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Implicit guarantees and the rise of shadow banking: The case of trust products ☆

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ABSTRACT

Implicit guarantees provided by financial intermediaries are a key component of China's shadow banking sector. We show theoretically that project screening by intermediaries, accompanied by their implicit guarantees to investors, can be the second-best arrangement and mitigate capital misallocation that favors state-owned enterprises (SOEs). Using a dataset of trusts' investment products, we find, consistent with our model, that *ex ante* expected yields reflect borrower risks and implicit guarantee strength, and risk sensitivity is reduced by strong guarantees. Regulations in 2018 restricting implicit guarantees lead to a weaker relationship between yield spread and guarantee strength, and more credit rationing of non-SOEs.

1. Introduction

Shadow banking has experienced exponential growth in China during the past two decades, especially since the 2008-09 global financial crisis (GFC) and the ensuing RMB 4 trillion stimulus implemented by the Chinese government. The sector has played an important role in financing the country's economic growth, but also leads to concerns about the magnitude of debt and the risk it adds to the financial system. At the core of the shadow banking sector is the wealth management products (WMPs) or

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investment products sponsored by financial intermediaries such as banks, trust companies, and securities firms, which constitute 52.3% of total shadow banking assets by 2020.[1] These products are marketed as alternatives to bank deposits to both individual and institutional investors, and the payoffs are backed by the underlying investment of the funds raised.

A central feature of these products is that investors expect implicit guarantees on the returns of risky investments (see, e.g., Dang, Liu, Wang, and Yao, 2019; Zhu, 2016). Although the product prospectuses clearly state that returns are contingent on the underlying investment payoffs and are not guaranteed, investors generally believe that the expected yields stated in the prospectuses are actually *promised* yields, and that the product-issuing and/or sponsoring financial company and/or other related parties (the distributing bank, their controlling shareholders, the government) will make up the shortfall if the underlying projects/borrowers fail to pay back the loans. In reality, such implicit guarantees to the investors are often honored (see Table A.1 in the Online Appendix A for ex post payoffs in default cases).

There is ongoing debate on the net benefits of implicit guarantees in China's financial system. Critics focus on the moral hazard problem any guarantees will induce, i.e., investors will lack incentives to collect information and price the products efficiently. Implicit guarantees provided to financial institutions may encourage them to take excessive risks, which can increase the overall risks and fragility of the entire financial system. However, while both traditional banking and the security (stock and bond) markets systematically favor state-owned enterprises (SOEs), shadow banking accompanied with implicit guarantees has played an important role in funding non-SOEs, especially small and medium-sized firms, which have been the engine of economic growth (see, e.g., Allen, Qian, Tu, and Yu, 2019).

We develop a theoretical model to understand the potential optimality of implicit guarantees in shadow banking. In a setting where investors rely on a financial intermediary to screen projects, we show that it is a second-best solution for the intermediary to provide implicit guarantees for the investors under reasonable conditions. On the one hand, an implicit guarantee incentivizes the intermediary to screen projects by making it bear the project risk. On the other hand, it gives the intermediary the flexibility of not paying in bad economic states when the cost of paying is particularly high. Thus, an implicit guarantee is preferred to an explicit guarantee or no guarantee when the social benefit of screening is high relative to the costs.

Under the framework of our model, we further investigate the efficiency of capital allocation with and without implicit guarantees. We examine a traditional banking system with explicit guarantees to investors and an extended banking system that also includes shadow banking with implicit guarantees. Consistent with the literature, there is capital misallocation between SOE and private sectors due to the systematic favoritism toward SOEs.[2] While misallocation exists in both banking systems, more private projects will be funded, and allocation efficiency improved when shadow banking with implicit guarantees is allowed. As a result, total output will also be higher.

By demonstrating the optimality of implicit guarantees, we shed light on why implicit guarantees have become a key feature of shadow banking and the important role they play in mitigating capital misallocation in China. We also derive several empirical predictions from the model. Under the equilibrium with implicit guarantees, the model predicts that the product yield increases with the risk of the underlying project and decreases with the strength of the guarantees. The yield-to-underlying-risk sensitivity will be reduced by the strength of the guarantees. In addition, the model predicts that imposing costs on the provision of guarantees will lead to declines in shadow banking as well as capital allocation to the non-SOE sector.

We empirically test these predictions by using a comprehensive sample of investment products sponsored by all 68 licensed trust companies. The trust industry is the largest nonbank financial industry in the last decade. As *non*-deposit-taking institutions, trust companies raise funds through the issuance of investment products. The trust industry plays an important role in shadow banking, as trust companies work closely with banks but are less regulated than banks. The proceeds from the trust products are then invested in a wide range of projects and (financial) assets, including loans to risky projects (e.g., real estate) and corporate sectors.

In our first set of tests, we examine the level of expected yields on the trust products. Consistent with the model's prediction, we find that the product yield spread depends on both the underlying investment risk as well as the strength of the implicit guarantee. Specifically, the yield spread is higher if the borrower is smaller, or from the risky real estate industry, or located in a province with lower GDP growth. We measure the (perceived) strength of the implicit guarantee by the sponsoring trust firm's size, the type of its controlling shareholders (whether it is an SOE, especially one controlled by the central government), and whether the product is sold through one of the five largest state-owned banks. Yield spreads are lower if the trust firm is larger or controlled by an SOE, or if the product is sold via one of the largest 5 banks. The yield depends on each of these variables as well as an implicit guarantee index (IG index) aggregated over these three dimensions.

A potential endogeneity issue is that products sponsored by different trust firms may have different risk levels. We address this issue in two ways: first, we use several events that changed the perceived strength of guarantees or the underlying borrower risk as 'quasi-experiments' and perform difference-in-differences (DiD) tests. Second, we

[1] This is based on a Moody's quarterly report on China Shadow Banking Monitor in June 2021.

[2] See, for example, Boyreau-Debray and Wei (2005), Dollar and Wei (2007), Song, Storesletten, and Zilibotti (2011), Song and Xiong (2018); Cong, Gao, Ponticelli, and Yang (2019). This systematic favoritism is due in part to policy directives for state-owned banks and the government's implicit guarantees provided to SOEs.

use a propensity-score matching (PSM) procedure where products sponsored by trusts with a high IG index are matched to products with similar underlying risk but sponsored by trusts with a low IG index. All of our main results are robust in the matched sample.

For the spread level test, we use China's stock market crash in 2015 as a negative shock to the strength of affected trust firms' implicit guarantees. The financial health of those trust firms that had invested the largest amounts in securities markets would have been more negatively affected by the stock market crash, and so would be the strength of their implicit guarantee. We find that investors are sensitive to the risk the sponsoring trust firm is exposed to. Specifically, yield spreads increase more for products sponsored by trusts that had invested the largest amounts in securities markets.

In the second set of tests, we examine the spread-to-risk sensitivity. Consistent with the model's prediction, we find strong implicit guarantees reduce the sensitivity of yield spread to the underlying investment risk. We show that yield spread is less sensitive to investment risk (as measured by borrower size, its provincial GDP growth, and whether it is in the real estate industry) when the guarantee is perceived to be stronger (i.e., when the IG index is higher).

We use the first high-profile default case of an investment product as a shock to the market perception about all trust products' risks. The spreads increase after this default case, but the effect is largely mitigated if the implicit guarantee is strong.

For the subsample of products invested in the real estate sector (which is the largest investment sector for trust products as well as for shadow banking in general), we measure local housing market risk following Glaeser, Huang, Ma, and Shleifer (2017). We find that the spread increases with the housing market risk, but the sensitivity is dampened by the strength of the implicit guarantee. We use staggered provincial implementations of a policy change during 2010-2011 restricting housing purchases (known as the "Order 10") as a shock to the real estate industry. Consistent with the notion that risk increases after the regulation, we find that the spreads of products investing in real estate increase. The spread increase, however, is smaller if the strength of implicit guarantee is higher.

In our final set of tests, we exploit a regulation shock in 2018 to examine the consequences when the implicit guarantee is restricted. In March 2018, the central government announced the guidelines for "Regulating the Asset Management Business of Financial Institutions," and prohibited implicit guarantees on newly issued products. These new regulations impose costs on the provision of implicit guarantees for trust companies.[3] As a result, the relationship between yield spread and our measures of guarantee strength is weakened, reflecting lower expectation on the 'delivery' of guarantees. At the aggregate level, we find that shadow banking in general, and the trust industry in particular, have declined in size since the announcement of the new regulations, as has been the funding to the non-SOE sector.

We obtain information on loan contracts (between borrower firms/projects and the issuing trusts) on a subsample of products and find that the size of products financing risky projects (in real estate, and commercial and industrial firms) fell more in the post-2018 period when the trust company's strength in providing guarantees is weaker, and when the borrower firm is privately owned. In particular, when a trust firm's guarantee strength is weak (IG index equals 1, the median), the size of its loans to non-SOE borrowers is reduced by more than half after 2018.

Our paper contributes to several literatures. First, it is related to the literature on implicit guarantees. The first strand of this literature includes empirical evidence on implicit recourse prior to the GFC, which is mainly through studies of credit-card securitization and generally shows that the market reacts favorably to such guarantees to investors (Higgins and Mason, 2004; Calomiris and Mason, 2004; Vermilyea, Webb, and Kish, 2008). In contrast, Acharya, Schnabl and Suarez (2013) argue that securitization without risk transfer due to banks' explicit guarantee to investors contributed to the GFC. Kacperczyk and Schnabl (2013) study implicit guarantees provided to money market funds by their sponsors and document evidence that such guarantees can induce different risk-taking behavior by the funds.

A second strand of implicit guarantee literature is on banks that are "too big to fail," and documents that the largest banks enjoy government subsidies, which positively impact the prices of their debt and equity securities (see Berndt, Duffie, and Zhu, 2022 and the papers referred to therein). Several papers examine the pricing of subordinated debt issued by US banks and document that the pricing changes as the perception of government guarantees to banks varies (Flannery and Sorescu, 1996; Sironi, 2003; Morgan and Stiroh, 2005; Balasubramnian and Cyree, 2011). Recently, Acharya, Anginer, and Warburton (2016) show that bond spreads are sensitive to risk for most financial institutions, but not for the largest financial institutions.

Our paper complements these two strands of studies by examining implicit guarantees in China's shadow banking sector. We demonstrate theoretically the (second-best) optimality of implicit guarantees—provided by financial intermediaries to the investors—and the important role they play in funding productive non-SOE projects/firms and mitigating capital misallocation of the traditional banking system that favors SOEs. Empirically, unlike the too-big-to-fail problem where the government guarantee is extended to only the largest banks, in our setting implicit guarantees are primarily offered by trust companies, whose guarantee strengths in covering investor losses following product failure vary. We measure the strength of implicit guarantees of trust products from various aspects and test the impact of implicit guarantees in a rich setting.

[3] The new regulations do not specify the punishment for violators (that provide implicit guarantees), and the transition period has been extended a few times. For more details, see http://www.pbc.gov.cn/en/3688253/3689009/3788480/3778722/index.html. Table A.1 in the Online Appendix A shows that trust firms continue to cover losses for investors in the post-2018 period, although the frequency is much lower and the reasons and process for such coverage are different than before.

