third of the outstanding enterprise bonds were pledged as collateral at the time of the policy shock. In other words, there was no immediate deleveraging pressure for investors who had already taken a leveraged position in these affected bonds, although the secondary market spot prices for the affected bonds are expected to have decreased immediately due to their fully eliminated pledgeability. This makes our policy shock particularly suitable to study the value of pledgeability as it is free from temporary fire sale pressure due to forced deleveraging. It is worth noting that a more general form of "fire sale," which reflects certain portfolio rebalancing activities in response to shocks, could still occur. For example, an investor might sell affected bond holdings given their lower pledgeability, or her bond holdings more broadly if she interprets the policy shock as a signal of weaker fundamentals. The first channel is what this paper tries to capture (see Section II.B). With respect to the second channel, as we explain in the next section, by exploiting dual-listed bonds, our estimation strategy is not affected by such fundamental shocks.

II. Data and Economic Framework

In this section, we describe the data and then lay out our theoretical framework. Guided by the theory, we examine the empirical properties of the exchange premium, which is defined as the price gap for dual-listed enterprise bonds on the exchange and interbank markets.

[11] It is well-documented that the local government debt problem is rooted in commercial banks (Bai, Hsieh, and Song (2016), Chen, He, and Liu (2020)), which are active only in the interbank market. Recall that almost all enterprise bond issuances were initially placed in the interbank market which was still the "home" market for enterprise bonds (Section I.A). Indeed, just one week before the policy shock we study, the National Association of Financial Market Institutional Investors (NAFMII, the regulator of the interbank market) issued a notice on December 1, 2014 pressing MCB underwriters to strictly abide by Doc. 43.

A. Data and Variable Construction

We obtain enterprise bond characteristics and exchange-market trading data from Wind Information Co. (WIND). Data on interbank market trading are from CFETS, the interbank market's trading platform. Our sample period is June 9, 2014 to June 8, 2015, a 12-month window around the event date. During this sample period, our dual-listed enterprise bond sample covers 82.7% of the total trading volume of all enterprise bonds (78.3% in terms of outstanding notional), or 22.0% of the total volume of all corporate bonds (20.8% in terms of outstanding notional). Table I summarizes our sample coverage.

For each bond-day observation, we obtain the conversion rates quoted by the exchange and convert them into haircuts based on equation (1). We use the RMB volume-weighted average clean prices to calculate enterprise bond yields, which are winsorized at the 0.5% and 99.5% levels. The credit spreads of the enterprise bonds are calculated relative to the matched China Development Bank (CDB) bond yields following the procedure of Ang, Bai, and Zhou (2023) and Liu, Lyu, and Yu (2017).[12]

Bond rating information comes from WIND. Rating agencies provide ratings at the bond as well as issuer level. Our study focuses on four rating categories: AAA, AA+, AA, and AA−, with the AA− category including AA− and below.[13] Following the industry standard, we take the lowest rating if a bond receives multiple ratings (Amstad and He (2020)). As mentioned in Section I.D, a small list of AA+ and AA bonds had been disqualified as collateral for repo transactions on the exchange market before the December 8, 2014 policy shock. To the extent that we link ratings to pledgeability, we reclassify these AA+ and AA bonds to be grouped with AA− ratings. More specifically, on May 29, 2014, the CSDC disqualified a bond's repo eligibility if its *issuer* rating was below AA or had an AA issuer rating but *a negative outlook*, with some degree of discretion determined by the CSDC. The CSDC issued five lists of affected bonds that were disqualified due to low issuer ratings. From all five of these lists, a total of 109 enterprise bonds (84.4% of them MCBs) were disqualified as collateral for repo transactions even though their bond ratings were AA or above. We hand collected such information based on the detailed CSDC announcements and adjusted bond ratings of these affected bonds to AA− after their first inclusion date. See Section A in the Appendix and Table AII for details.

We further exclude bonds that (i) were issued after the policy event to rule out the possibility that issuers may engage in rating shopping (for AAA ratings), (ii) experienced rating changes after the event to reduce contamination

[12] The CDB yield curves are commonly used as the risk-free benchmark by the bond market participants in China due to its state-backing, non-tax-exempt status (unlike Treasuries), and superior liquidity. We first compute the implied prices of the CDB bonds with matching cash flows, that is, the net present value of the same cash flows as promised by an enterprise bond discounted at the CDB bonds' zero-coupon rates, and then calculate the matching CDB yields. All of our empirical results are robust to using Treasury yields instead of CDB yields.

[13] Bonds with ratings below AA− are extremely rare in China during our sample period; on the day of the policy shock there was only one bond rated A+ out of the full sample of 1,613 enterprise bonds.

caused by (potentially endogenous) changes in post-event rating grouping, and (iii) had matured before the event date. These three filters affected our sample slightly, removing 32, 41, and 4 bond-day observations for 15, 6, and 2 unique bonds, respectively.

As the main empirical object, we construct "exchange premium" as the yield difference for the same bond between the two markets. Specifically, the exchange premium measure, $EXpremium_{ijt}$, is defined as the cross-market difference in the yields for bond i from rating category j on day t,

$$EXpremium_{ijt} = yield_{ijt}^{IB} - yield_{ijt}^{EX}, \tag{2}$$

where $j \in$ {AAA, AA+, AA, AA−}. A positive exchange premium means the price of a bond is higher on the exchange than on the interbank market.

We compute the exchange premia for all dual-listed enterprise bonds that satisfy the simultaneous trading criterion defined as follows (see Section B in the Appendix for more details). On a given day t when there is at least one transaction for a bond on one of the two markets, we use the nearest transaction data from the other market within the window $[t-2, t]$ to form a pair. We refer to this sample as the simultaneous trading sample, which contains about 10,000 bond-day observations for 978 unique bonds. The simultaneous trading sample covers 54% of all dual-listed bonds in our sample period (Table I).[14] The exchange premium for each pair is calculated as the yield on the interbank market minus the exchange market counterpart. In a robustness test, we also repeat our empirical exercises with the smaller sample of observations using the stricter same-day trading criterion.

We also conduct analysis on an alternative spread measure, namely, the spread over matched AAA, which is the difference between the credit spreads of AA+/AA-rated dual-listed enterprise bonds and those of the matched AAA-rated bonds but with similar pre-shock haircuts and yields, based on their trading prices on the exchange market (see Section IV.C for details).

Other market variables from WIND include the 10-year spot yield of CDB bonds, the spread between the one-day Shanghai exchange repo rate and the one-day Shanghai Interbank Offering Rate (SHIBOR), the term spread between the 10-year Treasury yield and the three-month Treasury yield, and aggregate stock market returns.

Table II reports summary statistics for the simultaneous trading sample, including summary statistics for exchange premia, conversion rates, and haircuts before and after the policy shock (see Table AIII in the Appendix for detailed variable definitions). The summary statistics for the same-day trading sample are reported in Internet Appendix Table IA.I.

[14] Since our observations are at the bond-day-rating level, we treat the same bond with different ratings at two points in time as different bonds for the purpose of reporting the summary statistics in this table. The number of unique dual-listed enterprise bonds is 1,771 and the simultaneous trading sample (978 unique bonds) covers 55.2% of all these dual-listed enterprise bonds. Among all bonds in the simultaneous trading sample, 851 are MCBs.

Table II

Summary Statistics

This table reports summary statistics for the simultaneous trading sample from June 9, 2014 to June 8, 2015. The table presents number of observations, mean, standard deviation, 10th percentile, median, and 90th percentile. Panel A presents summary statistics for key variables. Panel B presents summary statistics for exchange premia by rating. Panel C presents summary statistics for haircuts by rating.

	N	Mean	*SD*	P10	Median	P90
Panel A: All Variables						
EX premium	10,235	−0.04	0.48	−0.63	−0.02	0.50
EX premium$_{pre}$	5,069	0.07	0.40	−0.39	0.04	0.55
EX premium$_{post}$	5,166	−0.15	0.53	−0.76	−0.12	0.42
Haircut	10,235	68.64	38.01	15.77	100.00	100.00
Haircut$_{pre}$	5,069	42.32	32.60	8.12	30.90	100.00
Haircut$_{post}$	5,166	94.48	21.74	100.00	100.00	100.00
Conversion	10,235	33.24	40.37	0.00	0.00	88.00
Conversion$_{pre}$	5,069	61.22	34.79	0.00	73.00	97.00
Conversion$_{post}$	5,166	5.79	22.81	0.00	0.00	0.00
IB spread	10,235	2.41	0.79	1.42	2.44	3.40
EX spread	10,235	2.45	0.86	1.34	2.51	3.48
Matched spread	9,940	0.55	0.68	−0.15	0.47	1.38
Matched spread$_{pre}$	2,227	0.06	0.16	−0.13	0.04	0.27
Matched spread$_{post}$	7,713	0.69	0.71	−0.16	0.70	1.49
Matched spread$_{AA+}$	7,570	0.54	0.67	−0.14	0.46	1.37
Matched spread$_{AA}$	2,370	0.56	0.71	−0.16	0.48	1.43
$\Delta P^{high-low}$	10,235	0.44	1.44	−0.21	0.00	1.83
Maturity	10,235	5.10	1.61	2.97	5.26	6.72
Turnover	10,235	0.08	0.08	0.02	0.05	0.17
Market price	10,235	104.97	5.76	100.36	105.36	110.72
Volatility	10,235	0.02	0.02	0.00	0.01	0.04
CDB$_{spot}$	10,235	0.04	0.01	0.04	0.04	0.05
Term spread	10,235	0.01	0.00	0.00	0.00	0.01
GC001−SHIBOR	10,235	0.02	0.04	−0.00	0.01	0.06
Ret$_{stock}$	10,235	0.00	0.02	−0.01	0.00	0.02
Panel B: Exchange Premia by Rating (%)						
AAA	477	0.10	0.37	−0.37	0.03	0.59
AA+	3,077	0.01	0.48	−0.55	0.01	0.55
AA	5,162	−0.09	0.50	−0.71	−0.05	0.47
AA−	1,519	−0.02	0.45	−0.49	−0.01	0.47
Panel C: Haircuts by Rating (%)						
AAA	477	11.26	10.03	5.48	6.81	26.28
AA+	3,077	62.32	40.58	7.44	100.00	100.00
AA	5,162	68.49	35.46	29.81	100.00	100.00
AA−	1,519	100.00	0.00	100.00	100.00	100.00

B. The Economic Framework

Suppose a one-period corporate bond i with unit face value has rating j and random payoff $\widetilde{Y}_{i,t+1}$ at time $t+1$ (maturity). It is traded on two markets indexed by $m \in \{EX, IB\}$, but market segmentation prevents investors from buying this bond on one market and selling it on the other, a point we come back to shortly. Let h^m_{ijt} and p^m_{ijt} be the haircut per unit of face value and the price of the bond in market m at time t, respectively. We discuss the possibility of investor-dependent haircuts later in footnote .

Consider any marginal investor in market m, denoted by $I_m \in \mathbb{I}_m$, where $\mathbb{I}_m$ is the set of all marginal investors in market m. The investor chooses optimal consumption and asset holdings while facing a collateral constraint. The Euler equation for this investor reads[15]

$$p^m_{ijt} = \underbrace{\mathbb{E}_t[\widetilde{M}^{I_m}_{t+1}\widetilde{Y}_{i,t+1}]}_{\text{fundamental value}} + \underbrace{\overbrace{\lambda^{I_m}_t}^{\text{value of pledgeability}} \times \overbrace{\left(1 - h^m_{ijt}\right)}^{\text{pledgeability units}}}_{\text{pledgeability premium}}. \quad (3)$$

The first term on the right-hand side of equation (3) is standard: $\widetilde{M}^{I_m}_{t+1}$ is the pricing kernel for this marginal investor, which is determined by the ratio of marginal utility of consumption between $t+1$ and t; together, the first term captures the fundamental value of the bond from the perspective of the investor group I_m.

The second term on the right-hand side of equation (3), which is related to "specialness" in Duffie (1996), captures the pledgeability premium due to the collateral constraint. It is the product of the value of pledgeability $\lambda^{I_m}_t$ and the bond's degree of pledgeability $1 - h^m_{ijt}$, that is, the amount financed per unit of face value. The value of pledgeability $\lambda^{I_m}_t$, which represents the shadow value of relaxing the collateral constraint, is the Lagrange multiplier associated with the collateral constraint scaled by the marginal utility of the investor at time t.

Several points are worth emphasizing. First, equation (3), which is based on a standard optimal portfolio decision, applies to both markets. Our framework therefore matches well with Chinese financial institutions that actively trade in both the exchange and interbank markets and are constantly engaged in asset allocation decisions with various layers of risk management mandates, for example, exposure to interest rate risk, dollar duration, and value-at-risk.

Second, our theoretical framework allows for multiple marginal investors in each market. As explained in Section I.B, different investors participate in the two largely segmented bond markets in China. Using the notation from

[15] The investor chooses consumption c_t, collateralized borrowing B_t (or riskless saving if $B_t < 0$), and defaultable bond holding π^m_{ijt} in the two markets to maximize time-separable utility, $\mathbb{E}[\sum_{t=0}^{\infty} \beta^t u(c_t)]$. In each period, she faces a standard budget constraint plus a collateral constraint $B_t \leq \sum_{m\in\{EX,IB\}}(1 - h^m_{ijt})\pi^m_{ijt}$. The first-order condition with respect to π^m_{ijt}, if the solution is interior, implies equation (3).

our setting, $\mathbb{I}_{EX} = \{Retail, NBFI\}$, that is, wealthy retail investors and NBFIs, which include securities firms, mutual funds, and insurance companies, all of whom are sophisticated institutional investors, are marginal in the exchange market, while $\mathbb{I}_{IB} = \{Bank, NBFI\}$, that is, commercial banks and NBFIs, are marginal in the interbank market. Thus, NBFIs are common marginal investors in both markets. We offer empirical evidence for this point in the Internet Appendix IA.I by showing that NBFIs kept positive holdings and actively traded throughout our sample period (i.e., both before and after the 2014 policy shock). From now on, we analyze equation (3) from the perspective of a representative NBFI investor.