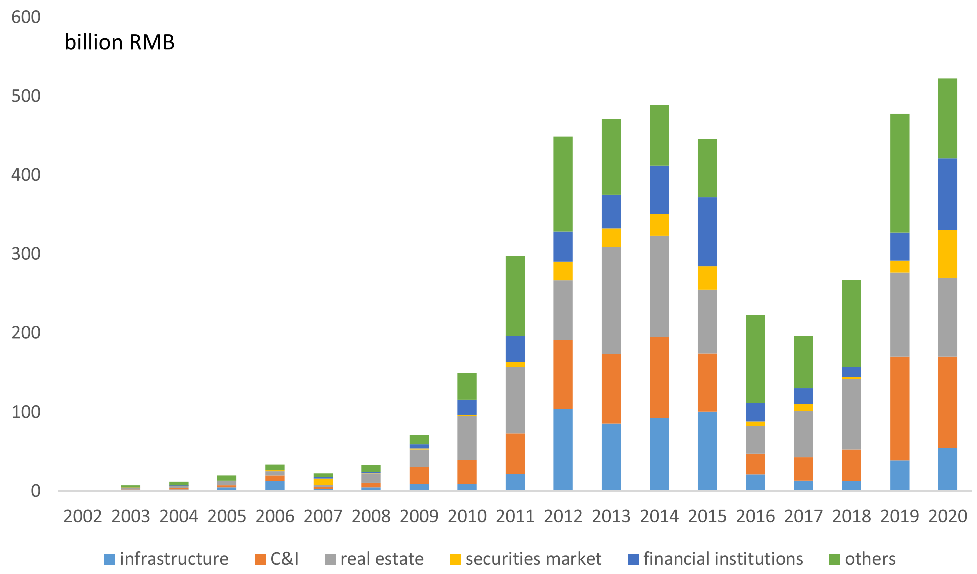

Fig. 1. Total issuance of the trust product sample: by industry and year.
This figure plots the total issuance of our sample products by year and by industry, from 2002 to 2020. We drop those products without yield or issuance volume information.

In a third strand of literature related to implicit guarantees, several papers study China's implicit government guarantees provided to SOEs and their impact on the allocation and pricing of credit to SOEs vs. non-SOEs. Cong, Gao, Ponticelli, and Yang (2019) study this issue for bank loans and Geng and Pan (2021) document an SOE premium for bonds. Jin, Wang, and Zhang (2022) conduct an event study to estimate the value of implicit government guarantees. Our paper differs by focusing on financial intermediaries' provision of implicit guarantees to investors. We show that this type of implicit guarantees, unlike government guarantees, can support the private sector, reduce capital misallocation, and improve social welfare. To this end, our paper sheds new light on the understanding of implicit guarantees in the Chinese capital markets and the overall economy.

Our paper also contributes to a burgeoning literature on China's shadow banking. Wang, Wang, Wang, and Zhou (2019) and Hachem and Song (2021) provide theoretical explanations related to the 'dual-track' system of interest rates and bank competition for the growth of the sector. Chen, He, and Liu (2020) argue that China's stimulus package in 2009 and the need to roll over the related bank loans led to the rapid growth of the sector. Allen, Qian, Tu, and Yu (2019) and Chen, Ren, and Zha (2018) study entrusted loans, another important form of shadow banking in China. Acharya, Qian, Su, and Yang (2021) show that small and medium-sized banks issue WMPs as a substitute for deposits and as a result of regulatory arbitrage. Huang, Huang, and Shao (2022) document evidence that banks with perceived higher risk are more likely to pay the expected yields on their WMPs to boost their reputation. We study the role of implicit guarantees provided to investors in shadow banking. Empirically, we are the first to provide an in-depth analysis of the trust industry, the largest nonbank financial industry during much of our sample period.

2. Institutional background about the trust industry

China has a bank-dominated financial system, with nonbank financial institutions experiencing fast growth in recent years (see, e.g., Allen et al., 2015, 2017). The first trust company, China International Trust and Investment Corporation (CITIC), was established in 1979. After that, the industry experienced several rounds of development, clean-up, and consolidations. In 2001, the Trust Law was enacted. The growth of this industry took off since 2010 (see Fig. 1 for the total issuance of our sample trust products by year, and Fig. A.1 in Online Appendix A for the industry asset size as a percentage of GDP over time). In 2012 it overtook the insurance industry as the largest nonbank financial sector (see Fig. A.2 in Online Appendix A for the asset size of each of the nonbank financial sectors by year). By 2020, the total asset size of the trust industry is RMB 20.5 trillion (US$ 3.04 trillion), or 20.2% of GDP. There are currently 68 licensed trust firms. Twenty-two of them are controlled by central SOEs, thirty-one are controlled by local SOEs, and the remaining fifteen are controlled by non-SOEs.

The fast growth of the trust industry since 2010 coincided with the rise of shadow banking—i.e., credit intermediation involving activities outside the traditional banking system. The annual shadow banking activities in China increased from 15 trillion RMB (US$ 2.22 trillion) in 2010 to a peak of 66 trillion RMB (US$ 9.76 trillion) in 2017 (see Fig. A.3 in the Online Appendix A for the sizes of total shadow banking activities and its components).[4] A

[4] As discussed in Section 5.4, the shadow banking sector started to shrink after the recent regulation change "*New Regulations on Asset Man-*

slew of recent studies explore theoretically and empirically the reasons behind the rise of the sector, including market responses to the distorted banking system that most small- and medium-sized firms have little access to, both the deposit and bank loan rates are below the market rates (Allen, Qian, Tu, and Yu , 2019), regulatory arbitrage to evade liquidity, interest rate, or credit control (Wang, Wang, Wang, and Zhou, 2019; Hachem and Song, 2021; Acharya, Qian, Su, and Yang, 2021), and the 4 trillion RMB stimulus package in 2009 (Chen, He, and Liu, 2020). The three most important components of this sector are: assets funded by WMPs issued by banks and securities firms (excluding entrusted and trust loans as underlying assets), entrusted loans, and trust loans.

Trust companies are lightly regulated compared to banks. For instance, banks are required to hold a 12.5%-14.5% deposit reserve, while trust companies are only required to hold a loss reserve equal to 5% of their after-tax profits. Bank lending is closely monitored by the regulators and is subject to tight monitoring, explicit restrictions, as well as informal guidance. Both the deposit rate and bank loan rate were tightly controlled until 2015; each bank's total loan amount is capped, and banks were also subject to a maximum of 75% loan-to-deposit ratio until 2015. Trust firms are not subject to these regulations. Since 2010, banks have been restricted from lending to certain industries including the real estate sector that accounts for 14% of GDP and receives about 26% of total investments in the economy.[5] Trust firms, on the other hand, are the only type of financial companies that can invest in any sector of the real economy as well as the capital market. They can make loans, take direct equity interest in firms, invest in marketable securities (both equity and debt securities) or investment products of other financial firms, or engage in financial leasing.[6]

Since the Chinese corporate bond market is dominated by large issuers with above-investment-grade ratings (see, e.g., Amstad and He, 2020), trust loans extended to real estate projects and industrial and commercial firms can be regarded as part of the "high yield" segment of the risky fixed income market, with the trust firms playing the role of rating agencies in the evaluation of investment projects and (borrower) firms. For high net-worth investors, trust products (typically require a minimum investment level of RMB 1 million) also provide an alternative class of *intermediated* financial assets, which complements investing in risky assets such as stocks and real estate directly (or through other financial institutions).

The trust industry plays a special role in facilitating shadow banking due to the so-called "bank-trust cooperation," i.e., banks invest in trust products to bypass the regulations. Banks can use either on-balance-sheet or off-balance-sheet (mainly WMPs) capital to invest in trust products, which then can invest in borrowers that banks cannot directly lend to. If using WMPs to purchase trust products, banks can also get around the reserve and liquidity regulations. To evade monitoring and potential crackdowns, banks sometimes invest in assets of other financial firms (e.g., securities firms, mutual funds, or their subsidiaries) first, which in turn purchase trust products. There can be multiple layers of these "pipeline investments."

agement" in March 2018. The size of the trust industry has also decreased since then.

[5] These are the average ratios during 2010-2020 based on the National Bureau of Statistics.

[6] Insurance companies, securities firms, and mutual funds cannot make loans; and commercial banks cannot invest in the stock market.

3. Theoretical analysis of implicit guarantees

In this section, we develop a model to understand the functioning and optimality of implicit guarantees. In Section 3.1, we examine the optimization problem of an intermediary who decides whether to screen projects and designs the payoff schemes. We demonstrate the optimality of implicit guarantees under certain conditions. In Section 3.2, we examine the model's implication on the efficiency of capital allocation with and without implicit guarantees. The model provides several testable hypotheses.

3.1. The baseline one-period model of the loan screening problem

Fig. 2 illustrates the timing and structure of the model. There is a single period with two dates, date 0 and date 1. At date 0, an investment project is available. If invested with the capital amount of 1, the project pays off $1+\delta$ at date 1 in the case of success and $1-\delta$ in the case of failure. The project is either of a normal risky type with probability $1-q$, or a bad project with probability q. The normal risky project's failure rate is p, and the bad project always fails. A representative investor provides capital. A financial intermediary has access to a screening technology, while the investor does not. Specifically, the financial intermediary can pay a screening cost of ξ to learn the project type and subsequently reject the bad project. Choosing to screen is denoted e $=$ 1, otherwise e $=$ 0. The financial intermediary and the investor share the project's payoff. We denote the financial intermediary's payoff by D_b, which can be negative, for instance, in the case that the financial intermediary covers the project loss for the investor at a cost of ϕ. At date 1, the financial intermediary is in either of the two states: (a) the normal state with probability $1-\pi$, where the unit cost of negative cash flow is $\phi=\phi_N$ (subscript N for the normal state) with $\phi_N>1$; and (b) the bad state with probability π where the unit funding cost goes up to $\phi=\phi_B$ (subscript B for the bad state) with $\phi_B>\phi_N$. This higher cost of finance in the bad state reflects the fact that, for example, the probability of costly bankruptcy is higher in the bad state.