Suppose that the representative NBFI investor has pricing kernel $\widetilde{M}_{t+1}^{NBFI}$ and scaled Lagrange multiplier λ_t^{NBFI}. Note that in a standard asset pricing framework both the pricing kernel and Lagrange multiplier are associated with the agent, not assets or markets. For clarity of exposition, in our main empirical analysis we assume that $\lambda_t^{NBFI} = \lambda$ is a constant within the event window; we leave discussion of time-varying λ_t^{NBFI} to Section IV.D.2. Then, equation (3) implies that the exchange premium in terms of the price differential for the same bond on the two markets is

$$p_{ijt}^{EX} - p_{ijt}^{IB} = \lambda\left(h_{ijt}^{IB} - h_{ijt}^{EX}\right), \tag{4}$$

where the asset fundamental component from equation (3), $\mathbb{E}_t[\widetilde{M}_{t+1}^{NBFI}\widetilde{Y}_{i,t+1}]$, drops out. We are interested in estimating the scaled Lagrange multiplier λ. Equation (4) shows that one can identify λ based on how the exchange premium in equation (2) changes in the data in response to relative changes in haircuts across the two markets. We discuss other economic factors further in Section IV.A.

C. Determinants of Haircuts and Exchange Premia

Before estimating the value of pledgeability, we first use kitchen sink regressions to examine how observed exchange premia and haircuts correlate with various bond- and market-level characteristics in the pre–policy shock period. This exercise has two goals. First, raw empirical patterns are important to inform us about how the two key variables—exchange premia and haircuts—are determined in the data. Second, in light of equation (4), we essentially use exchange-market haircuts to proxy for a bond's pledgeability differential across two markets to infer the value of pledgeability based on the OLS method. As discussed below in Section IV.B.3, which shows the full-sample OLS result, this approach suffers from certain endogeneity concerns, for example, unobservable but endogenous interbank haircuts changes. Nevertheless, this exercise provides a benchmark for our IV estimation, which exploits the policy shock as an instrument.

Exchange haircuts. We first examine the empirical pattern of exchange-market haricuts, which are inversely related to asset pledgeability. The exchange conversion rates published by the CSDC, which can map one-to-one to haircuts as shown in equation (1), are tightly linked to securities' credit ratings. The CSDC adopted a formula for how the conversion rates were set, which involves the bond's credit rating, market price, and volatility. However, the CSDC also made clear that the formula was only suggestive. By including an opaque term called "discount factor," the CSDC effectively reserved discretion in setting the conversion rate for each bond.

As shown in columns (1) and (2) of Table III, rating dummies explain 90% of the total variation in conversion rates, while a kitchen sink regression—including market prices, volatilities, and other bond/issuer characteristics—raises the R^2 only to 91%. There are many reasons why the CSDC relies primarily on credit ratings in setting conversion rates, chief among which are third-party objectiveness in credit risk assessment and poor secondary market liquidity. For the purpose of our study, the fact that bond haircuts largely depend on credit ratings implies that the policy shock that explicitly targeted AA+ and AA bonds will result in significant changes in exchange haircuts across bonds, that is, a strong first stage for the policy shock as an IV for the changes in exchange-market haircuts.

Exchange premia. Equation (4) suggests that, with common fundamentals, exchange premia should primarily reflect the differences in pledgeability premia in the two markets, after controlling for other nonfundamental factors, such as trade size and frequency. As shown in Table III, in both specifications (haircuts only in column (3) or including ratings and other potential determinants in column (4)) exchange premia are negatively related to the exchange haircuts at the 1% significance level. This is consistent with exchange premia being driven by pledgeability, a premise that forms the basis of our economic framework in Section II.B.

Column (4) in Table III shows that bonds with higher prices, MCBs, shorter maturity, and higher turnover have larger exchange premia before the shock. It is reassuring that column (4) demonstrates that once we include exchange-market haircuts and relevant characteristics variables, ratings no longer possess additional explanatory power relative to the benchmark AAA group. Because we are exploiting a policy shock that directly targets bond ratings, one particular concern may be that our specification misses some omitted variables that significantly affect exchange premia and yet are captured by the categorical rating variables. Column (2) suggests that this is not the case.

III. The Policy Shock and Exchange Premia

The policy shock serves as the IV in our paper to estimate the value of pledgeability. In this section, we document the market reactions of exchange premia to the policy shock, together with those for other policy events.

A. Market Reactions to the Policy Shock

We first present evidence on market reactions that support the premise that the policy shock on December 8, 2014 is unexpected. We also compare them to

Table III

Determinants of Conversion Rates and Exchange Premia

This table reports regression results of dual-listed enterprise bonds' exchange market conversion rates (columns (1) and (2)) and exchange premia (columns (3) and (4)) on rating dummies and control variables. Age is the number of years for the issuer's first bond issuance, Nbond is the number of bonds issued by the issuer, and OTR is a dummy variable for on-the-run bond of the issuer. The sample period is June 9, 2014 to December 8, 2014. Heteroskedasticity-consistent standard errors clustered by week are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The standard error for AA− in column (1) is undefined because the conversion rates of AA− bonds are always zero.

	Conversion Rates		Exchange Premia	
	(1)	(2)	(3)	(4)
Haircut			−0.22***	−0.27***
			(0.03)	(0.05)
Dummy_{AAA}	89.40***	−40.76		
	(1.35)	(25.23)		
Dummy_{AA+}	79.40***	−49.10*		0.00
	(1.06)	(25.54)		(0.05)
Dummy_{AA}	66.92***	−60.20**		−0.04
	(0.72)	(25.29)		(0.05)
Dummy_{AA-}	0.00	−124.94***		0.04
	(−)	(24.76)		(0.08)
Market price		0.95***		0.02***
		(0.20)		(0.00)
Volatility		−20.36		−0.10
		(23.80)		(0.89)
MCB		−3.29**		0.10**
		(1.39)		(0.04)
Age		0.19		−0.02*
		(0.36)		(0.01)
Nbond		−0.34***		0.01**
		(0.11)		(0.00)
OTR		−1.72**		0.03
		(0.83)		(0.02)
Maturity		1.66***		−0.03***
		(0.32)		(0.01)
Turnover		−1.97		0.34***
		(4.22)		(0.11)
Size		4.11***		0.01
		(0.73)		(0.02)
Leverage		−16.24***		−0.09
		(3.56)		(0.07)
Issuance		1.40*		0.01
		(0.74)		(0.01)
CDB_{spot}		291.43***		7.08
		(96.20)		(4.36)
Term spread		539.71*		−22.55*
		(273.02)		(12.39)
GC001−SHIBOR		−7.47		−0.22
		(5.80)		(0.19)
Ret_{stock}		−5.23		−2.52*
		(33.92)		(1.27)
R^2	0.90	0.91	0.03	0.11
N	5,069	5,069	5,069	5,069

the market reactions to a series of blacklisting announcements and the release of Doc. 43 before the policy shock.

Market reactions to the policy shock. What are the reactions from both markets? As a first pass, we examine the average credit spreads for all dual-listed enterprise bonds in four rating categories around the event, across two bond markets. Due to illiquidity, these credit spreads are based on observed transactions that are not necessarily matched with the same bonds; the evidence here should therefore be interpreted with caution. We use the simultaneous trading sample in Sections III.B and III.C, as well as in Section IV where we conduct our formal IV regression–based empirical analysis.

As shown in Panel A, row "Event 12/8," of Table IV, the average credit spreads for AA+ and AA bonds on the exchange market jumped up on the event date by 62 bps and 38 bps, respectively, both significant at the 1% level. This is in sharp contrast to the market reactions on the interbank market where the average credit spreads for AA+ and AA bonds actually *fell* by 8 bps and 9 bps on the event date. For AAA bonds, event-day average credit spreads fell in both the exchange and interbank markets by 15 bps and 24 bps, respectively, while credit spreads of AA− bonds rose on both markets by 61 bps and 24 bps. The exchange market reaction of AA− bonds (61 bps) is large at first glance. In a relative sense, this is about 20% of AA− bonds' credit spreads, comparable to that of AA bonds (17%) and much smaller than that of AA+ bonds (37%). However, this market reaction was temporary; in a longer [−3, 3]-day window the exchange market reaction of AA− bonds decreased to 31 bps. More importantly, in this longer [−3, 3]-day window the interbank market reaction caught up (40 bps), suggesting that the market reactions on AA− bonds were likely driven by investors adjusting their assessments of these bonds' fundamentals.

These market reactions are consistent with the premise that the policy shock hit AA+ and AA− bonds on the exchange market particularly hard. The last two columns highlight these different reactions across the treatment (AA+/AA) and control (AAA/AA−) groups in two bond markets: the relative increase in credit spreads for treated bonds on the exchange market is 55 bps (significant at the 1% level) larger than that in the interbank market, while the increase is 31 bps but insignificant for control bonds.

Comparison with market reactions to other events before the policy shock. As mentioned in Section I.D, before the aggressive move by the CSDC on December 8, 2014, two sets of events were relevant to our study: the release of Doc. 43, which provided a legal framework for addressing China's local government debt problem, and the release of five blacklists of individual bonds denied from repo eligibility by the CSDC.

We follow a similar procedure as above to calculate market reactions to the official release of Doc. 43. Results are reported in Panel A, row "Doc. 43," of Table IV. Consistent with the view that Doc. 43 hit the enterprise bond market with an adverse fundamental shock by casting doubt on implicit guarantees, we find that overall credit spreads of our dual-listed sample on both markets rose across all rating groups, although none of these changes are statistically significant except for AAA bonds on the exchange market, but credit spreads

Table IV

Market Reactions to the Policy Shock and Other Events

This table reports the average market reactions to the policy shock and other events. Average one-day post-announcement changes in credit spreads are reported in Panel A. Average haircuts of an anonymous major financial institution on the interbank market six/one months prior to and after the policy shock are reported in Panel B. The policy shock was on December 8, 2014, the release of Doc. 43 was on October 2, 2014, and the five announcements were made on May 29, 2014, June 27, 2014, August 1, 2014, September 5, 2014, and November 3, 2014, respectively. Due to the lack of trades on September 30, 2014 before the National Holiday (October 1, 2014 to October 7, 2014), trades in the two-day window before the holiday are used to calculate the pre-Doc. 43 credit spreads. The post-pre credit spread difference between the interbank and the exchange markets for treatment and control groups is presented in the last two columns and estimated in a regression on $post_t \times \mathbb{1}_{IB}$ that includes the $post_t$ dummy, the interbank market indicator $\mathbb{1}_{IB}$, and $rating_j \times post_t$ fixed effects. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Market Reactions by Market and Rating (bps)

	EX				IB				IB−EX	
	AAA	AA+	AA	AA−	AAA	AA+	AA	AA−	AA+ & AA	AAA & AA−
Policy	−14.69	61.61***	37.64***	60.52***	−24.33	−7.97	−9.12	23.87	−55.31***	−31.23
Shock	(17.40)	(12.10)	(13.47)	(18.99)	(32.26)	(13.39)	(8.20)	(21.49)	(11.96)	(24.37)
Doc. 43	−17.97*	5.58	6.73	1.46	17.86	11.23	7.66	−11.29	4.24	8.49
	(10.51)	(9.07)	(12.25)	(11.75)	(19.33)	(12.35)	(9.46)	(23.93)	(10.99)	(17.98)
Five	−0.41	3.27	4.55	8.21	−4.42	8.23	4.86	−19.15	1.75	−11.19
Blacklists	(7.35)	(4.57)	(5.05)	(8.67)	(11.58)	(6.51)	(3.60)	(23.75)	(4.89)	(12.16)

Panel B: Haircuts on the Interbank Market (%)

Sample period	AAA	AA+	AA	AA−
June 9, 2014 to December 8, 2014	8.38	12.93	32.03	35.66
	(0.56)	(0.96)	(1.53)	(7.01)
December 9, 2014 to June 8, 2015	13.76	14.38	31.23	37.20
	(0.44)	(1.25)	(1.28)	(8.89)
November 9, 2014 to December 8, 2014	7.41	11.44	28.85	33.64
	(0.85)	(1.87)	(3.12)	(14.11)
December 9, 2014 to January 8, 2015	17.24	16.53	32.14	37.18
	(1.10)	(2.24)	(2.88)	(22.37)

for those bonds actually fell. The same exercise repeated for the five blacklist announcements, in Panel A, row "Five Blacklists," of Table IV, shows small and insignificant market reactions on credit spreads.[16]

[16] In this exercise, we exclude bonds that were directly affected by the announcements. For these affected bonds, on the exchange the market reaction is −12 bps (insignificant) for AA+ bonds and 20 bps (significant at the 5% level) for AA bonds, consistent with a lower pledgeability premium once blacklisted. It is difficult to calculate the interbank market reactions due to lack of liquidity. Detailed market reactions for each of the five announcements are reported in Internet Appendix Table IA.II, and results are similar for a wider event window (e.g., [−1, 1]-day window) in consideration of potential information leakage.

We emphasize that the exchange premia remained almost unchanged in response to both events. For instance, the last two columns in Panel A of Table IV report a small and insignificant one-day reaction of 4 bps (8 bps) for the exchange premia of AA+/AA (AAA/AA−) bonds following the release of Doc. 43. This is in stark contrast to the change in exchange premia observed for "Event 12/8," and is crucial to our empirical framework: unlike the December, 8 2014 policy shock that hit the "liquidity" of one market, Doc. 43 largely affected the fundamental of the asset—if there was any effect—and hence left exchange premia largely intact.

There are well-grounded reasons for the sharp contrast between the significant market reactions in response to the "Event 12/8" policy, which represents a regulatory measure that targeted one specific market, and the lack of reactions to the other events. With respect to Doc. 43, as mentioned in Section I.D, "local government debt" was a focal theme of the economic and political agenda in 2014, and therefore Chinese investors may have anticipated the release of Doc. 43. In addition, this document likely did not materially alter market expectations about implicit government support for existing MCBs.[17]

Regarding the lack of market reactions to the five blacklists, we stress that it is routine for various bureau-level regulators in China (e.g., the CSDC) to issue small-scale notices occasionally;[18] and there is quite a difference between blacklisting individual bonds with inferior issuer ratings, a practice that seems more idiosyncratic, and a sweeping ban of pledgeability for AA+ and AA− bonds, which is more systematic. The policy shock in our study was therefore likely to be unexpected, as supported by the sharp market reactions in the data.