Both the financial intermediary and the investor have risk neutral utility over the date 1 cash flow and we normalize the investor's required rate of return to zero. The financial intermediary maximizes the objective function by deciding whether to screen ($e=1$ if screening and $e=0$ if not screening) and how to share the project cash flow with the investor (i.e., by designing the payment scheme D_b):

$$\max_{e,D_b} E(D_b)+E[(\phi-1)\cdot\min(D_b,0)]-\xi e.$$

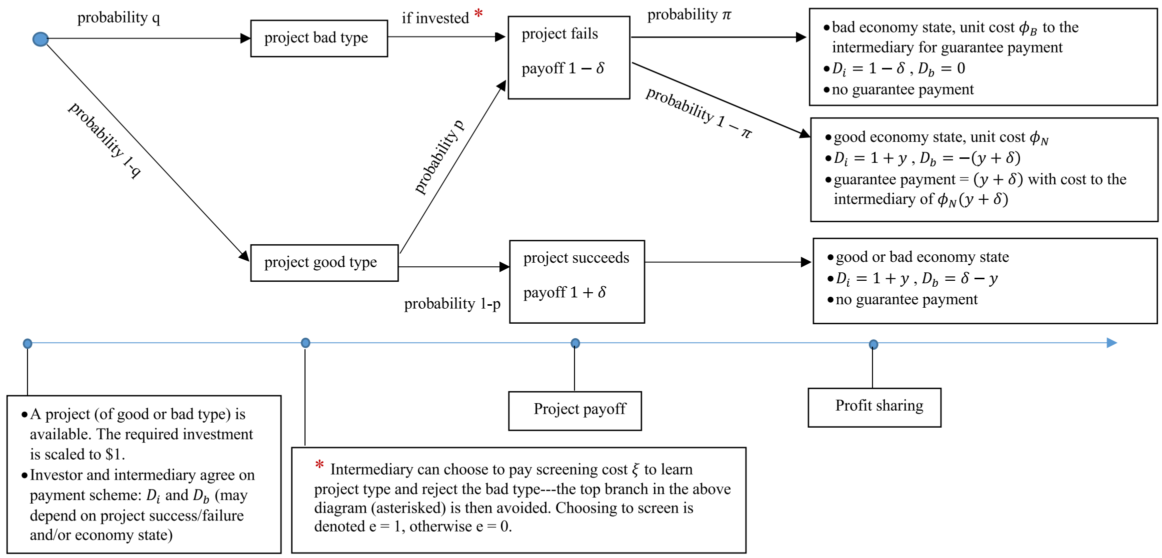

Fig. 2. The sequence of events and possible outcomes.
For illustration of the payment scheme, the D_i and D_b in the above diagram are based on case 1 of Proposition 2 (for implicit guarantees). For other cases (second best or explicit guarantees, and so on), D_i and D_b need to be replaced by their case-corresponding formulas accordingly. Furthermore, yield y also varies and is endogenously solved in Propositions 1 and 2. Finally, the cost of guarantees to the intermediary needs to reflect the appropriate funding cost of finance of ϕ_N or ϕ_B in the normal and bad states of the economy, respectively.

subject to the investor's participation constraint. In the above objective function, the first term is the expected direct cashflow from the project to the intermediary. The second term captures the additional financial cost incurred only when there is a negative cash flow. The combination of the first two terms is the expectation of overall cashflow to the intermediary, which is D_b if positive and ϕD_b (with $\phi > 1$ to represent the additional funding cost) if negative. For example, suppose the promised yield to the investor is 5%. In the case the project succeeds and pays 12%, with the initial investment set to 1, the investor gets the promised return of 5%, and the overall cashflow to the intermediary is the remainder of 7%. If, however, the project fails and loses 12%, and if the intermediary is to make a transfer of 17% to the investor to make up the project loss, due to some form of guarantee, then the intermediary's overall cashflow is negative $17\% \times \phi$. The additional amount of $17\%(\phi-1)$, on top of the direct loss of cashflow of 17% from the project, is due to the additional funding cost. The last term is the screening cost. The screening choice (i.e., $e = 0$ or 1) affects the expected payoff of a funded project and therefore the expected payoff to the intermediary (D_b) (see Online Appendix B.1 for full details).

In the first-best solution, the intermediary should screen if and only if the social benefit of avoiding the bad project outweighs the cost of screening. In contrast, in the second-best solution, the incentive compatibility constraint dictates that the intermediary compares its cash flows between screening and no-screening and screens only if doing so is beneficial to its own utility. We record the first-best (subscripted below by 1b) and second-best (subscripted by 2b) solutions in the following proposition. All proofs are provided in Online Appendix B.1. Hereafter, we denote the screening cost relative to the social benefit by η. That is, $\eta = \frac{\xi}{q\delta}$. There are a set of related notations that provide shorthand in the text: ρ_{2b}, η_{2b}, η_{ug}, η_0, η_1, η_{cg}, ρ_{cg}, and η'_{cg}. Their exact expressions are in Online Appendix B.1.

Proposition 1. First-Best Solution,

[Case 1.1] $\eta < 1$. The intermediary screens with the resulting utility:

$$u_{1b} = (1-q)(1-2p)\delta - \xi = u_{ns} + q\delta(1-\eta);$$

[Case 1.2] $\eta \geq 1$. The intermediary does not screen, and its utility is:

$$u_{ns} = ((1-q)(1-2p) - q)\delta.$$

Second-Best Solution:

[Case 2.1] $\eta < \eta_{2b}$. The intermediary screens, provides a conditional guarantee, and its utility is given by:

$$u_{2b} = u_{ns} + \rho_{2b} q\delta(\eta_{2b} - \eta).$$

If the project fails, the intermediary makes a payment to the investor in the amount of $\frac{\xi}{q(1-\pi)\phi_N}$, if it is in the normal state but makes no such payment in the bad state.

[Case 2.2] $\eta \geq \eta_{2b}$. The intermediary does not screen and provides no guarantee, and its utility is u_{ns}.

The utility loss, $u_{1b} - u_{2b} = (\rho_{2b} - 1)\xi > 0$ (shown in Online Appendix B.1), captures the cost of the moral hazard problem. Furthermore, the intermediary screens less in the second-best than socially optimal because $\eta_{2b} < 1$ (shown in Online Appendix B.1).

In the first best, the intermediary does not provide any guarantee because it is not socially optimal to incur additional funding costs in case of project failure. In the second best, however, the intermediary needs to be incentivized to screen by bearing some consequence of the project failure. It is optimal for it to make a payment to the investor in case of project failure in the normal state but for the investor to take the full loss in the bad state. In other words, the intermediary provides a conditional guarantee. When a project fails in normal times, it is reasonable to question whether the intermediary has screened the project properly. In contrast, in bad economic times, projects are likely to fail due to broad economic factors that are beyond the intermediary's control. Furthermore, under harsh economic conditions, the financial system may be under stress. Having the intermediary bearing the loss in those times adds further stress to the system, creating systemic risk.

In the second-best solution above, we solve the problem without constraining the form of the investor payoff. Below, we restrict the form to resemble a debt security. The investor's investment has a yield y.[7] If the project succeeds, the investor gets the promised payment $1+y$. If the project fails, the investor gets the full project payoff $1-\delta$. In addition, the intermediary can offer a guarantee to the investment and consequently makes up the loss of $y+\delta$. The guarantee can be unconditional or conditional. The unconditional guarantee renders the investor's cash flow risk free. Motivated by the second-best solution, we model the conditional guarantee by assuming that the intermediary makes up the shortfall only in the normal state. We solve the intermediary's optimal strategy.

Proposition 2. [When investor payoff mimics debt instruments] The solution is separated into four cases depending on the value of η.

[Case 1] $\eta \le \eta_0$. The intermediary screens and chooses the conditional guarantee strategy. The loan yield is

$$y = \frac{p\pi\delta}{1-p\pi}.$$

The investor's utility is 0. The intermediary's utility is

$$u_{cg} = u_{ns} + q\delta(\eta_{cg} - \eta).$$

[Case 2] $\eta \in (\eta_0, \eta_1)$. The intermediary screens and chooses the conditional guarantee strategy. The yield is:

$$y = \left(\frac{\eta}{(1-\pi)\phi_N} - 1\right)\delta.$$

The investor gets a positive utility. The intermediary's utility is

$$u_{cg} = u_{ns} + (\rho_{2b} + \rho_{cg})q\delta\left(\eta'_{cg} - \eta\right).$$

[Case 3] $\eta \in [\eta_1, \eta_{ug}]$. The intermediary screens and chooses the unconditional guarantee strategy. The yield is: $y = 0$. The investor's utility is 0. The intermediary's utility is

$$u_{ug} = u_{ns} + q\delta(\eta_{ug} - \eta).$$

[Case 4] $\eta > \eta_{ug}$. The intermediary does not screen and provides no guarantee. The yield is:

$$y = \frac{(1-q)p + q}{(1-q)(1-p)}.$$

The investor's utility is 0, and the intermediary's utility is u_{ns}.

The intuition of Proposition 2 is as follows. In Case 1 ($\eta \le \eta_0$), when the cost of screening (relative to the benefits) is low, the need to provide a conditional guarantee is enough incentive for the intermediary to screen projects. What determines the loan spread is the investor's participation constraint. When the screening cost is moderately high (Case 2), the intermediary needs more incentive to screen. It thus gives itself a riskier payoff by offering higher yields to the investor. In this case, the loan spread is determined by the intermediary's incentive compatibility constraint, not the investor's participation constraint (hence a surplus to the investor). This is optimal for the intermediary, compared to the off-equilibrium outcome without screening. In both cases, the screening cost is low enough that the intermediary only needs to offer conditional guarantees. When the screening cost is even higher (Case 3), the intermediary needs even stronger incentives (i.e., unconditional guarantees) to screen. Finally, when the screening cost is too high (case 4), it is no longer optimal to screen or provide guarantees. Overall, the condition for screening to take place is $\eta < \eta_{ug}$. The intermediary screens less here than in the second-best solution (i.e., $\eta_{ug} < \eta_{2b}$, shown in Online Appendix B.1) due to the constraint of the debt payoff form. We depict the intermediary utility and the loan yield in different ranges of η in Figs. B1 and B2 in Online Appendix B to illustrate the four cases of Proposition 2.

Proposition 3. When the conditional guarantee is optimal (i.e., when $\eta \le \eta_1$), we have the following comparative statistics:

$$\frac{\partial y}{\partial p} = \begin{cases} \frac{\pi(\delta+r)}{(1-p\pi)^2} > 0 & \text{when } \eta \le \eta_0 \\ 0 & \text{when } \eta_0 < \eta \le \eta_1; \end{cases}$$

$$\frac{\partial y}{\partial \pi} = \begin{cases} \frac{p(\delta+r)}{(1-p\pi)^2} > 0 & \text{when } \eta \le \eta_0 \\ \frac{\eta}{(1-\pi)^2\phi_N}\delta > 0 & \text{when } \eta_0 < \eta \le \eta_1; \end{cases}$$

$$\frac{\partial^2 y}{\partial \pi \partial p} = \begin{cases} \frac{(1+p\pi)(\delta+r)}{(1-p\pi)^3} > 0 & \text{when } \eta \le \eta_0 \\ 0 & \text{when } \eta_0 < \eta \le \eta_1. \end{cases}$$

Proposition 3 states that in the case of conditional guarantees, the loan yield (or yield spread) depends on two parameters: p and π. The parameter p represents the underlying project risk. The guarantee is by design not complete, leaving the investors bearing a portion of the investment risk. The higher the risk (higher p), the higher the spread.

[7] Note that we normalize the risk-neutral investor's required rate of return (i.e., the risk-free rate of return) to be zero. Hence y is both the yield and the yield spread.

The parameter π is the probability that the financial intermediary will be in a bad state in which it will not cover losses for the investor. The higher the probability, the less likely the guarantee will be honored. Proposition 3 says that the yield is an increasing function of π (i.e., a decreasing function of the strength of the guarantee). Furthermore, the stronger the guarantee, the better it shields investors from the investment risk. Thus, the loan spread's sensitivity to the project risk, $\frac{\partial y}{\partial p}$, is lower when it is sponsored by an intermediary with higher guarantee strength (lower π). In other words, a strong guarantee reduces the yield-to-underlying risk sensitivity.

3.1.1. Repeated game with implicit guarantees

The conditional-guarantee strategy involves the intermediary covering investment losses in normal times but not in bad states. Contracting explicitly such a strategy would require verifying the state the intermediary is in, which can be costly or simply impossible. The implicit guarantee is an efficient alternative if the fulfillment of the guarantee in the normal state is ex post incentive compatible. To establish the *ex post* incentive compatibility, we rely on the traditional argument of reputation-concern in repeated games. The detailed analysis is presented in Online Appendix B.2. Here we summarize the key results.

Under the condition that there is a sufficient gap of funding costs for the intermediary between the bad and the normal states, specifically when $\phi_B - \phi_N \geq \hat{\phi}$ (with the exact expression for $\hat{\phi}$ given in Online Appendix B.2), the equilibrium is characterized by the contingency-nature of the implicit guarantee—the intermediary voluntarily covers the loss of the loan in the normal state but not if in the bad state (Proposition A.1 in Online Appendix B.2). The condition, $\phi_B - \phi_N \geq \hat{\phi}$, is intuitive. The intermediary would voluntarily honor the guarantee under normal situations only if failing to do so carries a severe enough stigma on its reputation, i.e., being mistaken as in a substantially worse state than it is actually in.

Our results in Proposition 3 carry into the repeated game. We therefore have the following hypotheses under the equilibrium of the implicit guarantees:

Hypothesis I. The loan yield increases with the underlying investment risk and decreases with the strength of the implicit guarantee.

Hypothesis II. The yield sensitivity to the underlying investment risk is reduced by the strength of the implicit guarantee.

Both hypotheses relate product yields to the characteristics of the issuing trust firms, their shareholders, as well as the products themselves, including borrower/project information in the case of trust loans. In Section 5, we perform regression analyses using product information at issuance, based on the prospectuses to examine these hypotheses.

3.2. Capital (mis)allocation

We have demonstrated theoretically the optimality of implicit guarantees under reasonable conditions. In this subsection, we examine the implication of implicit guarantees on capital allocation between two economic sectors: the sector of SOEs and that of private companies (hereafter indexed by PS). To study this, we assume that the demand for capital comes from a continuum population of projects of different p's from both sectors.[8] Similarly to before, the intermediary needs to be incentivized to screen out bad projects that happen with probability q. Unlike the baseline model with elastic supply of capital, however, we now assume there is a fixed supply of total capital of one unit in order to study the allocation problem between the two sectors. The capital market clears at the equilibrium risk-free interest rate r, which is to be determined endogenously.

It is well known that Chinese banks give preferential treatments to SOEs compared to non-SOEs. This might be due to the government's policy directives for state-owned banks and/or the government's implicit guarantees provided to SOEs, the latter making all lenders favor SOEs. Such government support is more prominent during recessions or credit-tightening periods (Cong, Gao, Ponticelli, and Yang, 2019; Geng and Pan, 2021). Consistent with these observations, we model the SOE favoritism by assuming that when an intermediary needs to cover the loss of a SOE project, its funding cost is always 1, lower than that for a private project (i.e., ϕ_N or ϕ_B).

We compare two banking regimes: one is traditional banking (hereafter referred as the TB regime) where the financial intermediary funds all projects in the form of bank loans with explicit guarantees (i.e., the intermediary promises to bear the loss when a project fails), and the other is extended banking (hereafter referred by EB regime) where the intermediary has the added option of funding a project by selling investment products to investors while providing implicit guarantees to them (as in shadow banking), in addition to traditional banking. As a benchmark, we first solve for the socially optimal capital allocation, and then solve for the equilibrium in the TB regime, and finally, the equilibrium in the EB regime. We compare the capital allocation and the total outputs across the above three cases. We present the main conclusions in the following proposition and all the proofs are in Online Appendix B.3.

Proposition 4. Assuming $\eta < \eta_1$ (corresponding to cases 1 and 2 of Proposition 2), we have the following characterization of equilibria across different cases:

(i) It is socially optimal to fund projects with $p \in [0,\ p_{social}]$, where

$$p_{social} = F^{-1}\left(\frac{1}{2(1-q)}\right).$$

[8] We assume the same cumulative distribution function (CDF) for projects in both sectors and use $F(p)$ to denote the CDF: $F(x) = prob(p \leq x)$, which is continuous and strictly increasing. Our qualitative results do not depend on the assumption of the same CDFs across the two sectors. We further note that in the paper, we follow the de Finetti convention of not distinguishing in notation a set and its indicator function.

The total output of the economy is:

$$\Pi_{social} = 1 + \delta - 4(1 - q)\delta\, E(p\{p \le p_{social}\}).$$

(ii) In the TB regime, the intermediary provides bank loans to fund the investment projects. In equilibrium, SOE projects with $p \in [0,\ p_{SOE,TB}]$ and private projects with $p_i \in [0,\ p_{PS,TB}]$ are funded, where $p_{SOE,TB}$, $p_{PS,TB}$, and r_{TB} are jointly determined by the following three-equation system:

$$p_{SOE,TB} = \frac{1}{2} - \frac{r_{TB}}{2\delta} - \frac{\xi}{2\delta(1-q)}\ ;$$

$$p_{PS,TB} = \left(1 - \frac{\left(\bar{\phi} - 1\right)(r_{TB} + \delta)}{2\delta + \left(\bar{\phi} - 1\right)(r_{TB} + \delta)}\right) p_{SOE}(r_{TB});$$

and

$$(1 - q)[F(p_{SOE,TB}) + F(p_{PS,TB})] = 1.$$

The total output of the economy is:

$$\Pi_{TB} = 1 + \delta - 2(1 - q)\delta \times [E(p\{p \le p_{SOE,TB}\}) + E(p\{p \le p_{PS,TB}\})].$$

(iii) In the EB regime, the intermediary provides bank loans with explicit guarantees to SOE projects and use shadow banking with implicit guarantees to fund private projects. SOE projects with $p \in [0,\ p_{SOE,EB}]$ and private projects with $p \in [0,\ p_{PS,EB}]$ are funded, where $p_{SOE,SB}$, $p_{PS,EB}$, and r_{EB} are jointly determined by the following three-equation system:

$$p_{SOE,EB} = \frac{1}{2} - \frac{r_{EB}}{2\delta} - \frac{\xi}{2\delta(1-q)}\ ;$$

$$(1 - q)[(1 - 2p_{PS,EB})\delta - r_{EB} - p_{PS,EB}(1-\pi)(\phi_N - 1)(y + \delta)] = \xi;$$

where $y = \frac{r_{EB} + p_{PS,EB}\pi\delta}{1 - p_{PS,EB}\pi}$ if $\eta \le \eta_0(r_{EB})$ and $y = (\frac{\eta}{(1-\pi)\phi_N} - 1)\delta$ otherwise.

$$(1 - q)[F(p_{SOE,EB}) + F(p_{PS,EB})] = 1.$$

The total output of the economy is:

$$\Pi_{EB} = 1 + \delta - 2(1 - q)\delta\, [E(p\{p \le p_{SOE,EB}\}) + E(p\{p \le p_{PS,EB}\})].$$

Note that in the EB regime, SOE projects are still funded via bank loans because there is no extra cost for the intermediary to cover the investment loss for the investor. In contrast, once allowed, the intermediary will fund a private project via the implicit guarantee arrangement when $\eta \le \eta_1$. Implicit guarantees on the one hand incentivize the financial intermediary to screen projects and on the other hand limit its costs of funding private projects. We have the following corollary:

Corollary 1. Comparing to the socially optimal outcome, there exists capital misallocation in equilibrium in both TB and EB regimes. We have the following comparison:

$$p_{SOE,TB} - p_{PS,TB} > p_{SOE,EB} - p_{PS,EB} > 0;$$

and

$$\Pi_{TB} < \Pi_{EB} < \Pi_{social}.$$

In both regimes, $p_{SOE} > p_{social} > p_{PS}$. In other words, too many SOE projects and too few private projects are funded. This is consistent with the capital misallocation as documented in Hsieh and Klenow (2009) and Hsieh and Song (2015). It is socially optimal to fund projects in both the SOE and non-SOE sectors so that the marginal productivities of both sectors are equal (p can be viewed as an inverse measure of project productivity and p_{social} is the socially optimal marginal productivity). However, due to the favoritism toward SOEs, $p_{SOE} - p_{PS} > 0$. In other words, the marginal productivity of the SOE sector is lower than that of the PS sector because too many state-owned and too few private projects are funded, which represents capital misallocation. As a result, the total output will be lower than the socially optimal level. The larger the difference in the marginal productivity, the more severe the misallocation is.

Although there is capital misallocation in both regimes, the extent of distortion differs. We have $p_{SOE,EB} < p_{SOE,TB}$ (see Online Appendix B.3.), which means that the marginal productivity of SOE projects is higher and fewer SOE projects are funded in the EB regime than in the TB regime. In contrast, we have $p_{PS,EB} > p_{PS,TB}$, implying that more private projects are funded in EB regime. That is, there is a shift of capital allocation from the SOE sector to the private sector when we allow shadow banking (in EB regime).

Further, the difference in the marginal productivity across the two sectors is bigger in the TB regime ($p_{SOE,TB} - p_{PS,TB}$) than in the EB regime ($p_{SOE,EB} - p_{PS,EB}$), suggesting that the capital misallocation issue is more severe in the TB regime. Because of this, the economic output in the EB regime (Π_{EB}) is higher than that in the TB regime (Π_{TB}).

Our theoretical analysis shows that the intermediary is more willing to fund non-SOE projects in shadow banking, where implicit guarantees on the one hand provides incentives for it to screen projects and on the other hand controls its risk. If implicit guarantees are restricted, a big advantage of shadow banking is removed. We demonstrate the adverse effect in the following corollary by imposing a regulatory cost of an implicit guarantee on the intermediary.

Corollary 2. Assume a regulatory cost of c for the intermediary if it chooses an implicit guarantee. We have $\frac{dp_{SOE}}{dc} > 0$, and $\frac{dp_{PS,EB}}{dc} < 0$. Overall, we have

$$\frac{d(p_{SOE} - p_{PS,EB})}{dc} > 0, \text{ and } \frac{d\Pi}{dc} < 0.$$

From the corollary, as the regulatory cost of an implicit guarantee increases, there is more capital flowing to the SOE sector and less to the private sector, exacerbating the capital misallocation issue. Moreover, the economic output in the EB regime (Π_{EB}) is lower. We thus have the following hypothesis:

Hypothesis III. Restricting implicit guarantees will lead to declines in shadow banking and funding to the non-SOE sector.

We collect information on the loan contracts between borrower firms/projects and the trust firms (lenders) and examine the fraction of total credit going to SOEs and non-SOEs in Section 5 below. To test this hypothesis (and Corollary 2), we also regress loan contract terms on the characteristics of the trust firms as well as the borrowers/projects, and examine how a new set of regulations announced in 2018 aiming to curb shadow banking and the use of implicit guarantees affect the lending behavior of trust firms with various degrees of guarantee strength.

4. Data and variables

We obtain from iFind Database information on trust companies and all their investment products with public information from 2002 to 2020. Trust companies are required by the China Banking Regulatory Commission (CBRC) to release annual financial reports and key shareholder information. The CBRC also requires trusts to disclose information on products with multiple investors (known as Collective Investment Trusts, or CITs), including expected yield, maturity, issuance volume, tranches, investment threshold to the investors. Such disclosure is not mandatory for products with a single investor, i.e., Single Capital Trusts (SCT). We start with all the CITs and some of the SCTs with issuance information. We drop the products without expected yield information at issuance. Our sample includes 31,483 trust products issued by 68 trust companies from 2002 to 2020.