Haircut reactions on the interbank market. In contrast to the dramatic changes in haircuts on the exchange, there were only relatively small changes in the interbank haircuts during the same period. Based on a sample of repo transactions conducted by an anonymous major financial institution in China, Panel B of Table IV reports the average haircuts for enterprise bonds on the interbank market during the one-month and six-month windows before and after December 8, 2014. Based on the six-month window that is the same as our estimation window, the average interbank haircuts for the AA+ and AA group were essentially unchanged. The average interbank haircut for the AAA group did rise more, from 8.4% to 13.8%, but this 5.4-percentage-point increase only amounts to a 5.9% reduction in the degree of pledgeability, which was

[17] For the former view, recall that Chinese regulators started the pilot municipal bond program in May 2014 as mentioned in Section I.D. The latter view is supported by several contemporaneous industry research reports on the impact of Doc. 43, which argued that, at least in the short run, the emphasis on a stable transition meant that implicit government support for existing MCBs would likely continue. In fact, it took six more years (until October 2020) for the first MCB default—two private placement notes issued by Shenyang Shengjing—to finally take place.

[18] During the six-month pre-event period (June 9, 2014 to December 8, 2014), 35 circulars were issued by bureau-level (Ting-Ji in Chinese) financial market regulators in China, among which 11 were issued by CSDC. We do not see any significant market reaction across both markets on these circular announcement days.

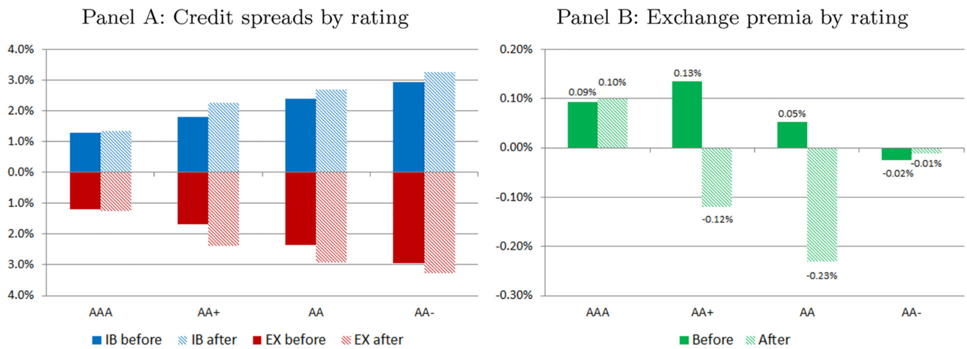

Figure 2. Exchange premia six months before and after the December 8, 2014 event. This figure plots the average credit spreads for each of the four rating categories on the interbank market and the exchange market (Panel A) and the average exchange premia (Panel B).

originally $1 - 8.4\% = 91.6\%$. In the one-month window, the tightening of collateralized funding in the interbank market is more evident, consistent with some temporary liquidity effects from the policy shock. For this reason, we examine the sensitivity of our estimates to the exclusion of the first post-event month. We discuss these issues in more detail in Section IV.B.1.

In addition, the release of Doc. 43 did not cause any changes in the interbank market haircut. According to the same proprietary data source that we use in Panel B of Table IV, the average interbank market haircut barely moved across all ratings for the one-month subperiod before and after Doc. 43: the average haircut of the four ratings (high to low) is 7.73%, 11.36%, 30.81%, and 30.32% for the one-month subperiod before the release of Doc. 43 on October 2, 2014, and is 8.15%, 13.13%, 30.54%, and 31.87% for the one-month subperiod after. Consistent with the market reactions of credit spreads, the lack of interbank haircut reactions following the release of Doc. 43 suggests that investors either anticipated the release of Doc. 43 or remained optimistic on the long-standing implicit guarantees at least for existing MCBs. To summarize, Doc. 43, if anything affecting enterprise bonds, should be a fundamental shock that hit both markets.

B. Exchange Premia across Ratings

We now examine the changes in exchange premia around the policy shock. Across four ratings, we first plot the average credit spreads on the two markets (Panel A of Figure 2) and the average exchange premia (Panel B of Figure 2) in the six-month window prior to the policy shock. We observe that AAA, AA+, and AA bonds enjoy positive exchange premia of 9 bps, 13 bps, and 5 bps, respectively, while there is a negative exchange premium, or in other words an exchange discount, of −2 bps for AA− bonds.

The pattern of average exchange premia across ratings is related to how pledgeability differs on the two markets. On the exchange, the pledgeability of a bond is determined solely by its haircut, which largely hinges on bond rating as shown in Section II.C. In addition, the conversion rates, with a one-to-one relation with haircuts as shown in equation (1), set by the CSDC are nondiscriminatory to all exchange investors.

Bond haircuts on the interbank market depend on ratings as well, as shown in Panel B of Table IV. However, even for the same bond, its haircut can vary significantly across counterparties. Large state-owned banks receive favorable haircuts, while NBFIs and smaller banks often complain about the difficulty of using even AAA bonds as collateral for repo transactions. Thus, although AAA bonds receive an average interbank haircut (about 8%, see Panel B of Table IV) that is lower than their exchange one (about 10%, see Figure 1), AAA bonds are actually more pledgeable on the exchange from the perspective of typical NBFIs. Furthermore, due to tighter financial constraints, NBFIs should value asset pledgeability more than large commercial banks. These factors contribute to a higher valuation for AAA bonds on the exchange relative to that on the interbank market, and hence a positive exchange premium. On the other end of the rating spectrum, AA− bonds never had pledgeability on the exchange, while in the interbank market OTC-based bilateral bargaining allows some large players, for example, state-owned institutions, to borrow against AA− bonds. Panel B of Table IV shows an average interbank haircut of 36% for AA− bonds for the anonymous institution. This explains a negative exchange premium for AA− bonds of −2 bps at the level of 10% significance. These observed patterns before the policy shock are consistent with our hypothesis of exchange premia being driven by the bond pledgeability (see Section II.B).

Since the policy shock in question sharply affects the rating-haircut relationship as shown in Figure 1, we expect corresponding changes in rating-dependent exchange premia afterward. Panel B of Figure 2 shows that exchange premia did indeed turn negative for bonds with AA+ and AA ratings, consistent with these bonds losing their pledgeability edge on the exchange. In contrast, exchange premia did not change much for AAA bonds (9 bps before versus 10 bps after) and rose slightly for AA− bonds (−2 bps before versus −1 bps after).

To formally examine the significance of changes in exchange premia post-policy shock, we first average daily exchange premia by rating and then test for statistical significance of the changes in exchange premia based on Newey-West standard errors with 10 lags. This method allows us to account for both cross-correlational and time-series correlation (see, e.g., Bertrand, Duflo, and Mullainathan (2004)). The changes in exchange premia are significant at the 1% level for AA+ and AA bonds, but insignificant for AAA and AA− bonds.

C. Dynamic Treatment Effects of the Policy Shock

We now study the dynamics of policy impact in a more formal regression-based approach. Let D_{jt} be the dummy variable for the treatment-group rating categories in the post–policy shock period, that is,

$$D_{jt} = \begin{cases} 1, & j \in \{\text{AA+}, \text{AA}\} \quad \& \quad t > 12/08/2014 \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

To ensure a sufficient number of observations for each rating group, we divide our sample period into 14 subperiods (with 28 calendar days or four weeks in each subperiod), which are indexed by k, with $k \in \{-6, \ldots, 0, 1, \ldots, 7\}$. The dummy variable D^k_{jt} equals 1 for the treatment group bonds $j \in \{AA+, AA\}$ in the subperiod $k > 0$, and 0 otherwise; $k = 0$ indicates the subperiod right before the policy shock. We run the following standard regression to obtain the policy's dynamic treatment impact, which helps us assess the key identification assumption of a common trend shared between treatment and (either one of) control groups:

$$EXpremium_{ijt} = \sum_{k=-6}^{7} d_k D^k_{jt} + a_i + b_j + c_t + X'_{it}e + u_{ijt}\,. \tag{6}$$

In equation (6), we include bond and rating fixed effects, as a bond's rating may change over time. We also add weekly time fixed effects, as daily fixed effects are too stringent given the low frequency of bond trading in our sample. We also include daily market-level controls including CDB spot rates, term spreads, the spread between the one-day exchange repo rate and interbank lending rate, and stock market returns. Because the policy hit the exchange during after-hours on Monday (December 8, 2014), we define weekly fixed effects based on the "event week," that is, the seven-day interval from Tuesday to the following Monday. Four bond-level time-varying controls, namely, time-to-maturity, turnover, price, and volatility, are also included.

Figure 3 shows the point estimate, d_k, of each subperiod and the associated 95% confidence interval by normalizing the coefficient immediately before the event date to zero (i.e., $d_0 = 0$). As Panel A of the figure shows, the average exchange premia for the treated AA+/AA and control AAA/AA− bonds share a common trend before the policy shock. The diff-in-diff coefficients before the event are insignificantly different from the one immediately before the event. After the event, exchange premia for the treated group become significantly lower relative to the control group. Consistent with Figure 2, the gap ranges between −16 and −36 bps and remains significant half a year later.

We repeat the above exercise for two different control groups, in particular, excluding AAA or AA− bonds. We find quantitatively similar results as reported in Panels B and C of Figure 3. Both panels with low- and high-rating control groups show insignificant pre-event trends, suggesting that the common trend assumption largely holds in our study.

We stress that Figure 3 rules out many alternative mechanisms in which the policy change represents some aggregate fundamental shock to which the treatment and control groups differ in their sensitivities. The implied

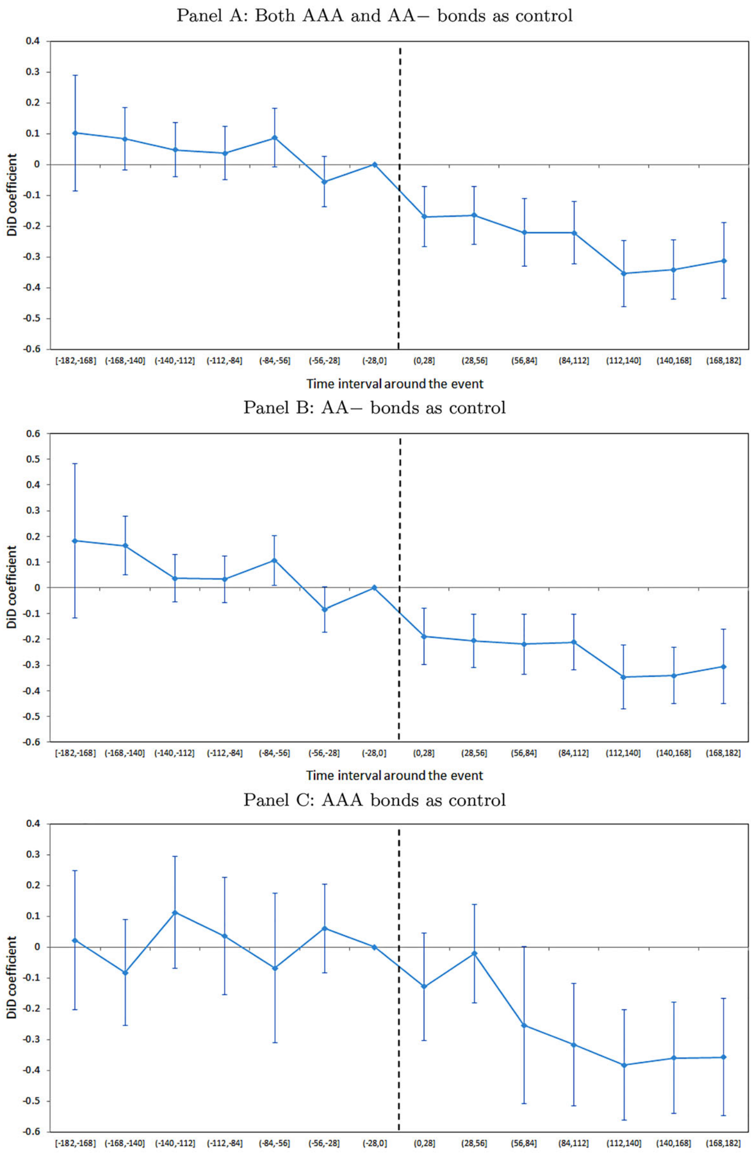

Figure 3. Diff-in-diff estimation of exchange premia. This figure plots the estimated coefficients $\hat{d_k}$ along with their confidence intervals calculated from heteroskedasticity-robust standard errors in the diff-in-diff specification of equation (6). The point estimate immediately before the event date is normalized to zero (hence a zero standard error). The dotted line indicates the event on December 8, 2014. The sample period is June 9, 2014 to June 8, 2015, which is divided into 14 28-day subperiods. Event-week fixed effects, where a week is defined as Tuesday to the following Monday, are included. Panel A corresponds to the control group consisting of both AAA and AA− bonds, and Panel B (C) to the control group consisting of only AA− (AAA) bonds. (Color figure can be viewed at wileyonlinelibrary.com)

responses under such mechanisms tend to be monotonic in ratings, which are not what the data show: relative to the middle-rating treatment group, Figure 3 shows that exchange premia of AA− and/or AAA bonds dropped in response to the policy shock.[19]

IV. Estimating the Value of Pledgeability

We present the standard 2SLS estimation procedure in this section. After revisiting the theoretical framework, we explain the empirical design. We then estimate the value of pledgeability based on two different methods, both of which use the policy shock as an instrument for asset pledgeability changes.

A. Economic Framework Revisited and Research Design

In the economic framework that we lay out in Section II.B, the NBFIs' Euler equation (3) implies that the exchange premium satisfies equation (4), which is reproduced here:

$$p_{ijt}^{EX} - p_{ijt}^{IB} = \lambda\left(h_{ijt}^{IB} - h_{ijt}^{EX}\right).$$

We aim to estimate λ that captures the funding constraint faced by the common marginal NBFI investors.