For information on the underlying investment targets, iFind provides the industry and location information. Based on China Trustee Association's classification, the industry or type of investment for each product is in one of the following categories: real estate, infrastructure, commercial and industrial firms, financial institutions, securities market, and others (involving multiple projects in multiple industries). For product funds going to the 'real sectors' (i.e., excluding financial sector products), we hand collect information on the loan contract terms for a subset of products, and match this set of variables with borrower characteristics.

We manually collect the underlying borrower identity from the prospectuses.[9] For capital (raised from product issuance) invested in real estate, infrastructure, commercial & industrial (C&I, hereafter) firms, and financial institutions, we are able to obtain the borrower names for 60.0%, 53.7%, 51.2% and 19.3% of products, respectively. The majority of firm borrowers are non-SOEs. We match the borrower's name with information in State Administration for Industry and Commerce (SAIC) and obtain the borrowers' up-to-date registered capital. We obtain information on borrower size for 11,636 products. We retrieve provincial-level economic information from WIND Database and treasury bond yields from the website of China Bond.

4.1. Measures of trust firms' implicit guarantees

We measure the strength of implicit guarantees behind an investment product based on several considerations: the trust firm's equity capital, the trust firm's ownership type, and the sales channel. First, the larger the trust firm's equity capital, the more financial cushion it has to buffer losses and honor the implicit guarantee. Ideally, we would use the firm's market value of equity, but most of the trusts (66 out of 68) are not publicly traded. Hence, we use their registered capital.

Second, we classify trust companies into three groups based on their ownership type: those controlled by central SOEs, local SOEs, and non-SOEs, respectively. The market believes that for a firm backed by SOEs, especially central SOEs, the SOEs are more likely to honor their implicit guarantees for both financial and political reasons. Financially, SOEs are privileged to have access to more and cheaper capital such as bank loans. Politically, SOEs have the incentive to appease investors to maintain "social stability." Therefore, we conjecture that trusts controlled by central SOEs provide stronger guarantees than those controlled by local SOEs, whose guarantees are in turn stronger than trusts controlled by non-SOEs.

Third, we consider whether the product is sold via one of the largest banks (the Big 5 banks). These large banks are all state-owned and are believed to have the full support of the central government. They have never failed in paying any of their deposits and WMPs. Many investors believe that they also stand behind the products they help sell, even if they are not the sponsors of these products. Hence, selling via a Big 5 bank strengthens the implicit guarantee behind a product.[10]

Finally, we construct an index of implicit guarantee (i.e., IG index) based on variables with three dimensions. Specifically, we aggregate the following variables: an indicator equal to 1 if the trust's registered capital is in the top tercile among all trusts, and 0 otherwise; another indicator equal to 1 if the product is sold via a Big 5 bank, and 0 otherwise; and an indicator variable based on the trust's ownership type (it is equal to 2 if the trust is controlled by a central SOE, to 1 if it is controlled by a local SOE, and 0 otherwise). Thus, the index ranges from 0 to 4, with a higher value indicating a higher strength of guarantee.

4.2. Measures of the underlying investment risk

We measure the underlying investment risk based on three types of information we collect: the industry, the location, and the borrower size when available. First, it is reasonable to think that investments in real estate tend to have high risk. Second, the investment risk is correlated with local economic conditions: the risk tends to be

[9] The borrower identity is not always disclosed. There are no specific borrowers for products invested in "securities markets" and names are often missing for those invested in "others."

[10] Big 5 banks refer to Bank of China (BOC), Industrial and Commercial Bank of China (ICBC), China Construction Bank (CCB), Agricultural Bank of China (ABC), and Bank of Communications (BOComm). Together their deposits constitute more than 40% of all bank deposits.

Table 1
Summary statistics.
This table reports the descriptive statistics for the sample of trust products issued during 2002-2020. We drop those without yield and issuance volume information. All variables are defined in the Appendix.

Variable	Obs.	Mean	STD	Min	Median	Max
Expected yield (%)	31,483	8.720	1.884	0.080	8.800	44.260
Yield spread (%)	31,483	5.832	1.844	-3.628	5.963	41.512
Central SOE	31,483	0.269	0.444	0.000	0.000	1.000
Local SOE	31,483	0.412	0.492	0.000	0.000	1.000
Reg cap (mn)	31,483	5,179.340	3,510.320	300.000	4,000.000	15,000.000
Sale bank big5	31,483	0.081	0.273	0.000	0	1.000
IG Index	31,483	1.346	0.944	0.000	1.000	4.000
GDP growth (%)	31,363	9.142	6.112	-6.600	8.539	24.198
i.real estate	30,954	0.190	0.394	0.000	0.000	1.000
Borrower size (mn)	11,636	1,156.941	3,066.682	0.030	300	68,821.120
Maturity (month)	30,898	19.784	14.158	0.040	18	360.000
Structure	31,224	0.177	0.382	0.000	0	1.000
Inv threshold (k)	25,299	1,057.362	1,281.498	10	1000	150,000
Collateral	31,483	0.255	0.436	0.000	0.000	1.000

Table 2
Industry distribution of investment capital raised from trust products: 2002-2020.
This table reports the industry distribution of investment targets of funds raised through trust product issuance in our sample from 2002 to 2020.

Industries	Total issuance volume (bn RMB)	Percentage (%)	Product #	Percentage of product # (%)
Real estate	1003.55	23.92	5,947	18.89
C&I	815.27	19.44	6,259	19.88
Infrastructure	598.76	14.27	5,687	18.06
Financial institutions	474.34	11.31	2,998	9.52
Securities market	216.50	5.16	2,802	8.90
Others	1086.37	25.90	7,790	24.74
TOTAL	**4,194.78**	**100**	**31,483**	**100**

lower in more prosperous areas. Hence, we use the GDP growth rate of the city where the borrower is located as an inverse measure for investment risk. If the city information is missing, we use the provincial GDP growth instead. Third, we use borrower size as another negative measure for the underlying investment risk. The requirements of the data significantly reduce the sample size. We therefore conduct regression tests with and without including this variable.

Table 1 presents the summary statistics of the main variables (see Appendix for detailed definitions for all the variables). *Expected yield* is the yield marketed in the product prospectus, ranging from 0.08% to 44.26% with a mean value of 8.72%. *Yield spread*, our measure of product pricing, is the difference between the expected yield and the yield of a matched Treasury bond based on the month of the product issuance and maturity. The yield spread ranges from −3.63% to 41.51% with a mean value of 5.83%.

For implicit guarantee measures, 27% of our sample products are sponsored by central SOE trusts and 41% are sponsored by local SOEs; 8% are sold via Big 5 banks. The trust firm's registered capital ranges from 300 million RMB to 15.0 billion RMB. The IG index ranges between 0 and 4 and has a mean (median) of 1.3 (1).

In terms of the underlying investment risk, 19% of the products are invested in the real estate industry. The local GDP growth rate ranges between -6.6% to 24.2%, with a mean of 9.1%. The average borrower has a size of 1.2 billion RMB. Table 1 also reports a number of other product characteristics, including product maturity, whether collateral is provided by the underlying borrower, whether the product is structured (i.e., has multiple tranches), and the investment threshold (i.e., the minimum investment required). We control these variables in our analyses. If a product has multiple tranches, we use the expected yield of the senior tranche.

Table 2 reports the industry distribution of the underlying investment targets sorted by both the issuance volume and the number of trust products. The largest investment industry is real estate, attracting 24% of the funds flow. The percentage of capital invested in commercial and industrial firms, infrastructure projects, financial institutions, securities market, and others are 19%, 14%, 11%, 5% and 26%, respectively. A product is classified as "others" if the capital raised from the product invests in multiple firms/projects in multiple industries. By manually going over the prospectuses of these products, we find that in more than 80% of the cases, at least part of the funds is invested in real estate. Thus, an upper limit of the estimate on the fraction of funds going to real estate would be the sum of 24% and 80% of funds from "others" products ($24\% + 80\% \times 26\% = 45\%$). In other words, our estimate of trust products invested in the real estate is 24%-45%. Consistent with Allen, Qian, Tu, and Yu (2019), we find real estate constitutes the most important type of investment for the shadow banking sector. This is especially true after banks are restricted from lending to the industry starting from 2010 (see Fig. 1). Fig. 1 depicts the total issuance of our sample by industry over time. The volume has been rising fast since 2009, especially for those products investing in the real estate and "others" industries.

5. Empirical results

5.1. Implicit guarantees and yield spread

We test Hypothesis I in this section, that is, the product yield spread depends on both the underlying investment risk, as well as the strength of the implicit guarantee behind the product. We estimate the following regression model:

$$\begin{aligned} Yield\ spread_{i,t} = {} & \beta_0 + \beta_1 * Implicit\ guarantee\ strength_{i,t} \\ & + \beta_2 * Underlying\ investment\ risk_{i,t} \\ & + \beta_3 * control\ variables_{i,t} + e_{it} \end{aligned} \quad (1)$$

To measure implicit guarantee strength, we use *central SOE* (equal to 1 if the trust is controlled by a central SOE), *local SOE* (equal to 1 if the trust is controlled by a local SOE), *Log Reg cap* (the natural logarithm of the trust's registered capital), *Sale bank big5* (whether the product is distributed by a Big 5 bank), as well as the *IG index*. In addition, we obtain the size of the trust's controlling shareholder for the subperiod of 2013-2020.[11] We use this as an additional measure for guarantee strength for the subsample. To measure the underlying investment risk, we use *GDP growth* (the GDP growth of the city/province where the investment is located), *Log borrowersize* (the natural logarithm of the borrower's registered capital), and *i.real restate* (an indicator variable equal to one if the investment is in the real estate industry). We also include indicators for other industries except for the C&I industry. The local GDP growth and the sizes of the trust and its controlling shareholder are measured based on data available prior to the product issuance. For control variables, we include product characteristics such as *Maturity, Structure, Log Inv threshold, Collateral* (definitions are in the Appendix). In addition to industry dummies, we include year fixed effects in all the regression models. Standard errors are clustered at the trust firm and year levels.

Table 3 presents the regression results. In Panel A, Column 1 uses the full sample. Column 2 includes *Log borrowersize,* which reduces the sample size by 58%. Columns 3-4 use the subperiod of 2013-2020 so that we can include *Log Shrld size* (the natural logarithm of the controlling shareholder's assets) as an additional measure for guarantee strength. Columns 5-6 use the full sample and includes trust firm fixed effects; thus, time invariant variables such as *central SOE, local SOE* and *Log Reg cap* drop out in these models.

Recall that Hypothesis I predicts a negative β_1 (i.e., negative coefficients on all the guarantee strength variables) and a positive β_2 (more specifically, a positive coefficient on *i.real estate*, and negative coefficients on the two inverse measures of risk: *Log borrowersize* and *GDP growth*). Consistent with the model predictions, the implicit guarantee measures generally have negative and statistically significant coefficients across specifications. The impact is also economically significant. Take the estimates in Columns 1-2 for example, compared to products sponsored by non-SOE trusts, products sponsored by central SOE trusts tend to have lower yield spreads by 49-71 basis points (bps), those sponsored by local SOE trusts have lower spreads by 39-40 bps. In comparison, the sample mean for yield spread is 5.8%. If the product is sold via a Big 5 bank, the yield is lower by 10-27 bps. One standard-deviation increase in the trust size (*Log Reg cap*) decreases the spread by 14-21 bps. Finally, for the subsample in Columns 3-4, a one-standard-deviation increase in the controlling shareholder size (*Log Shrld size*) is associated with 45-61 bps increase in the yield spread.

For the underlying investment risk measures, we find consistently positive coefficients on *i.real estate* and negative coefficients on *GDP growth. Log borrowersize* is negative across the specifications, albeit insignificant in Columns (4) and (6). Again, take the estimates in Columns 1-2 for example, compared to investments in C&I, the product spread is higher by 27-32 bps if the funds are invested in real estate. Interestingly, the coefficients on other industry dummies are negative, suggesting loans to C&I firms are viewed as less risky than real estate investments only. A one-standard-deviation increase in *Log borrowersize* decreases the spread by 3.7 bps, while a one-standard-deviation in local *GDP growth* decreases the spread by 7.8-17.0 bps.

Looking at the control variables, we observe positive coefficients on *collateral*. This is consistent with the banking literature that nonprice terms such as collateral are used as complements to yields to manage the investment risk (e.g., Flannery, 1986; Berger and Udell, 1990; Dennis, Nandy, and Sharpe, 2000; Qian and Strahan, 2007; Graham, Li, and Qiu, 2008). Products with longer maturity and higher investment minimum amount provide higher yield spreads.

Table 3, Panel B, reports the regression results using the aggregate *IG index* to measure implicit guarantee strength. Columns 1 uses the full sample, Column 2 includes *Log borrowersize* and thus has a much smaller sample size, Columns 3-4 include trust firm fixed effects. The coefficients on *IG index* are statistically significant and negative in all the specifications. Take Columns 1 and 2, for example, a one-standard-deviation increase in *IG index* reduces the spread by 25-33 bps.

Next, we use the 2015 stock market crash as a negative shock to trust firms' financial health and therefore the strength of their implicit guarantee behind all of its products. We examine whether product pricing is sensitive to the extent of the risk the sponsoring trust is exposed to. China's stock market had a bubble-like run from 2014 to the summer of 2015. The Shanghai Stock Exchange Composite Index increased from 2,038 to 4,612 from June 2014 to May 2015 (an 126% increase in a year) and peaked on June 12, 2015 at 5,166. The market plunged on June 12, 2015 and dropped by 27% in the next 15 trading days and reached the bottom around 3,000 toward the end of August (a 43% drop from the peak).

In the year preceding the market crash, the trust industry had significantly expanded its issuance of products

[11] Most controlling shareholders of the trust firms are non-public firms and *iFind* provides information on their financials only for the period of 2013-2020.

invested in the securities market, likely influenced by the stock market boom. In the four quarters ending in June 2015, the RMB volume of these products in our sample are 6.3, 9.0, 8.2, and 14.9 billion, respectively, and the share of these products out of all products are 5.3%, 7.0%, 6.7%, and 14.0%, respectively.

Many of these products experienced large losses due to the stock market crash. There were news reports about defaults in some securities market products in late 2015. Since trusts do not have to disclose defaults, there can be many more unknown default cases. We hypothesize that trust firms with more funds invested in the securities market were more exposed to the stock market risk and experienced a negative shock due to the market crash. This shock would adversely affect the firm's financial health and therefore its strength of guarantees. Hypothesis I predicts that the product yield will increase for these affected trusts after the shock, all else equal. This will affect all

Table 3
Determinants of yield spreads: The role of implicit guarantees and underlying risk.
This table reports the results from examining the determinants of *ex ante* yield spreads (the difference between expected yield at issue and the matched treasury bond interest rate based on the month of issuance and maturity) of the trust products. The dependent variable is the product yield spread. Panel A reports the regressions results using trust firm characteristics such as ownership type (*Central SOE, Local SOE*), trust firm size (*Log Reg cap*), and the size of the trust firm's controlling shareholder (*Log Shrld size*) as the main explanatory variables; Panel B reports of the results using the *IG index* as the main explanatory variable: *IG index* is defined as the summation of the values of *SOE, Sale bank big5*, and *Large tfirm* indicators, where *SOE* equals to 2 for central SOEs, or equals to 1 for local SOEs, *Sale bank big5* equals to 1 if the product is sold via a Big-5 bank, and *Large tfirm* equals to 1 if the product is issued by a trust firm whose registered capital is in the top tercile among all trust. All other variables are defined in the Appendix. Standard errors are clustered at the firm and year levels and reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Panel A. Implicit guarantees and ex ante yield spreads

	Dep. Var.=Product expected yield spread (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Implicit guarantee variables						
Central SOE	-0.709***	-0.499***	-0.567***	-0.454***		
	(0.111)	(0.107)	(0.122)	(0.137)		
Local SOE	-0.390***	-0.397***	-0.357***	-0.463***		
	(0.0943)	(0.0854)	(0.113)	(0.107)		
Log Reg cap	-0.260***	-0.182***	-0.439***	-0.215***		
	(0.0583)	(0.0459)	(0.0963)	(0.0701)		
Sale bank big5	-0.272***	-0.109*	-0.144	-0.0474	-0.203***	-0.0674
	(0.0739)	(0.0618)	(0.0874)	(0.0752)	(0.0786)	(0.0591)
Log Shrld size			-0.0640*	-0.0864***		
			(0.0344)	(0.0295)		
Borrower characteristics						
i.real estate	0.270***	0.323***	0.143*	0.231***	0.190***	0.275***
	(0.0544)	(0.0619)	(0.0734)	(0.0822)	(0.0534)	(0.0536)
GDP growth	-0.0273***	-0.0127**	-0.0134	-0.00262	-0.0255***	-0.00783*
	(0.00882)	(0.00565)	(0.0105)	(0.00668)	(0.00665)	(0.00447)
Log borrowersize		-0.0215*		-0.0118		-0.0130
		(0.0122)		(0.0165)		(0.0106)
i.infrastructure	-0.0799	-0.0391	0.0439	-0.00111	-0.0856*	-0.0785
	(0.0537)	(0.0550)	(0.0614)	(0.0585)	(0.0502)	(0.0513)
i.securities market	-1.358***	0.444*	-1.131***	0.258	-1.597***	0.838**
	(0.309)	(0.256)	(0.419)	(0.223)	(0.248)	(0.393)
i.fin institutions	-0.545***	-0.566***	-0.812***	-0.970***	-0.378***	-0.399***
	(0.120)	(0.150)	(0.169)	(0.132)	(0.124)	(0.127)
i.others	-0.389***	-0.144*	-0.571***	0.0476	-0.374***	-0.108
	(0.0674)	(0.0793)	(0.0847)	(0.110)	(0.0690)	(0.0824)
Product characteristics						
Maturity	0.0227***	0.0456***	0.0279***	0.0463***	0.0223***	0.0437***
	(0.00438)	(0.00591)	(0.00736)	(0.00965)	(0.00438)	(0.00568)
Structure	0.298***	0.344***	0.362***	0.333***	0.281***	0.273***
	(0.0895)	(0.0753)	(0.107)	(0.0824)	(0.0824)	(0.0769)
Log Inv threshold	0.412***	0.583***	0.294*	0.369	0.403***	0.568***
	(0.104)	(0.0995)	(0.171)	(0.240)	(0.104)	(0.104)
Collateral	0.386***	0.197***	0.354***	0.125*	0.447***	0.250***
	(0.0576)	(0.0545)	(0.0663)	(0.0684)	(0.0560)	(0.0490)
Cons.	1.540***	1.241	6.227***	5.770***	2.429***	2.033**
	(0.498)	(0.855)	(0.854)	(1.343)	(0.664)	(0.922)
Year FE	YES	YES	YES	YES	YES	YES
Trust firm FE	NO	NO	NO	NO	YES	YES
Province FE	Yes	Yes	Yes	Yes	No	No
Obs.	24,292	10,290	12,651	5,810	24,299	10,295
adj. R-sq	0.466	0.475	0.483	0.470	0.491	0.517

(*continued on next page*)

Table 3
(*continued*)

Panel B. Implicit guarantees and ex ante yield spreads: IG index				
	Dep. Var. =Product expected yield spread (%)			
	(1)	(2)	(3)	(4)
IG index	-0.354***	-0.269***	-0.269***	-0.286***
	(0.0401)	(0.0380)	(0.0649)	(0.0466)
Borrower characteristics				
i.real estate	0.268***	0.319***	0.198***	0.291***
	(0.0545)	(0.0627)	(0.0543)	(0.0539)
GDP growth	-0.0262***	-0.0129**	-0.0243***	-0.00803*
	(0.00861)	(0.00564)	(0.00658)	(0.00450)
Log borrowersize		-0.0228*		-0.0112
		(0.0122)		(0.0108)
i.infrastructure	-0.0464	-0.0247	-0.0748	-0.0651
	(0.0511)	(0.0550)	(0.0513)	(0.0520)
i.securities market	-1.335***	0.470*	-1.629***	0.708*
	(0.328)	(0.256)	(0.253)	(0.365)
i.fin institutions	-0.559***	-0.598***	-0.416***	-0.412***
	(0.119)	(0.156)	(0.122)	(0.128)
i.others	-0.407***	-0.157**	-0.407***	-0.128
	(0.0677)	(0.0792)	(0.0686)	(0.0828)
Product characteristics				
Maturity	0.0231***	0.0456***	0.0223***	0.0429***
	(0.00444)	(0.00590)	(0.00437)	(0.00564)
Structure	0.283***	0.346***	0.281***	0.287***
	(0.0912)	(0.0745)	(0.0828)	(0.0763)
Log Inv threshold	0.426***	0.594***	0.410***	0.570***
	(0.106)	(0.0997)	(0.105)	(0.103)
Collateral	0.418***	0.199***	0.447***	0.267***
	(0.0628)	(0.0561)	(0.0558)	(0.0482)
Cons.	0.922*	0.696	1.272**	0.402
	(0.508)	(0.828)	(0.610)	(0.885)
Year FE	YES	YES	YES	YES
Trust firm FE	NO	NO	YES	YES
Province FE	YES	YES	NO	NO
Obs.	24,292	10,290	24,292	10,290
adj. R-sq	0.462	0.474	0.489	0.516

types of products, and not just the yields of securities market products.

We conduct a DiD test around the shock. We measure a trust firm's exposure to the stock market, *stk exposure*, as the volume of its securities products (in log terms) that were outstanding by the end of May 2015 and due in the half year after the stock market crash between July and December 2015. We then examine the yield spreads of the products that were issued 18 months before and after the stock market crash. Products issued in June 2015 were excluded because they were issued in the middle of the crash. We estimate the following regression:

$$\begin{aligned} Yield\ spread_{i,t} &= \beta_0 + \beta_1 * Post\ crash_t + \beta_2 * Stk\ exposure_i \\ &\quad + \beta_3 * Post\ crash_t * Stk\ exposure_i \\ &\quad + \beta_4 * control\ variables_{i,t} + e_{it} \end{aligned} \tag{2}$$

Post crash is equal to one if a product was issued between July 2015 and December 2016, and zero if the product was issued between December 2013 and May 2015. Hypothesis I predicts $\beta_3 > 0$. That is, products sponsored by trusts with greater exposure to the stock market crash will have to offer higher yields due to their lowered strength of guarantee.