A couple of points are worth noting before we proceed to estimation. First, in deriving equation (4), we have been assuming that market segmentation completely prevents investors including the NBFIs from arbitraging away the exchange premium. In Section I.B, we discuss in detail the significant arbitrage frictions—in particular the long settlement delays in the process of transferring custody across the two markets. Nonetheless, at least in theory, arbitrage forces tend to bring the exchange premium inside a certain arbitrage bound, which could affect our estimation. We discuss the potential implication in Section IV.B.4.

Second, we stress the significance of NBFIs as common marginal investors for our study. They help make our empirical design robust to the presence of noncommon investors, including retail investors in the exchange market and commercial banks in the interbank market, and their reactions to the policy shock, regardless of whether they are fundamental-driven or not.

To see this, suppose that retail investors were previously less informed about the risks of AA-rated enterprise bonds than institutional investors and were

[19] Figure A3 in the Appendix also shows the raw time series of average exchange premia without any control for three rating groups: AAA, AA+/AA, and AA−. A qualitatively similar pattern obtains: the treatment shares a similar trend with both the higher and lower rating groups before the event, treated AA+/AA bonds fell while control groups rose in response to the policy shock, and the three groups return to a similar trend after the shock. The advantage of the regression-based approach is that the added fixed effects and controls not only absorb the aggregate trend, but also address the concern of changing bond characteristics before and after the event. For robustness, we present an alternative version of Figure 3 and Figure A3 in the Appendix based on the sampling frequency of 14 days in Figures IA.4 and IA.5 in the Internet Appendix.

awakened by the policy shock. This could lead them to revise downward their beliefs on AA bonds and sell them. In response to a depressed price in the exchange market, NBFIs will start buying the affected bonds in this market. Such purchases, if significant enough, could change the NBFIs' pricing kernel that applies to both markets,[20] which could lead them to sell their AA holdings in the interbank market at the same time. The NBFIs would keep adjusting their holdings until their Euler equations are restored in both markets. As a result, it is easy to see from equation (4) that the reactions of the retail investors would not have affected the exchange premium before or after the policy shock.

The remainder of this section carries out two empirical approaches to estimate the value of pledgeability based on equation (4). As the main result of this paper, the first strategy exploits the exchange premium of simultaneously traded bonds. In addition, to address the potential downward bias of exchange-premium-based estimators due to cross-market arbitrage, we consider another diff-in-diff estimation using nontreated AAA enterprise bonds with matched pre-event characteristics as controls. Because AAA-matched estimates are likely upward biased under almost all plausible mechanisms that could contaminate the identification, the two sets of estimates together provide a range for the magnitude of the value of pledgeability in the context of Chinese corporate bond markets.

B. Pledgeability and Asset Prices: Exchange Premia

In this section, we estimate the shadow cost of capital using exchange premia, based on a standard 2SLS estimation procedure.

B.1. 2SLS Estimation Procedure

Equation (4) lays the foundation for us to empirically estimate the value of pledgeability λ, and we have shown that equation (4) is robust to market reactions of noncommon investors, that is, retail investors in the exchange market and banks in the interbank market, to the policy shock. Nevertheless, factors besides changes in pledgeability, such as market liquidity, could affect bond pricing in each market. Although the simple model above does not consider these factors, we summarize them in reduced form by adding a residual term μ_{ijt}^{m} to Euler equation (3). The exchange premium in equation (4) then becomes

$$p_{ijt}^{EX} - p_{ijt}^{IB} = \lambda\left(h_{ijt}^{IB} - h_{ijt}^{EX}\right) + \mu_{ijt}^{EX} - \mu_{ijt}^{IB}. \tag{7}$$

[20] The NBFIs' scaled Lagrange multiplier λ_t could change as well, a concern we address later in Section IV.D.2. However, any equilibrium effects of such portfolio rebalancing are likely to be quite small, since retail investors only held 0.6% of enterprise bonds on the exchange market by 2014, compared to 18% for securities firms. Also, in this example we are implicitly assuming that NBFIs are buying when retail investors are selling on the exchange market; the logic is the same if NBFIs are also selling.

We make two additional assumptions in estimating λ from equation (7). First, we assume that μ_{ijt}^m, which captures nonpledgeability-related liquidity effects, satisfies

$$\mu_{ijt}^m = \mu_{ijt} + \mu_i^m + \mu_j^m + \mu_t^m + \epsilon_{ijt}^m, \quad (8)$$

where ϵ_{ijt}^m are independent and identically distributed across bond, rating, and time. The assumption in equation (8) rules out rating-time variation in the residuals that differ across the two markets. One mechanism that potentially violates this assumption is a market-specific flight-to-quality effect, in which the policy shock might trigger the purchase of high-quality AAA bonds in the two markets to a different degree. We discuss the issue of market-specific flight-to-AAA in more detail in Section IV.B.4. Another potential concern is that retail investors may panic and sell in the exchange.[21] As discussed in Section II.B, this concern is addressed by having NBFIs as common marginal investors.

Next, since we do not directly observe the haircuts on the interbank market, we follow the spirit of equation (8) and assume that the interbank haircuts satisfy[22]

$$h_{ijt}^{IB} = h_i^{IB} + h_j^{IB} + h_t^{IB}, \quad (9)$$

that is, any time-variation in haircuts on the interbank market is common across bonds with different ratings. Consistent with this assumption, the interbank haircuts of enterprise bonds in the four rating groups appear to have largely experienced a parallel shift in their haircuts after the policy shock (Panel B of Table IV). Although the average interbank haircuts for AAA bonds rose relatively more than the other rating categories, especially in the first month after the policy shock, the economic magnitude of the difference is relatively small.[23] Nevertheless, we connect this rise of interbank AAA haircuts to a potential flight-to-quality effect in Section IV.B.4, and explain why this contributes to a potential downward bias of our estimate $\hat{\lambda}$.

[21] As mentioned in Section I.D, the new CSDC policy did not force investors to delever—it still allowed them to roll over all existing repos on the exchange. Hence our empirical setting should be free from the textbook version of "fire sales" of AA/AA+ bonds.

[22] Given the OTC nature of the interbank market, the interbank haircut could be investor-specific. Because we focus on NBFIs only, our setting assumes that NBFIs as a group receive similar haircuts in the interbank market.

[23] Recall that equation (4) shows that the degree of pledgeability depends on $1 - h$, which captures the funding available per unit of bond. Thus, if we want to gauge the *relative* change in pledgeability, we should normalize the change in haircuts by $1 - h$, that is, $(h_{post} - h_{pre})/(1 - h_{pre})$. An increase in AAA haircut from 8.38% to 13.76% therefore leads to a 5.9% reduction in pledgeability.

Denoting $\Delta\mu_u \equiv \mu_u^{EX} - \mu_u^{IB}$, where $u \in \{i, j, t\}$, the price differential can be expressed as

$$p_{ijt}^{EX} - p_{ijt}^{IB} = \underbrace{-\lambda \cdot h_{ijt}^{EX}}_{\text{identifies } \lambda} + \underbrace{\left(\lambda \cdot h_i^{IB} + \Delta\mu_i\right)}_{\alpha_i\text{: bond fixed effect}} + \underbrace{\left(\lambda \cdot h_j^{IB} + \Delta\mu_j\right)}_{\alpha_j\text{: rating fixed effect}} + \underbrace{\left(\lambda \cdot h_t^{IB} + \Delta\mu_t\right)}_{\alpha_t\text{: time fixed effect}}. \tag{10}$$

In other words, the value of pledgeability, λ, can be identified from the responses of exchange premia to the rating-time-dependent haircuts on the exchange market by a standard 2SLS regression. More specifically, recall that for each bond i with rating j, we construct its exchange premium $EXpremium_{ijt}$ on some trading day t, as in equation (2), where D_{jt} is the dummy variable for the treatment group in the post-policy shock period in equation (5). To use D_{jt} as an instrument to estimate the impact of changes in haircuts on the exchange premium, we estimate the first stage as

$$haircut_{ijt} = \beta D_{jt} + \rho_i + \kappa_j + \eta_t + X_{it}'\gamma + \upsilon_{ijt}\,. \tag{11}$$

The second stage of the 2SLS is

$$EXpremium_{ijt} = \delta\,\widehat{haircut}_{ijt} + \alpha_i + \alpha_j + \alpha_t + X_{it}'\theta + \xi_{ijt}\,, \tag{12}$$

where $\widehat{haircut}_{ijt}$ are the first-stage fitted values for exchange market haircuts. The coefficient of interest is δ, which equals the negative Lagrange multiplier $-\lambda$ in equation (10).

As in equation (6), the regression includes bond, rating, and weekly time fixed effects, as well as other relevant controls; see the discussion after equation (6) in Section III.C. In effect, the 2SLS identifies the value of pledgeability λ using a diff-in-diff approach. It compares the average change in the exchange premium for treated bonds after the policy shock against the average change for the control group; and this relative difference in the average change in exchange premium is then scaled by the average change in the exchange haircut for the treated bonds to determine $\delta = -\lambda$.[24]

B.2. IV Estimation Results: Exchange Premia

Table V reports the results of IV estimation following the procedure outlined in Section II.B, based on different samples. Overall, the coefficient estimates are statistically significant across the different samples and specifications, although the economic magnitude varies somewhat depending on the control group.

[24] More formally, the estimated $\hat{\delta}$ in the second-stage 2SLS regression is equivalent to the haircut-change-adjusted pricing effect of the policy shock in a reduced-form diff-in-diff regression, that is, replacing time-varying dummies D_{jt}^k with D_{jt} in equation (6), and then scaling the estimated coefficient of D_{jt} by the first-stage coefficient in the 2SLS regression (see, e.g., Pischke (2018)).

Table V

IV Estimation

This table reports the results of IV regressions using the simultaneous trading sample. Panels A and B present results for the first- and second-stage regressions. Columns (1) and (2) present results using the full sample, without and with control variables, respectively. Column (3) presents results using a subsample of AA+, AA, and AA− bonds. Column (4) presents results using a subsample of AA+, AA, and AAA bonds. Column (5) presents results using a subsample of AA+, AAA, and AA− bonds. Column (6) presents results using a subsample of AA, AAA, and AA− bonds. The sample period is June 9, 2014 to June 8, 2015. Heteroskedasticity-consistent standard errors clustered by week are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: First Stage

Dependent:	Full		Exclude AAA	Exclude AA−	Exclude AA	Exclude AA+
Haircut	(1)	(2)	(3)	(4)	(5)	(6)
Shock	68.00***	68.20***	68.27***	67.83***	74.82***	63.67***
	(0.64)	(0.65)	(0.67)	(0.64)	(0.88)	(0.79)
Controls	–	✓	✓	✓	✓	✓
Bond FE	–	✓	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓
R^2	0.85	0.95	0.95	0.95	0.97	0.96
N	10,235	10,070	9,615	8,550	4,993	7,039

Panel B: Second Stage

Dependent:	Full		Exclude AAA	Exclude AA−	Exclude AA	Exclude AA+
EX Premia	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Haircut}$	−0.39***	−0.39***	−0.40***	−0.33***	−0.38***	−0.40***
	(0.05)	(0.05)	(0.05)	(0.10)	(0.05)	(0.05)
Maturity		2.75***	2.84***	3.06***	3.30***	1.85*
		(0.80)	(0.82)	(0.86)	(1.02)	(0.93)
Turnover		0.12	0.10	0.13	0.23	0.09
		(0.09)	(0.09)	(0.10)	(0.14)	(0.10)
Market price		−0.00	−0.00	−0.00	−0.01	−0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Volatility		0.03	−0.07	0.20	−0.65	0.24
		(1.04)	(1.06)	(1.13)	(1.71)	(0.77)
CDB_{spot}		−28.15**	−30.47***	−20.06*	−34.60**	−27.66*
		(11.05)	(11.36)	(11.36)	(12.94)	(15.22)
Term spread		27.95*	28.48*	28.01	36.52**	23.77
		(15.85)	(15.51)	(17.08)	(17.47)	(18.22)
GC001−SHIBOR		−0.15	−0.15	−0.07	−0.10	−0.27**
		(0.15)	(0.15)	(0.14)	(0.19)	(0.13)
Ret_{stock}		0.46	0.43	0.48	0.41	0.42
		(0.43)	(0.43)	(0.49)	(0.42)	(0.47)
Bond FE	–	✓	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓
R^2	0.12	0.48	0.47	0.49	0.41	0.53
N	10,235	10,070	9,615	8,550	4,993	7,039

For ease of exposition, exchange premia as well as the estimated coefficients in the first stage are quoted in percentages, while explanatory variables are quoted in raw values. For the full sample, we report results based on two different specifications, one with bond fixed effects and other bond- and market-level controls (column (2)) and the other without (column (1)), while for other subsamples we only report results with all control variables. The standard errors in parentheses are clustered by week.[25]

The first stage, which regresses exchange haircuts on the policy shock dummies and other controls as in equation (11), is quite strong across various samples. This result is expected given the sharp dependence of bond-level haircuts on credit ratings (see Table III) and the nature of the policy shock, which specifically targeted at ratings.

In the second stage, columns (1) and (2) report the estimation results based on the full simultaneous trading sample, without and with other control variables. Both columns report the same estimated $\hat{\lambda} = 0.39$, implying that an increase in the haircut from 0% to 100% would increase bond yields on the exchange by 39 bps; recall that we are always concerned with the estimated $\hat{\lambda}$, which is $-\hat{\delta}$ reported in Table V.

Column (3) reports the result with the subsample that excludes AAA bonds, that is, using only AA− bonds as the control group, while column (4) reports the result with the subsample excluding AA− bonds, that is, using only AAA bonds as the control group. As emphasized in Section III.C, a unique feature of our empirical setting is that the control group consists of both higher- and lower-rating bonds relative to the treated group. We find that these two subsamples yield different estimates for $\hat{\lambda}$, but they differ only slightly. Column (3), which uses only AA− bonds as a control, produces a similar estimated $\hat{\lambda}$ compared to the full sample (0.40 versus. 0.39). The magnitude of $\hat{\lambda}$ in column (4), which uses only AAA bonds as a control, is a bit smaller (0.33). As we explain shortly, this difference is likely due to a standard flight-to-quality effect.

Finally, column (5) is the subsample excluding AA bonds (i.e., using only AA+ bonds as the treated group), while column (6) excludes AA+ bonds (i.e., using only AA bonds as the treated group). It is informative to compare their implied estimates as their corresponding first-stage results (Panel A of Table V) show that the AA+ groups experienced a larger haircut shock (75%) than the AA group (64%). However, we obtain essentially the same estimates of $\hat{\lambda}$ across these two subsamples (0.38 and 0.40) as well as the full sample (0.39), suggesting not only the robustness of our result, but also a potential linear relation between the pledgeability premium and the haircut (as our theoretical framework imposes in equation (3)).

[25] The clustered standard error estimator is consistent as the number of clusters increases (Angrist and Pischke (2008)), and a simple rule-of-thumb is to have more than 50 clusters (Cameron and Miller (2015)). Meanwhile, for two-way clustering, the number of clusters should be counted independently for two dimensions (Cameron, Gelbach, and Miller (2011)). The small number of bond ratings in our exercise makes the two-way clustered standard error less applicable.

Table VI

IV Estimation: Additional Results

This table reports additional results for the IV regressions. Panels A and B present results for the first- and second-stage regressions. Column (1, MCB) presents results using the MCBs only. Column (2, Maturity^{long}) presents results using a subsample of bonds for which the time-to-maturity as of the day of trade is above median. Column (3, Excl. Mth 1) presents results using the subsample without the first post-event month. Column (4, 2SWLS) presents results using two-stage weighted least squares, where the weight is equal to the inverse of the number of observations for each bond. Column (5, Continuous) presents results using (1−haircut^{pre}) as the shock size for AA+ and AA bonds, where haircut^{pre} is the average haircut for bond i rating j before the policy shock. Heteroskedasticity-consistent standard errors clustered by week are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: First Stage

Dependent:	MCB	Maturity^{long}	Excl. Mth 1	2SWLS	Continuous
Haircut	(1)	(2)	(3)	(4)	(5)
Shock	68.34***	69.65***	68.26***	67.49***	99.65***
	(0.75)	(0.95)	(0.70)	(0.76)	(0.50)
Controls	✓	✓	✓	✓	✓
Bond FE	✓	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓
R^2	0.95	0.97	0.96	0.97	0.99
N	8,513	4,995	9,132	10,070	10,070

Panel B: Second Stage

Dependent:	MCB	Maturity^{long}	Excl. Mth 1	2SWLS	Continuous
EX Premia	(1)	(2)	(3)	(4)	(5)
$\widehat{Haircut}$	−0.34***	−0.46***	−0.43***	−0.41***	−0.34***
	(0.05)	(0.06)	(0.04)	(0.06)	(0.05)
Controls	✓	✓	✓	✓	✓
Bond FE	✓	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓
R^2	0.47	0.58	0.51	0.57	0.48
N	8,513	4,995	9,132	10,070	10,070

B.3. Robustness and Other Tests

Robustness tests. Table VI presents results of several robustness checks of our IV estimations based on the 2SLS procedure, with Panel A (B) reporting the first- (second-) stage results. Column (1) uses the MCB subsample only; the estimate is slightly smaller ($\hat{\lambda} = 0.34$) but within the one-standard-error band of the estimate in the full sample. Since our policy shock was part of the broader government agenda to rein in local government debt, one might be concerned that the shock also represents a fundamental shock, especially to

MCBs, which are the bonds issued by LGFVs. However, the fact that we obtain similar estimates for the value of pledgeability based on the full and MCB samples indicates the robustness of our empirical design to such concerns.

Column (2) uses the subsample with long-maturity bonds, which are defined as those with above median time to maturity as of the day of trade, and reports a greater second-stage estimate ($\hat{\lambda} = 0.46$) than does the full sample, consistent with the finding in He and Milbradt (2014) and Chen et al. (2018) that long-term bonds with worse endogenous secondary market liquidity are more sensitive to their pledgeability.

Column (3) uses the subsample without the first post-event month; this addresses the concern of potential temporary selling pressure, temporary tightening of interbank collateralized funding resulting from the policy shock, or temporary changes in settlement delays.[26] However, as we stress in the last paragraph of Section I.D, the policy drafted by the CSDC was designed to forestall fire sales of AA/AA+ bonds, which had already been in a levered position. Consistent with this policy intention, we find a slightly larger effect ($\hat{\lambda} = 0.43$) when we exclude the first post-event month.

Columns (4) and (5) are based on slightly modified versions of 2SLS. In column (4), we employ the two-stage weighted least squares (2SWLS) in both stages with the weight equal to the inverse of the number of observations of each bond. The resulting estimate of $\hat{\lambda} = 0.41$ is similar to that estimated using the 2SLS method.

Column (5), which we dub as "Continuous," uses $D_{jt} \times (1 - haircut_{ij}^{pre})$ as our IV, as opposed to the treatment-rating-post-policy dummy D_{jt} defined in equation (5). Here, $haircut_{ij}^{pre}$ is the average haircut for bond i rating j before the policy shock, which essentially captures (potentially) endogenous within-rating haircut variation. This continuous version of IV, which produces an estimate of 0.34, is used in Macchiavelli and Zhou (2022) and shares a similar spirit to the Bartik instrument (Goldsmith-Pinkham, Sorkin, and Swift (2020)).

We prefer our dummy instrument as it does not rely on endogenous within-rating haircut variation, which could potentially lead to identification issues. In fact, the "Continuous" 2SLS method is close to a standard OLS that delivers $\hat{\lambda}_{OLS} = 0.37$ (see Table IA.III in the Internet Appendix; the OLS method uses within-bond time-varying haircuts as well for identification). Relative to 2SLS, both methods produce a somewhat lower estimate, which is potentially driven by unobservable interbank haircuts.[27] To see this, following a deterioration in credit quality of some dual-listed bond on a given day, the exchange would adjust its haircut h_{ijt}^{EX} upward. The bond's interbank haircut h_{ijt}^{IB}, which we do not

[26] One potential concern is that the length of settlement delays could have changed for the treatment group following the policy shock. For example, it is possible that the cross-market transfer of depository may take longer due to an influx of transfer requests immediately after the policy shock. The transfer process is likely to revert back to normal, however, shortly afterward.

[27] This result is consistent with column (4) in Table III, which uses OLS and produces an even lower coefficient based on the pre-policy subsample.

observe, should also rise in response. As a result, the observed change in exchange haircut tends to be greater than the actual change of $h_{ijt}^{IB} - h_{ijt}^{EX}$, which determines exchange premia according to equation (4). The OLS regression that ignores the response in the interbank market haircuts then leads to an under-bias for $\hat{\lambda}$. Our method, which relies only on rating-level haircut changes and not on within-rating bond-level variation, largely avoids this concern due to the interbank haircut information as can be seen in Panel B in Table IV. There, we observe almost zero rating-level interbank haircut changes after the policy shock, except for the AAA-rating with the caveat of the flight-to-quality effect that we discuss in Section IV.B.4.

Secondary market liquidity. Does the shock to pledgeability affect an asset's secondary market liquidity? Chen et al. (2018) argue that this is the case. Under that mechanism, reduced pledgeability raises the opportunity costs of holding an illiquid asset, which in turn raises its liquidity premium. Our empirical methodology estimates the total value of pledgeability.[28] Our setting of dual-listed enterprise bonds again provides an ideal setting to test this theoretical prediction, as we can compare how the liquidity of the treated bonds changes differentially on the two markets while the fundamentals are exactly the same.

Due to data limitations, we cannot construct commonly used liquidity measures such as market-specific turnover or bid-ask spreads. We instead measure the cross-market difference in liquidity by computing the difference in the daily price range, which captures price volatility, across the two markets.[29] With the same fundamental, the excess price volatility in one market versus the other can arguably be attributed to a difference in liquidity. As reported in Table VII, following the policy shock the daily price range of the treated bonds rose relative to the control group, suggesting a deterioration in exchange market liquidity relative to that of the interbank market. This result is consistent with the prediction of Chen et al. (2018). The result based on the full sample (column (2)) implies that if the haircut increased from 0% to 100%, the daily price range would have gone up by 0.41%, or 29% of a standard deviation of an individual bond's daily exchange price range.

[28] Empirically, controlling for the rating-level turnover by market leads to a similar but slightly lower (0.008) $\hat{\lambda}$ estimate; see Tables IA.IV and IA.V in the Internet Appendix. This is consistent with Chen et al. (2018), who suggest that controlling for bond/rating-level liquidity measures may lead to underestimation of $\hat{\lambda}$ due to over-controlling.

[29] Although the total amount outstanding is available, we do not observe the quantity of a given bond that is registered in a specific market; this makes cross-market turnover comparison less reliable. With that said, we find that the relative turnover decrease between the exchange and interbank markets is larger for treated bonds after the policy shock (Table IA.VI in the Internet Appendix). For the bid-ask spread, such data are not available on the interbank market; it is also infeasible to estimate the effective spread based on Roll (1984) due to limited transactions. In the Internet Appendix IA.II, we repeat the analysis for the same-day trading sample and under different methodologies to clean outliers. The findings are quantitatively similar. Finally, in Internet Appendix Figure IA.7, we plot the time series of RMB value of enterprise bonds and Treasury bonds in custody for the interbank and exchange markets.

Table VII

IV Estimation: Impacts on Liquidity

This table reports second-stage results of IV regressions using the difference in the price range between the exchange and interbank markets as the dependent variable. The price range in percentage is defined as the daily high minus daily low divided by the average of the two. Columns (1) and (2) present results using full sample, without and with control variables, respectively. Column (3) presents results using a subsample of AA+, AA, and AA− bonds. Column (4) presents results using a subsample of AA+, AA, and AAA bonds. Column (5) presents results using a subsample of AA+, AAA, and AA− bonds. Column (6) presents results using a subsample of AA, AAA, and AA− bonds. The sample period is June 9, 2014 to June 8, 2015. Heteroskedasticity-consistent standard errors clustered by week are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: First Stage

Dependent:	Full		Exclude AAA	Exclude AA−	Exclude AA	Exclude AA+
Haircut	(1)	(2)	(3)	(4)	(5)	(6)
Shock	68.00***	68.23***	68.28***	67.97***	74.87***	63.68***
	(0.64)	(0.66)	(0.68)	(0.67)	(0.88)	(0.79)
Controls	–	✓	✓	✓	✓	✓
Bond FE	–	✓	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓
R^2	0.85	0.95	0.95	0.95	0.97	0.96
N	10,235	10,070	9,615	8,550	4,993	7,039

Panel B: Second Stage

Dependent:	Full		Exclude AAA	Exclude AA−	Exclude AA	Exclude AA+
$\Delta P^{high-low}$	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Haircut}$	0.48***	0.41***	0.43**	0.35*	0.41**	0.42***
	(0.14)	(0.14)	(0.16)	(0.20)	(0.17)	(0.15)
Maturity		−10.59***	−10.31***	−11.65***	−10.39**	−10.02***
		(3.59)	(3.64)	(3.98)	(4.47)	(3.70)
Turnover		−2.50***	−2.50***	−2.32***	−3.05***	−2.41***
		(0.28)	(0.29)	(0.31)	(0.46)	(0.34)
Market price		−0.01	−0.01	−0.01	−0.01	−0.00
		(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
CDB_{spot}		58.98	56.03	43.49	68.74	81.36*
		(45.94)	(46.35)	(60.70)	(48.97)	(48.18)
Term spread		19.09	25.52	25.91	−50.67	40.13
		(38.51)	(39.13)	(46.01)	(46.45)	(41.31)
GC001−SHIBOR		−0.63	−0.51	−0.61	−1.70	0.13
		(0.79)	(0.80)	(0.87)	(1.22)	(0.53)
Ret_{stock}		−0.58	−0.69	−0.71	−1.82	0.72
		(1.22)	(1.25)	(1.35)	(2.39)	(0.74)
Bond FE	–	✓	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓
R^2	0.08	0.26	0.25	0.27	0.25	0.27
N	10,235	10,070	9,615	8,550	4,993	7,039

B.4. Discussions on Potential Biases

Flight-to-quality effect: Exchange or interbank? A smaller estimated $\hat{\lambda}$ (about a difference of 6 bps) with AAA bonds as the control is likely due to a flight-to-quality effect—upon the policy shock, it is plausible that institutional investors started increasing the holdings of AAA bonds on both markets. As we explain below, given the unique institutional structure in China, the flight-to-quality effect is likely to be stronger on the interbank market. Consequently, the exchange premium of AAA bonds would decline after the event as the interbank prices of AAA bonds rose relative to their exchange counterparts. This would bias the estimate of $\lambda\,(=-\delta)$ downward, as suggested by Table V.

What drove a stronger flight-to-quality effect in the interbank market in this episode? First, recall that the policy shock still allowed investors to continue rolling over existing repos on the exchange market and thus did not directly force investors to delever those affected AA and AA+ bonds, which limited the temporary selling pressure of AA/AA+ bonds on the exchange market. Second, the exchange market is more "retail" oriented while the interbank market is a "wholesale" market. When financial institutions scrambled for liquidity following the policy shock, they tended to turn to the interbank market to cover any large-scale liquidity shortages.

In fact, this might be the underlying force that drove up the AAA bonds' interbank haircuts documented in Panel B of Table IV. Although we do not have detailed enterprise bond holding data for NBFIs in the two markets, we are able to obtain data on the enterprise bond holdings from an anonymous institutional investor around the policy shock. Their average daily holdings of AAA enterprise bonds on the interbank market increased by 61.6% from the month before to the month after the policy shock, while the increase was only 16.8% on the exchange. These statistics are consistent with our interpretation of the stronger flight-to-quality effect in the interbank market.

Cross-market arbitrage: Implication on λ estimation. Suppose that investors face a fixed transaction cost of $C > 0$ to transfer bonds across two markets (for simplicity, we assume the same cost for cross-market transfers in either direction); C takes into account all potential illiquidity costs and time delays as mentioned in Section I.B. That is, NBFIs have the option of spending C to enhance the pledgeability of a bond by transferring it to one of the markets.

Recall that the value of pledgeability λ, which is a deep structural parameter linked to the NBFIs' Lagrange multiplier, captures the pricing difference of two bonds with identical fundamentals—one with full pledgeability and the other with no pledgeability. Our theoretical framework in Section II.B so far assumes that $C = \infty$, as investors cannot enhance the pledgeability of the bond with zero pledgeability, that is, an AA+/AA bond on the exchange post the policy shock. In essence, to estimate λ, we take advantage of the dual-listing feature of the Chinese bond markets that helps us isolate asset fundamental factors but ignores the option of enhancing pledgeability (at some cost).