Table 4 reports the results. Column 1 shows that the interaction term *Post crash***Stk exposure* is significantly positive, consistent with Hypothesis I. We further estimate a dynamic DiD regression in Column 2. Specifically, we replace the *Post crash* dummy with several time-period indicators and interact each indicator with *Stk exposure*. The time indicators, *Time()*, are defined for each 6-month window of the three-year period before and after the crash. For example, *Time(0)* equals to 1 if the product was issued during July 2015 – December 2015, the first six months after the crash; *Time(-1)* equals to 1 if the product was issued during December 2014 – May 2015, the six-month immediately before the crash; and so forth.

Table 4, Column 2, reports the result of the dynamic regression. We find that the interactions of *Stk exposure* with *Time(1)* and *Time(2)* are positive and significant, whereas *Stk exposure* * *Time(-3)*, *Stk exposure* * *Time(-2)*, and *stk exposure* * *Time(-1)* are all insignificant. This suggests that in all the three periods before the stock market crash, there is no significant difference in yield spreads of the products issued by trust firms with high and low exposure to the stock market. Thus, the parallel trend assumption for the DiD test is satisfied. The significant positive coefficients on *Stk exposure* * *Time(1)* and *Stk exposure* * *Time(2)* again

Table 4
Stock market crash and yield spreads of trust products.
This table reports the results of regressions examining the impact of stock market crash on trust products' *ex ante* pricing. The dependent variable is the product yield spread. *Post crash* is equal to 1 if the product was issued between July 1, 2015 to December 31, 2016 (in the 18 months after the stock market crash), and 0 if the product was issued between December 1, 2013 to May 31, 2015 (in the 18 months before the stock market crash). Indicator variables *Time()* are defined for each 6-month period around the market crash in the 3-year period, e.g., *Time(0)* equals to 1 if the product was issued during July 2015 – December 2015, the first six months after the crash; *Time(-1)* equals to 1 if the product issued during December 2014 – May 2015, the six-month immediately before the crash, and so forth. *Stk exposure* is defined as the natural logarithm of the volume of the securities market products that was outstanding by the end of May 2015 and due between July to December in 2015. Other controls include *Maturity, Structure, Long Inv Threshold, Collateral, IG index, GDP growth, i.real estate, i.infrastructure, i.securities market, i.fin institutions, and i.others*. All other variables are defined in the Appendix. Standard errors are clustered at the firm and year levels and reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dep. Var. = Product expected yield spread (%)	
	(1)	(2)
Stk exposure	-0.00246	-0.0179
	(0.0206)	(0.0291)
Post crash	-1.260***	
	(0.342)	
Stk exposure× Post crash	0.0719**	
	(0.0348)	
Stk exposure× Time(-3)		0.0478
		(0.0342)
Stk exposure×Time(-2)		0.0298
		(0.0384)
Stk exposure×Time(-1)		0.00189
		(0.0355)
Stk exposure×Time(1)		0.0932**
		(0.0410)
Stk exposure× Time(2)		0.0772**
		(0.0374)
Cons.	YES	YES
Other controls	YES	YES
Time FE	NO	YES
Obs	6,802	6,888
adj. R-sq	0.465	0.517

confirm that the positive effect of *Stk exposure* on yields happens in periods after the stock market crash. Fig. 3 depicts the coefficients of these interaction terms and their 95% confidence intervals.

In short, the evidence in this section supports Hypothesis I, that is, the product's yields not only depend on the underlying investment risk, but also the strength of the implicit guarantee behind the product.

5.2. Implicit guarantees and spread-to-risk sensitivity

We test Hypothesis II in this subsection, i.e., the yield spread is less sensitive to the underlying investment risk when the strength of the implicit guarantee is greater. Specifically, we estimate the following model:

$$\begin{aligned} Yield\ spread_{i,t} = \beta_0 &+ \beta_1 * Implicit\ guarantee\ strength_{i,t} \\ &+ \beta_2 * Underlying\ investment\ risk_{i,t} \\ &+ \beta_3 * Implicit\ guarantee\ strength_{i,t} \\ &* Underlying\ investment\ risk_{i,t} \\ &+ \beta_4 * control\ variables_{i,t} + e_{it} \qquad (3) \end{aligned}$$

Hypothesis II predicts that for each measure of underlying risk (*i.real estate* is a positive measure of risk and *GDP growth* and *Log borrowersize* are negative measures),

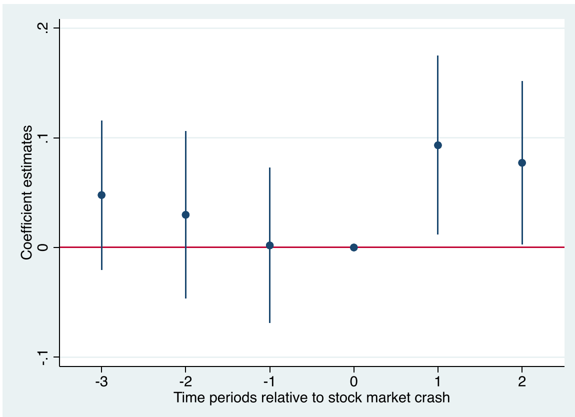

Fig. 3. Stock market crash and yield spreads of trust products.
This figure plots the time trend of the treatment effect estimates around the stock market crash in June 2015, as explained in Section 5.1 and in Column 2 of Table 4. For each time period, we plot the point estimate (the solid circle) and the 95% confidence interval (the vertical lines intersecting the solid circles). Time indicators are defined for each 6-month period around the market crash in the 3-year period, e.g., *Time(0)* denotes the period during July 2015 – December 2015, the first six months after the crash; *Time(-1)* denotes the period during December 2014 – May 2015, the six-month immediately before the crash, and so forth.

Table 5
Spread sensitivity to the investment risks of trust products: The role of implicit guarantees.
This table reports the results of regressions examining the effects of investors' expectation of implicit guarantees on the risk sensitivity of product pricing. The dependent variable is the product expected yield spread. The key explanatory variable, *IG index,* is defined as the summation of the values of *SOE, Sale bank big5*, and *Large tfirm* indicators, where *SOE* equals to 2 for central SOEs, or equals to 1 for local SOEs, *Sale bank big5* equals to 1 if the product is sold via a Big-5 bank, and *Large tfirm* equals to 1 if the product is issued by a trust whose registered capital is in the top tercile among all trust firms. Other controls include *Maturity, Structure, Long Inv Threshold, Collateral, i.infrastructure, i.securities market, i.fin institutions, and i.others.* All other variables are defined in the Appendix. Standard errors are clustered at the firm and year levels and reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dep. Var. = Product expected yield spread (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GDP growth	-0.0388***	-0.0170**	-0.0354***	-0.0181***	-0.0283***	-0.0196***	-0.0240***	-0.0118**
	(0.0143)	(0.00777)	(0.0105)	(0.00663)	(0.00968)	(0.00721)	(0.00807)	(0.00591)
i.real estate	0.154	0.478***	0.279***	0.447***	0.271***	0.400***	0.254***	0.326***
	(0.0963)	(0.0736)	(0.0656)	(0.0611)	(0.0686)	(0.0681)	(0.0564)	(0.0639)
Log borrowersize		-0.0167		-0.0135		-0.0283**		-0.0332**
		(0.0194)		(0.0143)		(0.0125)		(0.0133)
IG index	-0.461***	-0.185						
	(0.0818)	(0.249)						
IG index× GDP growth	0.0101	0.00372						
	(0.00655)	(0.00348)						
IG index× i.real estate	0.0917	-0.116**						
	(0.0599)	(0.0533)						
IG index× Log borrowersize		-0.00380						
		(0.0119)						
Central SOE			-1.048***	0.0893				
			(0.186)	(0.604)				
Central SOE× GDP growth			0.0431***	0.0199**				
			(0.0131)	(0.00919)				
Central SOE× i.real estate			0.0195	-0.450***				
			(0.128)	(0.121)				
Central SOE× Log borrowersize				-0.0278				
				(0.0286)				
Large tfirm					-0.598***	-0.566		
					(0.173)	(0.549)		
Large tfirm× GDP growth					0.0151	0.0248***		
					(0.0133)	(0.00960)		
Large tfirm× i.real estate					0.0510	-0.203		
					(0.111)	(0.124)		
Large tfirm× Log borrowersize						0.000979		
						(0.0269)		
Sale bank big5							-0.271	-0.132
							(0.178)	(0.599)
Sale bank big5× GDP growth							0.00286	-0.0143
							(0.0119)	(0.0126)
Sale bank big5× i.real estate							0.206	-0.114
							(0.131)	(0.152)
Sale bank big5×Log borrowersize								0.0121
								(0.0303)
Cons.	YES	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	24,292	10,290	24,292	10,290	24,292	10,290	24,292	10,290
adj. R-sq	0.464	0.475	0.456	0.464	0.441	0.462	0.431	0.449

β_3 will be of opposite sign to β_2. In all regressions standard errors are clustered at the firm and year level.

Table 5 presents the regression results. In Columns 1 and 2 the guarantee strength is measured by *IG index*. In each of the remaining columns, we use a component of the IG index as the guarantee strength measure, i.e., the ownership type, whether the size of the trust is in the top tercile, and whether the product is sold via a Big 5 bank.

In Columns 1 and 2 (Column 2 includes *Log borrowersize* as a control), we find estimates of β_1 and β_2 are consistent with those in Table 3. That is, the yield spread is negatively related with *IG index*; the spread is positively related with *i.real estate* and negatively related with *GDP growth* and *Log borrowersize.* In Column 2, for β_3, we find a significantly negative coefficient on *IG index×i.real estate*, a positive but insignificant coefficient on *IG index×GDP growth,* and a positive but insignificant coefficient on *IG index×Log borrowersize*. Based on Column 2, if *IG index* increases by one, the marginal effect of *i.real estate* on the spread decreases from 0.478 to 0.362 (the sensitivity decreases by 24%). The results are therefore consistent with Hypothesis II in that high *IG index* reduces the spread-to-underlying-risk sensitivity. Results in the remaining columns are overall consistent with the hypothesis as well.

Next, we explore a shock to the perceived risk to all products and examine how product pricing changes afterwards depending on the strength of implicit guarantee. Specifically, we study the first high-profile default case in early 2014—*Credit Equals Gold No.1 Product* issued by China Credit Trust. This product had an issuance amount of 3 billion RMB, larger than 99% of products. There might be default cases before 2014, but none of them received much media coverage or public attention like this case. The product was due on January 31, 2014. In late 2013, there were widespread concerns that the underlying company for this product would not be able to pay.[12] In response to investor concerns about the likely default, the product's distributing bank, ICBC, rejected compensating investors in January 2014. The sponsoring trust, China Credit Trust, whose controlling shareholder is People's Insurance Company of China (PICC), a central SOE, waited till the due day to announce that they would be responsible for the losses. Before this incident, investors seemed to take it for granted that the yields are promised and guaranteed. With this product, for a long while the risk seemed very real that investors would bear huge losses. The event made many investors realize there is indeed risk from investing in trust products.