As mentioned toward the end of Section II.B, we rely on equation (4) for our empirical design. When C is finite, costly arbitrage across two markets essentially places a bound on the absolute value of exchange premia. We therefore need to modify equation (4) to respect the arbitrage bound:

$$\underbrace{p_{ijt}^{EX} - p_{ijt}^{IB}}_{\text{exchange premia}} = \max\left[\min\left[\underbrace{\lambda\left(h_{ijt}^{IB} - h_{ijt}^{EX}\right)}_{\text{Equation (4), wedge in pledgeability premia}}, C\right], -C\right]. \tag{13}$$

As a result, the equilibrium exchange premia after taking arbitrage into account differs from the wedge in pledgeability premia across two markets. Since we are ultimately interested in the value of pledgeability λ as opposed to the equilibrium exchange premia $p_{ijt}^{EX} - p_{ijt}^{IB}$, this introduces bias into our exchange premia–based estimator $\hat{\lambda}$.

One can formally show that the exchange premium–based estimation tends to underestimate λ due to the binding constraints in equation (13); see the Internet Appendix IA.III for the proof. The arbitrage force squeezes the equilibrium price wedge, which then only partially reflects λ. Intuitively, the option to enhance pledgeability, as well as the possibility to do so in the future, tends to counter the negative shock to exchange haircuts, and market prices should reflect this option. At the extreme of $C = 0$, investors can avoid the exchange policy shock perfectly by exercising the costless option; we should observe $p_{ijt}^{EX} - p_{ijt}^{IB} = 0$ always and hence $\hat{\lambda} = 0$. At the other extreme of $C = \infty$, the option of enhancing is always out of the money, and equation (4) always holds yielding an unbiased $\hat{\lambda}$. In Section I.B, we discuss the significant frictions of cross-market arbitrage, in particular settlement delays. Although estimating the effective arbitrage cost C that these frictions imply is beyond the scope of this paper, we have some empirical evidence suggesting that C is indeed large, which explains why the negative bias of the exchange premia–based estimate of $\hat{\lambda}$ is likely small.[30]

[30] Exchange premia of large magnitudes occur relatively frequently in our sample, with 12% of our sample having absolute exchange premia exceeding 50 bps, which is consistent with the presence of significant arbitrage costs. One way to quantify these arbitrage costs is through back-testing the cross-market arbitrage strategy. We find that when the trading threshold for the exchange premium is 50 bps, the realized annualized Sharpe ratio is only 1.04 and 0.56 in the pre- and post-policy sample, respectively, once the effects of settlement delays and market liquidity are taken into account. We also note that the effects of cross-market arbitrage should be taken into account if researchers are interested in estimating the predicted change in the exchange premium $p_{ijt}^{EX} - p_{ijt}^{IB}$ given an exogenous change in exchange haircuts, which is different from the value of pledgeability that we are estimating. Our arbitrage strategy is to buy RMB 10 million of the bond on the interbank market (based on the typical minimum trade size in this market) whenever the exchange premium of a dual-listed bond is above a pre-specified trading threshold (say 50 bps); we then sell the bond as quickly as possible on the exchange, subject to the settlement delay for change of depository (five working days) and a restriction on the pace of selling (the amount of selling is capped at 20% of the daily volume). A similar strategy in the opposite direction is implemented when the exchange premium is sufficiently negative. See Internet Appendix Figure IA.8 for details.

C. Pledgeability and Asset Prices: Matched-AAA Bonds

This section proposes a method to partially address the potential downward-bias problem in the exchange premium–based approach. Recall that the unexpected policy shock hit the exchange market by only disqualifying AA/AA+ enterprise bonds' pledgeability without affecting AAA bonds. We therefore construct the pricing wedges of AA+ and AA enterprise bonds over "similar" AAA enterprise bonds using their yields on the exchange market only.

C.1. Premia over Matched-AAA Exchange Bonds

The question is how to choose "similar" exchange AAA bonds. For each treated enterprise bond, we match it with exchange-traded AAA enterprise bonds with similar pre-event haircut and credit spreads. Note that this "matching" approach, which is in the same spirit as Hand, Holthausen, and Leftwich (1992) and Bao, O'Hara, and Zhou (2018), is widely used in the literature on the implications of ratings on bond pricing.

Under the framework established in Section IV.B, $h^{EX}_{\text{treated},t} - h^{EX}_{\text{matched-AAA},t} = 0$ for $t \leq$ December 8, 2014, while after the policy shock $h^{EX}_{\text{treated},t} - h^{EX}_{\text{matched-AAA},t}$ increases. One can therefore express the matched-AAA premium as

$$p^{EX}_{\text{treated},t} - p^{EX}_{\text{matched-AAA},t} = \underbrace{\lambda\left(h^{EX}_{\text{matched-AAA},t} - h^{EX}_{\text{treated},t}\right)}_{\text{identifies } \lambda}$$
$$+ \underbrace{\mathbb{E}_t\left[\widetilde{M}^{NBFI}_{t+1}\left(\widetilde{Y}_{\text{treated},t+1} - \widetilde{Y}_{\text{matched-AAA},t+1}\right)\right]}_{\text{fundamental residual: 0 if matched well}}$$
$$+ \underbrace{\mu^{EX}_{\text{treated},t} - \mu^{EX}_{\text{matched-AAA},t}}_{\text{liquidity residual}}. \tag{14}$$

In equation (14), the first right-hand term identifies λ, which is the focus of our study. The second righthand term, the "fundamental residual," captures the fundamental difference between the matched-bond-pair; if the matching is perfect, this term should be exactly zero, or more precisely, we only need the difference to stay constant. The final "liquidity residual" term captures the liquidity differential between treated and control bonds, which could be affected by the policy shock. Since matching is never ideal, both the second and third terms might be correlated with the policy shock.

Since our first exchange-premium approach in Section IV.B provides a lower bound for $\hat{\lambda}$, we aim to design the matched-AAA approach above to deliver an upper bound, or overestimation, of $\hat{\lambda}$. That is, we are more tolerant of potential mechanisms that produce a positive correlation between the terms in the second line of equation (14) and the policy-induced change in exchange haircuts in the first line.

Indeed, all plausible economic mechanisms in this context that could contaminate our estimate in the matched-AAA approach seem to satisfy this "positive correlation" condition. Recall that the policy shock represents a negative shock to pledgeability. All three of the leading endogeneity concerns below generate a negative shock to the second line in equation (14):

(i) The CSDC has some private information about the deteriorating quality of AA+/AA bonds, and hence releases liquidity-tightening rules on these bonds. The market views the policy shock as the negative signal of the treated AA+/AA bonds, leading to a negative shock to the "fundamental residual" term.

(ii) The matched AAA bonds with better fundamentals have a smaller beta than those of treated AA/AA+ bonds, so that the "fundamental residual" term has a positive beta. Because the liquidity-tightening policy shock is likely to represent a negative aggregate market shock, this again implies a negative shock to the "fundamental residual" term.

(iii) The policy shock represents a liquidity-tightening event, and the resulting flight-to-liquidity effect raises the prices of matched AAA bonds, perhaps due to better uncontrolled fundamentals, that is, beyond the observable controls we add in the regressions. This effect also leads to a negative shock to the "liquidity residual" term.

C.2. IV Estimation Results: Matched-AAA Premium

We match each bond-day observation of AA+/AA bonds on the exchange market with AAA bond-day observations that have the same haircut and credit spread during the pre-event window. Our matching procedure, which is detailed in Section C in the Appendix, results in very similar pre-event haircuts and credit spreads for the treatment group (AA+ and AA) and the matched AAA benchmarks. Figure 4 shows the differences in haircuts and credit spreads of the bonds in the treatment and matched groups. Before the event date, the average haircuts are 13.7% and 13.5% for treatment and control bonds, respectively, with average credit spreads of 1.30% and 1.25% for treatment and control bonds. After the policy shock, the haircuts and credit spreads of these two groups diverge, as expected.

We follow the same two-stage IV estimation method laid out in Section IV.B.1, but replace the exchange premium with the difference between a treatment bond's exchange yield and the average yields of all matched exchange AAA bonds on the same day of trade. Table VIII reports the results.[31] The first stage is reported in Panel A and confirms that the policy shock is a

[31] To be consistent with the definition of the exchange premium and interpretation of the economic magnitude, the dependent variable is defined as the yields of matched AAA enterprise bonds minus those of AA+/AA enterprise bonds. Since our sample includes only treated AA/AA+ bonds (and their premia over the AAA benchmarks), we do not include the weekly time fixed effects as our treatment dummy only reflects the time-series variation coming from before and after the event.

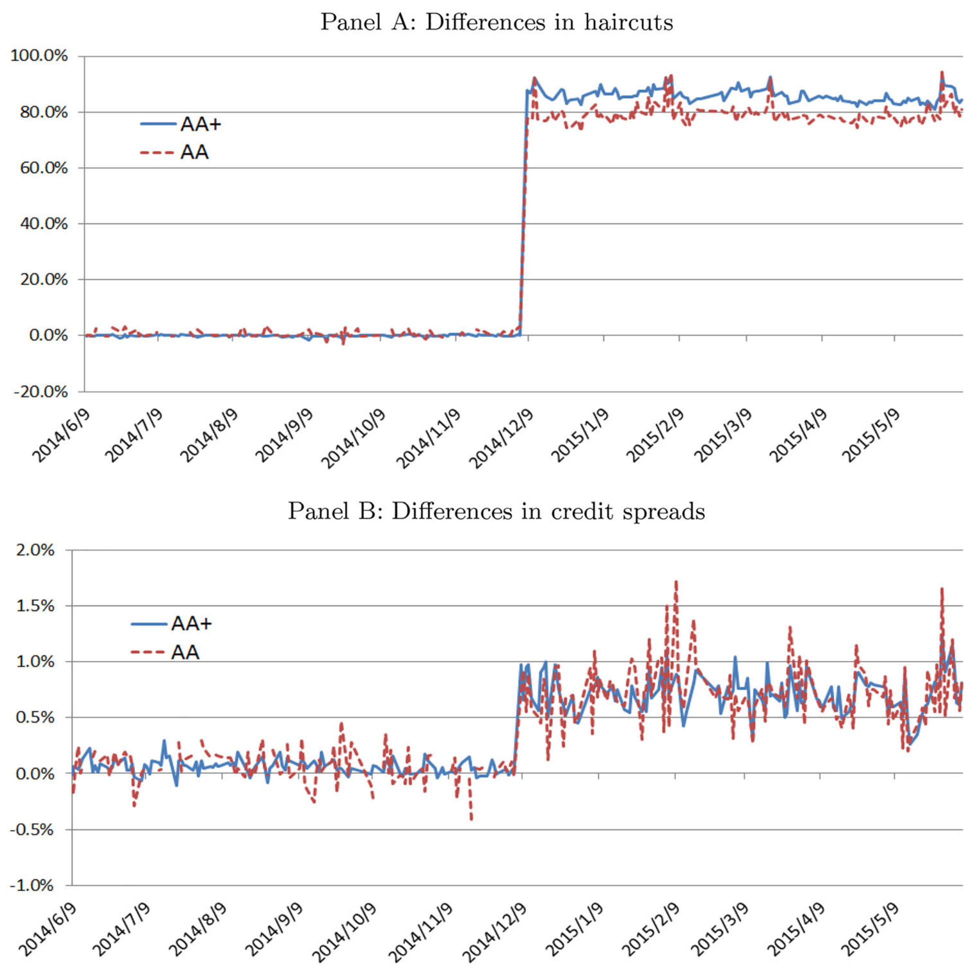

Figure 4. Differences in haircuts and exchange credit spreads between AA+/AA and matched AAA bonds. This figure plots differences in AA+/AA dual-listed enterprise bonds' haircut and the exchange market credit spread with respect to matched AAA bonds. Panels A and B plot the differences in haircut and credit spread for AA+/AA bonds with matched AAA bonds, respectively. The matching variables include the pre-event exchange market credit spread and haircut with the matching procedures in Section C in the Appendix. The sample period is June 9, 2014 to June 8, 2015. (Color figure can be viewed at wileyonlinelibrary.com)

strong IV. The estimated coefficients in the second-stage regressions are consistent with our conjecture (Panel B of Table VIII): a 100% increase in the haircut of AA+/AA bonds translates into a 85 bps decrease in the pledgeability premium, the effect of which is larger than the estimate of 39 bps from the exchange premia–based approach (column (2) of Table V).

Overall, our IV estimation provides a lower bound of 39 bps and an upper bound of 85 bps on bond yields when the haircut increases from 0% to

Table VIII

IV Estimation Using Matched AAA Bonds as Benchmark

This table reports results of IV regressions using the matched AAA bonds as a benchmark. The dependent variable is the credit spread between the matched AAA bonds and that of AA+/AA dual-listed enterprise bonds, where the matching criteria include the credit spread and the haircut before December 8, 2014. Panels A and B present results for the first and second stages. The sample period is June 9, 2014 to June 8, 2015. Heteroskedasticity-consistent standard errors clustered by week are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: First Stage

Dependent:	Full		AA+	AA
Haircut	(1)	(2)	(3)	(4)
Shock	86.17***	84.85***	86.82***	77.67***
	(0.90)	(1.23)	(0.87)	(1.35)
Controls	–	✓	✓	✓
Bond FE	–	✓	✓	✓
Rating FE	✓	✓	✓	✓
R^2	0.98	0.99	0.99	0.98
N	9,940	9,897	7,548	2,349

Panel B: Second Stage

Dependent:	Full		AA+	AA
$\text{Spread}^{matched-AAA}$	(1)	(2)	(3)	(4)
$\widehat{Haircut}$	−0.74***	−0.85***	−0.84***	−0.84***
	(0.02)	(0.04)	(0.04)	(0.10)
Maturity		0.03	0.07	−0.09
		(0.11)	(0.10)	(0.20)
Turnover		2.22*	1.23	5.94*
		(1.29)	(1.06)	(2.98)
Market price		−0.00	−0.00	0.01
		(0.00)	(0.00)	(0.01)
Volatility		0.12	−1.03	2.19*
		(0.99)	(1.34)	(1.29)
CDB_{spot}		−10.28**	−10.32**	−7.96
		(4.62)	(4.15)	(9.08)
Term spread		−0.91	−3.54	5.72
		(5.55)	(4.74)	(10.30)
GC001−SHIBOR		−0.17	−0.12	−0.43
		(0.30)	(0.25)	(0.54)
Ret_{stock}		0.77	1.00	0.11
		(0.64)	(0.63)	(0.88)
Bond FE	–	✓	✓	✓
Rating FE	✓	✓	✓	✓
R^2	0.15	0.55	0.56	0.54
N	9,940	9,897	7,548	2,349

100%. Taking the two numbers together, the average impact on credit spreads for a 100% increase in the haircut is around 62 bps, which translates into a 3.29% price change for an average dual-listed enterprise bond as we discuss more next.

D. Discussions on Estimated $\hat{\lambda}$

This section examines two further questions: What is the economic magnitude of the estimated $\hat{\lambda}$? And what if the Lagrange multiplier λ of the representative marginal investor is time-varying?

D.1. Economic Magnitude of λ

To examine the economic significance of the value of pledgeability λ, we first translate the impact of changes in the haircut on bond yields to dollar terms. Consider a bond with a face value of 100 RMB. The average enterprise bond in our sample has a coupon rate of 6.81% and a maturity of 7.33 years. The yield to maturity is 6.46%. When the haircut increases from 0% to 100%, the yield to maturity would increase by 39 bps based on the exchange premium estimate, and the price would drop from RMB 106.5 to 104.3, a decrease of RMB 2.2 or 2.1%. Based on the estimate of premia over matched AAA bonds, the yield increase would be 85 bps, and the price drop would be RMB 4.8 or 4.5%.

Next, in practice, the marginal NBFI investor is not always financially constrained. As modeled in Chen et al. (2018), agents are financially constrained only when hit by liquidity shocks. We therefore extend the formula in equation (3) to take into account the probability of liquidity shocks:

$$\begin{aligned}&\text{Pledgeability premium}\\&\quad= \underbrace{\text{Freq. of liq. shocks} \times \text{Shadow cost of capital}}_{\text{value of pledgeability, } \lambda} \times (1 - \text{haircut}).\end{aligned}$$

The pledgeability premium will be higher when the marginal investor is more frequently in a liquidity-constrained state, and/or when she faces a higher shadow cost of capital in the constrained state. The shadow cost of capital can be measured as the gap between the interest-rate spread of collateralized and uncollateralized financing, that is, as a form of financing risk premium (n.b., uncollateralized financing is default adjusted as in, for example, Gilchrist and Zakrajsek (2012)). The premium is also higher for assets with smaller haircuts.

Through the lens of the formula above, we can infer the shadow cost of capital for NBFIs in the exchange market. Before the policy shock, about 35% of the enterprise bonds on the exchange were used as repo collateral on a typical day. If we interpret this number as the frequency of a typical bond investor

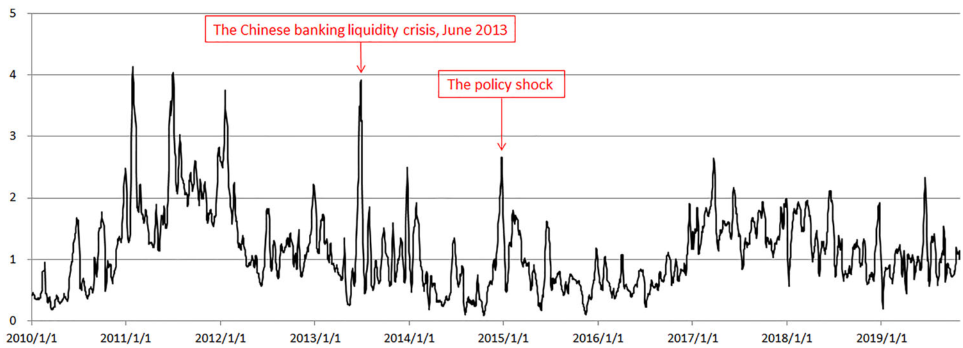

Figure 5. Spread between the interbank market repo rate and the CDB bond yield. This figure plots the daily spread in percentage between the one-month interbank market repo rate for all financial institutions and the CDB bond yield calculated from CDB bonds with one-month maturity. Two events, the CDSC policy shock on December 8, 2014 studied by this paper and the Chinese banking liquidity crisis during June 2013 analyzed in Hachem and Song (2021), are indicated. The sample period is January 1, 2010 to October 31, 2019. (Color figure can be viewed at wileyonlinelibrary.com)

being liquidity constrained,[32] then the value of pledgeability estimates of 39 bps to 85 bps, which are for a bond with a 0% haircut, imply a shadow cost of capital of 1.1% to 2.4% per annum.

Finally, to put into perspective our estimate of the value of pledgeability and shadow cost of capital during the historical episode around the end of 2014, in Figure 5 we plot the time series of the spread between the interbank market repo rate for all financial institutions and the risk-free CDB yield; this spread is a widely used indicator of funding constraints in the Chinese bond markets. Consistent with the policy shock tightening the funding constraints faced by financial institutions, the spread did spike up on the day of the policy shock as indicated in Figure 5. In the longer sample, we also see other periods, for example, the June 2013 Chinese banking liquidity crisis indicated in the figure, with even higher repo spreads. The value of pledgeability is likely to be higher during these crisis episodes.

D.2. Time-Varying λ_t

We have so far assumed $\lambda_t = \lambda$ as in equation (4). Nevertheless, in light of the discussion toward the end of Section II.B, it is plausible that the Lagrange multiplier with respect to the collateral constraint of our representative NBFIs

[32] This interpretation is consistent with the notion of liquidity shocks being idiosyncratic, such as in the framework of Chen et al. (2018). One can also take a more aggregate perspective and gauge the frequency of liquidity shocks based on the time-serious evolution of the repo-CDB spread shown in Figure 5. If one interprets liquidity events as those with a repo-CDB spread above the three-sigma cutoff, then the annual frequency is about 40%, similar to our estimate of 35% above.

spiked after the policy shock, given the noticeable negative market reactions following the unexpected move by the CSDC. More specifically, λ_t was likely to rise in response to the policy shock, that is, $\lambda_{pre} < \lambda_{post}$, where λ_{pre} is the average Lagrange multiplier before the shock and λ_{post} is that after.

As we show in the Internet Appendix IA.IV, our inferences remain unchanged as long as we focus on λ_{post}—our two approaches deliver an underestimate of λ_{post} (39 bps) and an overestimate of λ_{post} (85 bps), respectively. The first part is intuitive as our exchange premia–based procedure in Section IV.B produces some weighted average of λ_{pre} and λ_{post}, hence an underestimate of λ_{post}. For the potential upward bias based on the second method using matched-AAA bonds as a benchmark, the Internet Appendix IA.IV shows that the estimated $\hat{\lambda}$ reflects not only the effect of elevated haircuts of treated AA+/AA bonds, but also the rising λ_t, both as a result of the policy shock. That is, our empirical methodologies and their resulting estimations are robust to a rising λ_t following the shock, to the extent that one is interested in the higher post-shock Lagrange multiplier λ_{post}.

V. Conclusion

The equilibrium price of an asset depends not only on its fundamental, but also its pledgeability. The Chinese corporate bond markets provide an ideal laboratory to study the effect of pledgeability empirically given that some bonds with identical fundamentals are simultaneously traded in two parallel markets—the centralized exchange market and the decentralized OTC interbank market. The differences in pledgeability lead to identical corporate bonds having different prices on the two markets. By exploiting a policy shock that dramatically reduced the pledgeability of bonds rated below AAA and above AA− on the exchange market, we are able to establish a causal effect of asset pledgeability on prices. Estimates based on IVs imply that a 100% increase in the haircut increases credit spreads by 39 bps to 85 bps.

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Appendix

A. Bond Rating Classification

Multiple bond ratings. Five major rating agencies offer rating services to bond issuers in China.[33] To determine the unique bond rating, we follow the market convention of "the lowest rating principle." That is, if there are multiple ratings available for the same bond on a given day, we use the lowest one as the bond rating.

[33] These five rating agencies are Chengxin (Chengxin Securities Rating and Chengxin International Rating), Lianhe (China United Rating and China Lianhe Rating), and Dagong Global Credit Rating. For a comprehensive review of the rating agencies, see Amstad and He (2020).

Bond rating reclassification. We classify our sample into four rating groups for each bond-day observation: AAA, AA+, AA, and AA− (including below-AA− rating). When a bond is included on one of the five blacklists, its bond rating is adjusted to AA− and this rule applies to all of its bond-day observations thereafter.

B. Construction of Exchange Premium

The exchange premium is the credit spread between the interbank yield and the exchange yield for the same bond, based on the prices of either "simultaneous" or "same-day" transactions from the two markets.

The pairing procedure for "simultaneous trading" is as follows (the case of "same-day trading" is straightforward):

(i) For days with interbank market trading, we match trading day t's interbank market credit spread with the closest exchange market daily credit spread within the window [t-2, t]. Specifically, if this bond has nonzero trading on day t on the exchange market, the exchange premium is the difference between the day t interbank market credit spread and the day t exchange market credit spread. If this bond does not have any trading on day t on the exchange market but has nonzero trading on trading day $t-1$ ($t-2$), the exchange premium is the difference between day t interbank market credit spread and the day $t-1$ ($t-2$) exchange market credit spread.

(ii) For days with exchange market trading, we match day t's exchange market credit spread with the closest interbank market daily credit spread within the window [$t-2$, t]. Because we have already paired the same-day two-market trades in step 1, the exchange market day t observation is dropped if the bond has nonzero interbank market trading on day t. Otherwise, the exchange premium is the difference between the trading day $t-1$ ($t-2$) interbank market credit spread and the trading day t exchange market credit spread.

(iii) If a paired trade spans the event day December 8, 2014, that is, the trading day on one market is before the event day while the trading day on the other market is after, the paired observation is dropped. A total of 35 observations are dropped, including one AAA, 11 AA+, 20 AA, and three AA− observations.

C. Matching Procedures of AA+ and AA Enterprise Bonds with AAA Enterprise Bonds

We match exchange market listed AA+ and AA-rated enterprise bonds with AAA-rated enterprise bonds as a benchmark along two dimensions: haircut and matching CDB credit spread. The matching is conducted at the bond-day level in the six-month window before the event date, that is, from June 9, 2014 to December 8, 2014. For any AA+/AA bond that was ever traded in the six-month window after the event date (December 9, 2014 to June 8, 2015), the average credit spread of all nonzero trading AAA bonds that belong to the set of pre-event matched AAA bonds with respect to the AA+/AA bond is used as the benchmark. The following steps describe the pre-event matching procedures and how we benchmark AA+/AA bonds with matched AAA bonds.

(i) For a daily observation of an AA+ or AA-rated bond with nonzero exchange market trading in the six-month pre-event window, the five nonzero trading AAA-rated bonds that have the smallest absolute differences in haircut with respect to the AA+/AA bond on the day of trade are considered candidate benchmark bonds.

(ii) To ensure that an AA+ or AA bond's haircut is close enough to those of the candidate AAA bonds, an AA+ or AA bond's bond-day observation is dropped if the fifth smallest absolute haircut difference between an AA+ or an AA bond and the candidate AAA bond is larger than the median value of all absolute haircut differences. The candidate AAA bond pool for the AA+ or AA bond i on day t is denoted by $\text{AAA}_{i,t}^{haircut}$.

(iii) For a daily observation of an AA+ or AA rated bond with nonzero exchange market trading in the six-month pre-event window, the five nonzero trading AAA-rated bonds that have the smallest absolute differences in matching CDB credit spread with respect to the AA+/AA bond on the day of trade are kept as candidate benchmark bonds.

(iv) To ensure that an AA+ or AA bond's matching CDB credit spread is close enough to those of the candidate AAA bonds, an AA+ or AA bond's bond-day observation is dropped if the fifth smallest absolute credit spread difference between an AA+ or AA bond and the candidate AAA bond is larger than the median value of all absolute credit spread differences. The candidate AAA bond pool for the AA+ or AA bond i on day t is denoted as $\text{AAA}_{i,t}^{yieldspread}$.

(v) AAA bonds that belong to both $\text{AAA}_{i,t}^{haircut}$ and $\text{AAA}_{i,t}^{yieldspread}$ are denoted as a matched set of AAA bonds for AA+ or AA bond i on day t, $\text{AAA}_{i,t}^{matched}$.

(vi) For any AA+ or AA bond i day t observation in the six-month pre-event window, the average credit spread of AAA bonds belonging to $\text{AAA}_{i,t}^{matched}$ is taken as the benchmark.

(vii) For any AA+ or AA bond i, the union of all its matched bond sets $\text{AAA}_{i,t}^{matched}$ across its nonzero trading days T_i is denoted by $\text{AAA}_{i}^{matched} = \bigcup_{t\in T_i} \text{AAA}_{i,t}^{matched}$.

(viii) For any AA+ or AA bond i day τ observation in the six-month post-event window, the average credit spread of AAA bonds with nonzero trading on day τ belonging to $\text{AAA}_{i}^{matched}$ is taken as the benchmark.

D. Additional Results

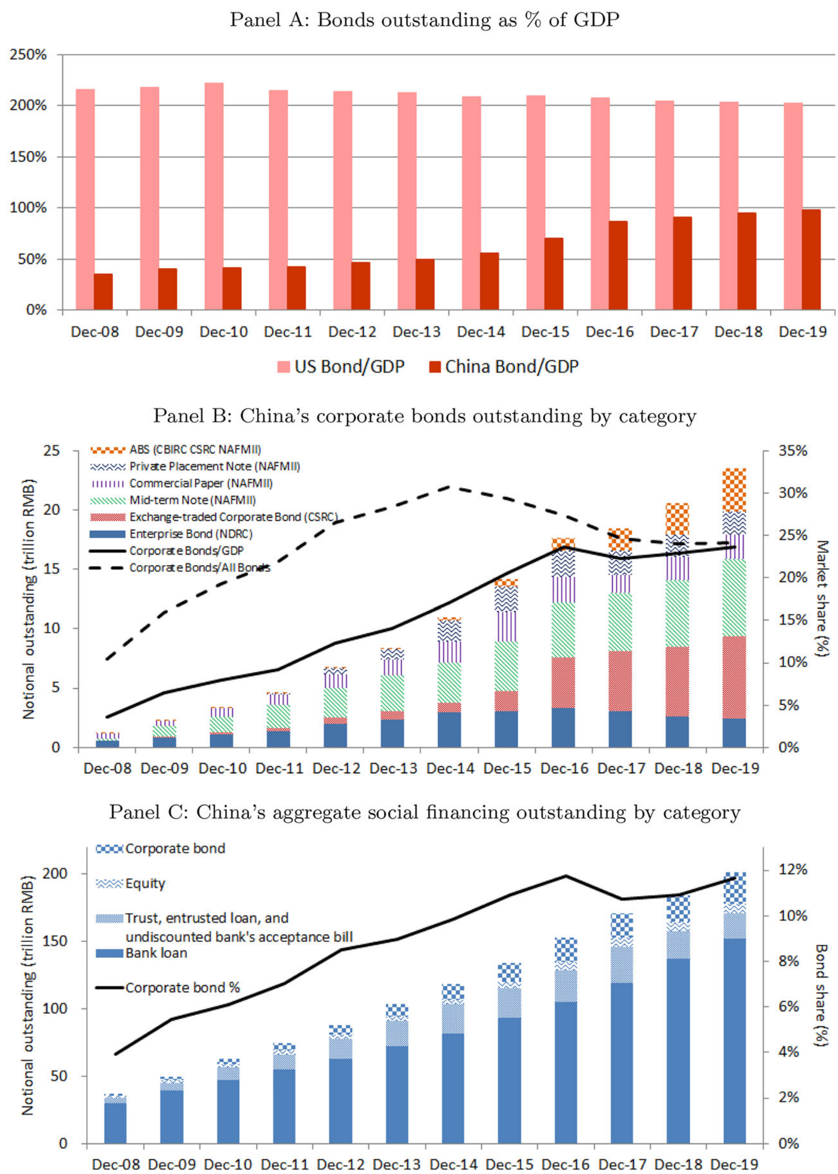

Figure A1. China's bond market. This figure plots statistics for China's bond market from 2008 to 2019. Panel A plots bonds outstanding as a percentage of GDP in China and the United States, Panel B plots China's corporate bonds outstanding by category (with corresponding regulators in parentheses), and Panel C plots PBoC aggregate social financing outstanding by category. For more details, see Amstad and He (2020). (Color figure can be viewed at wileyonlinelibrary.com)

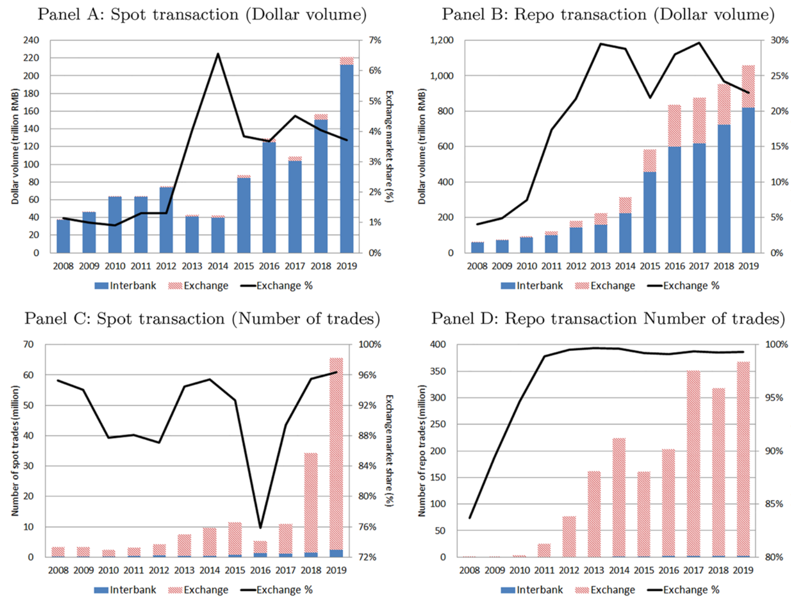

Figure A2. China's interbank and exchange bond markets. This figure plots China's two bond markets from 2008 to 2019. Panels A and B plot spot and repo transaction RMB volume, respectively, of all bonds on the interbank and exchange markets. Panels C and D plot the number of trades for spot and repo transactions, respectively, in these two markets. Although the interbank market has the dominant market share for both spot and repo transactions based on dollar volume, the opposite is true based on the number of trades. Data on interbank market transactions are from China Foreign Exchange Trade System (CFETS) and data on exchange market transactions are from the Statistics Annuals of Shanghai exchange and Shenzhen exchange. (Color figure can be viewed at wileyonlinelibrary.com)

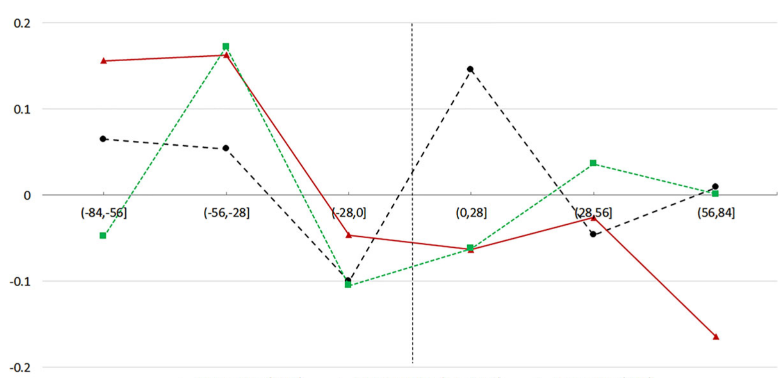

Figure A3. Exchange premia dynamics. This figure presents the average exchange premia by bond rating and subperiod. The three bond-rating groups include the treated group (AA+ and AA), the AAA group, and the AA− group. The sample of simultaneous trading is a [−12, 12]-week window around event day December 8, 2014. The sample is divided into six subperiods with 28 calendar days each. (Color figure can be viewed at wileyonlinelibrary.com)

Table AI

China's Bond Market Liquidity

This table reports various measures of China's bond market liquidity. *ZDays* is the time-series average of the fraction of bonds that do not trade on a given day. $ZDays_{w/trade}$ is the time-series average of the fraction of bonds that do not trade on a given day, excluding bonds that do not have any single trade over the sample period. *Turnover* is the average daily turnover across all bond-day observations where a zero is recorded on days without trade. *Amihud* is the average Amihud (2002) measure across all bonds, where a bond's Amihud measure is estimated using its all nonzero daily trading observations and multiplied by 10^6. Panel A presents comparison of liquidity between China's two bond markets and the U.S. bond market. Panel B presents exchange market liquidity measures for all exchange-traded bonds, enterprise bonds, and exchange-traded corporate bonds. Panel C presents the interbank market liquidity measures for all interbank-traded bonds, enterprise bonds, mid-term notes, and commercial paper. In Panel A, the sample period is January 1, 2012 to December 31, 2017 for China's two markets and the sample period is January 1, 2010 to December 31, 2014 for the U.S. market, where the U.S. market liquidity measures are from Anderson and Stulz (2017). In Panels B and C, the sample period is June 9, 2014 to June 8, 2015.

Panel A: China and U.S. Comparison

	China: Interbank	China: Exchange	U.S.
ZDays	0.88856	0.81326	0.78820
$ZDays_{w/trade}$	0.88768	0.79798	0.70940
Turnover	0.01212	0.00099	0.00150
Amihud	0.00016	2.54233	0.48810

Panel B: China's Exchange Bond Market Liquidity

	All	Enterprise Bond	Exchange-Traded Corporate Bond
ZDays	0.80693	0.83215	0.75485
$ZDays_{w/trade}$	0.77092	0.80758	0.68604
Turnover	0.00109	0.00050	0.00231
Amihud	2.93788	3.79992	1.06712

Panel C: China's Interbank Bond Market Liquidity

	All	Enterprise bond	Mid-term note	Commercial paper
ZDays	0.90284	0.92185	0.92419	0.83746
$ZDays_{w/trade}$	0.89786	0.91462	0.92160	0.83451
Turnover	0.00984	0.00801	0.00757	0.01647
Amihud	0.00021	0.00040	0.00023	0.00005

Table AII

The Five Blacklists of Repo Disqualified Enterprise Bonds

This table presents the security codes of enterprise bonds in the five blacklists announced by CSDC. The five lists were released on May 29, 2014, June 27, 2014, August 1, 2014, September 5, 2014, and November 3, 2014. MCBs are indicated with ⋆. Bonds in the simultaneous sample are indicated with #.

May 29, 2014	August 1, 2014		September 5, 2014
122535.SH #	122509.SH ⋆ #	124364.SH ⋆ #	111039.SZ
122683.SH #	122539.SH ⋆ #	124373.SH ⋆ #	111047.SZ ⋆ #
122989.SH ⋆ #	122541.SH #	124457.SH ⋆ #	124132.SH ⋆ #
124102.SH #	122562.SH ⋆ #	124459.SH ⋆	
	122568.SH ⋆ #	124495.SH #	
June 27, 2014	122582.SH ⋆ #	124541.SH ⋆	November 3, 2014
122522.SH ⋆ #	122601.SH ⋆ #	124562.SH ⋆ #	111064.SZ ⋆ #
122542.SH ⋆ #	122662.SH ⋆ #	124572.SH ⋆ #	122590.SH ⋆ #
122556.SH ⋆ #	122694.SH ⋆ #	124688.SH ⋆ #	122687.SH ⋆ #
122753.SH ⋆ #	122721.SH ⋆ #	124706.SH ⋆ #	122811.SH
122769.SH ⋆ #	122754.SH ⋆ #	124716.SH ⋆ #	124001.SH ⋆ #
122812.SH ⋆ #	122759.SH	124734.SH ⋆ #	124039.SH ⋆
122843.SH ⋆ #	122807.SH	124766.SH ⋆ #	124231.SH ⋆ #
122857.SH ⋆ #	122841.SH ⋆		124267.SH ⋆
122883.SH ⋆ #	122918.SH ⋆ #		124378.SH ⋆ #
122931.SH ⋆	122945.SH ⋆ #		124478.SH ⋆ #
122936.SH ⋆ #	124010.SH ⋆ #		124509.SH ⋆ #
122937.SH ⋆ #	124025.SH ⋆ #		124521.SH ⋆ #
124018.SH ⋆ #	124038.SH #		124587.SH ⋆
124019.SH ⋆ #	124061.SH ⋆ #		124611.SH ⋆ #
124076.SH ⋆ #	124079.SH ⋆ #		124632.SH ⋆ #
124100.SH ⋆ #	124092.SH #		124730.SH ⋆
124127.SH ⋆ #	124104.SH ⋆ #		124802.SH ⋆ #
124131.SH ⋆ #	124130.SH #		124812.SH ⋆
124262.SH ⋆ #	124175.SH ⋆ #		124852.SH ⋆ #
124272.SH ⋆ #	124178.SH ⋆ #		124864.SH ⋆
124316.SH ⋆ #	124202.SH ⋆		
124334.SH ⋆ #	124218.SH #		
124351.SH ⋆ #	124223.SH #		
124396.SH ⋆ #	124256.SH #		
124469.SH ⋆ #	124260.SH ⋆ #		
124512.SH ⋆ #	124274.SH #		
124564.SH ⋆	124309.SH #		
124627.SH ⋆	124324.SH ⋆ #		
124656.SH ⋆ #	124329.SH ⋆		
124699.SH ⋆	124354.SH ⋆		
124749.SH ⋆ #	124360.SH ⋆ #		
124754.SH ⋆ #			

Table AIII
Variable Definitions

Variable	Definition
Dependent variables	
EX premium	Exchange premium in terms of percentage, given as the interbank market credit spread minus the simultaneous exchange market credit spread
EX premium_{pre}	Exchange premium of the subsample before the policy shock from June 9, 2014 to December 8, 2014
EX premium_{post}	Exchange premium of the subsample after the policy shock from June 9, 2014 to June 8, 2015
Matched spread	Credit spread in percentage terms is the exchange market AA+/AA-rated bond credit spread minus the matched AAA-rated bond credit spread
Explanatory variables	
Haircut	The percentage of levered investors' own money needed for the margin account to borrow using the underlying bond as collateral
Haircut_{pre}	Haircut of the subsample before the policy shock from June 9, 2014 to December 8, 2014
Haircut_{post}	Haircut of the subsample after the policy shock from December 9, 2014 to June 8, 2015
Conversion	The rate (%) between the value of exchange market standard bond that can be converted from one unit of pledgeable bonds
Conversion_{pre}	Conversion rate of the subsample before the policy shock from June 9, 2014 to December 8, 2014
Conversion_{post}	Conversion rate of the subsample after the policy shock from December 9, 2014 to June 8, 2015
Bond-day level variables	
IB spread	The interbank market credit spread defined as the bond trading price implied yield to maturity minus the matching China Development Bank bond yield
EX spread	The exchange market credit spread defined as bond trading price implied yield to maturity minus the matching China Development Bank bond yield
$\Delta P^{high-low}$	The difference in daily price range between the exchange market and interbank market, where the price range in percentage terms is defined as the daily high minus the low clean price divided by the average of the two
Maturity	The number of years to maturity as of the day of trade
Turnover	The total number of shares traded in both the interbank and exchange markets over the number of shares outstanding
Market price	The average invoice trading price of the most recent five nonzero trading days of the exchange market
Volatility	The highest close price minus the lowest close price divided by the average of the two over the past five nonzero trading days of the exchange market
Day level variables	
CDB_{spot}	10-year China Development Bank spot yield as of the day of trade
Term spread	10-year Treasury yield minus one-year Treasury yield as of the day of trade
GC001−SHIBOR	Spread of one-day Shanghai exchange repo rate over one-day Shanghai Interbank Offering Rate as of the day of trade
Ret_{stock}	Daily return of Shanghai Composite Index as of the day of trade

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.