We use this default case as a negative shock to the perceived risk to all trust products that are issued in the two years after the shock and conduct the following DiD tests.

$$\begin{aligned} Yield\ spread_{i,t} = {} & \beta_0 + \beta_1 * Post\ default_t \\ & + \beta_2 * Post\ default_t * IG\ index_{i,t} \\ & + \beta_3 * IG\ index_{i,t} \\ & + \beta_4 * control\ variables_{i,t} + e_{it} \qquad (4) \end{aligned}$$

We consider a sample of products that are issued in the four years around the shock. *Post default* is a dummy equal to 1 if the product is issued during February 2014 – January 2016 and 0 if the product is issued during February 2012 – January 2014. We conjecture that investors perceive all products as riskier after the default case, hence we expect to see a positive β_1. Hypothesis II predicts, however, that this impact of the negative shock will be mitigated by the strength of the implicit guarantee. In other words, we expect $\beta_2 < 0$.

Column 1 of Table 6 presents the regression results for the DiD test. Consistent with Hypotheses I and II, we find a significantly positive coefficient on *Post default*, and a significantly negative coefficient on *Post default * IG index*. The estimates show that yield spreads on average increase by 39 bps after the shock. Nonetheless, the impact is largely mitigated if *IG index* increases by one.

Column 2 of Table 6 further presents the results of a dynamic DiD test. Specifically, we replace *Post default* with several time indictors for each 6-month window around the default shock: for example, *Time(0)* equals to 1 if the product was issued during February 2014- July 2014, and *Time(-1)* equals one if the product was issued during August 2013- January 2014, and so forth. We interact each time indicator with *IG index*. Fig. 4 depicts the estimate of each interaction term and their 95% confidence intervals. Column 2 of Table 6 and Fig. 4 show that the coefficients on the interaction terms for the periods before the shock are mostly insignificant (with one exception that is significantly positive). This suggests that before the shock, products with higher guarantee strength do not have a decreasing trend compared to other products, thus satisfying the

Table 6
The first high-profile default case as a negative shock to perceived underlying risk.
This table reports the results of regressions examining the impact of the first high-profile default case in the trust industry (in January 2014) on the pricing of implicit guarantees. The dependent variable is the product yield spread. *Post default* is defined as 1 if the product is issued after February 1, 2014, and 0 otherwise. We consider the sample of products issued in the 24 months before and after the default case, i.e., February 2012 to January 2016. Indicator variables, *Time()*, are defined for the eight 6-month periods around January 2014 in the 4-year period, e.g., *Time(0)* equals to 1 if the product was issued during February 2014- July 2014, and *Time(-1)* equals one if the product was issued during August 2013-January 2014, and so forth. Other controls include *Maturity, Structure, Long Inv Threshold, Collateral, i.infrastructure, i.securities market, i.fin institutions, and i.others.* All other variables are defined in the Appendix. Standard errors are clustered at the firm and year levels and reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dep. Var. = Product expected yield spread (%)	
	(1)	(2)
IG index	-0.132	-0.302***
	(0.105)	(0.0598)
Post default	0.387**	
	(0.155)	
IG index* Post default	-0.241**	
	(0.120)	
IG index×Time(-4)		0.286***
		(0.0919)
IG index×Time(-3)		-0.0384
		(0.0884)
IG index×Time(-2)		0.169
		(0.123)
IG index×Time(-1)		-0.0743
		(0.0531)
IG index×Time(1)		-0.135***
		(0.0364)
IG index×Time(2)		-0.109
		(0.0674)
IG index× Time(3)		-0.106*
		(0.0583)
i.real estate	0.269***	0.336***
	(0.0750)	(0.0956)
GDP growth	0.00485	-0.00715
	(0.0140)	(0.0111)
Log borrowersize	-0.0270	-0.0288
	(0.0171)	(0.0230)
Cons.	YES	YES
Other controls	YES	YES
Time FE	NO	YES
Obs.	7,021	7,021
adj. R-sq	0.317	0.442

[12] The underlying borrower was a company in Shanxi Province and the product proceeds were intended to fund acquisitions of four coal mines. However, by early 2012, only two of the four mines were in production and the company's founder was arrested for other illegal activities.

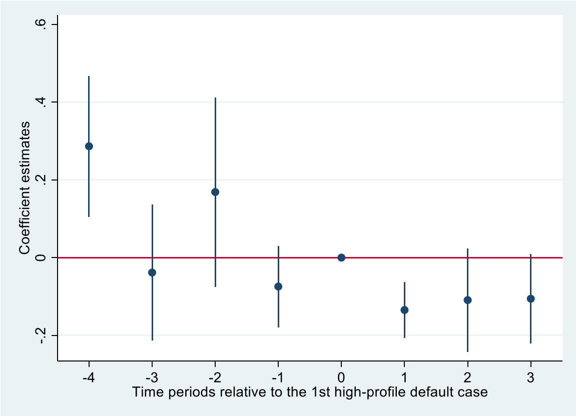

Fig. 4. The first high-profile default case and yield spreads of trust products.
This figure plots the time trend of the treatment effect estimates around the first high-profile trust product default case in January 2014, as explained in Section 5.2 and reported in Column 2 of Table 6. For each time period, we plot the point estimate (the solid circle) and the 95% confidence interval (the vertical lines intersecting the solid circles). Time indicators are defined for the eight 6-month periods around January 2014 in the 4-year period, e.g., *Time(0)* denotes the period during February 2014 – July 2014, and *Time(-1)* denotes the period during August 2013 – January 2014, and so forth.

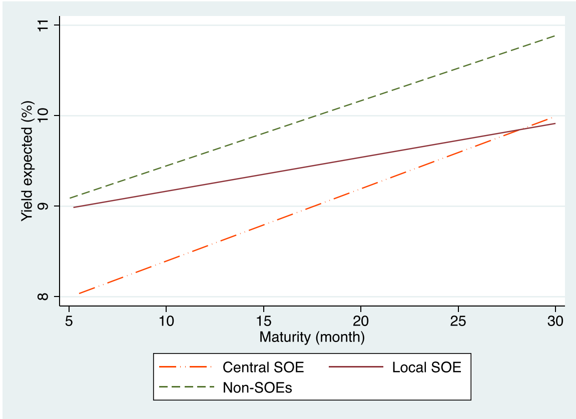

Fig. 5. Yield curve of real estate trust products.
This figure plots predicted yield curves of real estate products issued by different types of trust firms: those ultimately owned by central SOEs, local SOEs, and non-SOEs, respectively. For each group, we regress expected yield on product maturity and calculate the predicted yields. Considering the possible selection issue, we use one-to-one matched product sample based on product features *Log borrowersize* and *GDP growth* (of the location of the project). After matching, we obtain 1,005 products issued by central-SOE-controlled trust companies, 1,005 products issued by local-SOE-controlled trust companies, and 1,005 products issued by non-SOE-controlled trust companies, respectively.

parallel trend condition. All the coefficients on the interactions for the post-default periods are negative and two out of the three of them are significant. This is again consistent with Hypothesis II.

5.3. Additional tests for product pricing

5.3.1. The subsample of real estate products

We conduct additional tests with the subsample of real estate products. Real estate accounts for the most important type of investment for the shadow banking sector in general (e.g., see Allen, Qian, Tu, and Yu, 2019), and for trust products in particular. A key feature about real estate investments is that location is the most important determinant of the underlying investment risk. In this subsection, we construct another underlying risk measure for real estate products, i.e., the local housing market risk, and test Hypotheses I and II with respect to this risk.

Fig. 5 presents yield comparison among real estate products sponsored by different types of trust companies. We plot the yield curves (yield versus maturity) using a linear function, for central SOE-, local SOE-, and non-SOE-backed trusts. We use a matched sample using the PSM method: for each product issued by a central SOE trust, we find a matching product sponsored by a local SOE (or a non-SOE) trust that has the closest propensity score based on *Log borrowersize* and *GDP growth*. The figure shows that on average the products issued by central SOE trusts have the lowest yields across maturities, whereas those issued by non-SOE trusts have the highest yields. The yield curves confirm that products with strong implicit guarantees backed by central SOEs are associated with lower yields for the trust products.

Following Glaeser, Huang, Ma, and Shleifer (2017), we measure local housing market risk, *Hmarket risk*, as the regression residual of the average housing price per square meter in a province (scaled by disposable income per capita) on the province's GDP growth. We use *Hmarket risk* as an additional underlying risk measure for real estate products and re-estimate Eq. (3). Table 7 presents the regression results. Column 1 includes *IG index* and *Hmarket risk* but not their interaction term. Column 2 adds the interaction term of *IG index* and *Hmarket risk*, as well as the other two risk measures (*GDP growth* and *Log borrowersize*) and their interactions with IG index. Consistent with previous tables, the coefficient on *IG index* is significantly negative and the coefficient on *Hmarket risk* is significantly positive in both Column 1 and 2. Thus, consistent with Hypothesis I, the yield spread decreases with the guarantee strength and increases with the underlying risk. In addition, the coefficient on *IG index*×*Hmarket risk* is significantly negative. This is consistent with Hypotheses II, that is, the spread-to-risk sensitivity is reduced by the guarantee strength. A one-standard-deviation increase in *Hmarket risk* increases yield spread by 24 bps; but if *IG index* increases by one, the marginal effect of *Hmarket risk* is reduced by about 50% (from 0.0606 to 0.0305).

Next, we use a policy change in 2010 as a negative shock to the real estate market and examine how that affects the pricing of real estate trust products and how the impact depends on the strength of implicit guarantee.

On April 17, 2010, the State Council announced the "Order 10" in order to curb speculative activities in the housing market and the soaring housing prices. Following this guidance, on April 30, 2010, Beijing issued a rule restricting each household to buying no more than two properties in the city, becoming the first city adopting the "housing purchase restriction." During the period of April 2010 – April 2011, each province implemented new rules restricting housing purchases, usually limiting the number of

Table 7
Real estate product subsample: yield spread and housing market risk.
This table reports the results of regressions examining the effect of investor expectation of implicit guarantees on sensitivity of product pricing to housing market risk based on the subsample of real estate products. The dependent variable is the product yield spread. *Hmarket risk* is defined as the residual of the regression of housing prices (adjusted by disposable income per capita) on GDP growth by province (Glaeser et al., 2017). All other variables are defined in the Appendix. Standard errors are clustered at the firm and year levels and reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dep. Var. = Product expected yield spread (%)	
	(1)	(2)
IG index	-0.371***	-1.193**
	(0.0536)	(0.485)
Hmarket risk	0.0162*	0.0606***
	(0.00973)	(0.0143)
IG index×Hmarket risk		-0.0301***
		(0.00770)
IG index×GDP growth		0.000923
		(0.00440)
IG index×Log borrowersize		0.0430
		(0.0269)
GDP growth		-0.0149*
		(0.00776)
Log borrowersize		-0.102**
		(0.0432)
Maturity	0.0416***	0.0418***
	(0.0108)	(0.0107)
Structure	0.305***	0.290***
	(0.0883)	(0.0903)
Log Inv threshold	0.735***	0.777***
	(0.231)	(0.228)
Collateral	0.131	0.0905
	(0.102)	(0.0993)
Cons	-2.549**	-0.328
	(1.221)	(1.202)
Year FE	YES	YES
Province FE	YES	YES
Obs.	3,282	3,282
adj. R-sq	0.466	0.472

properties one can buy and the amount of loans one can take. These restrictions slowed housing price increases nationwide and led to price decreases in many cities in the next couple of years. Based on the data from the National Bureau of Statistics, during May 2010-December 2011, the national average housing market price decreased by 1.7%, whereas in the two years before April 2010, the price increased by 34.7%. In particular, the average housing prices in Shanghai and Beijing decreased by 17.6% and 24.3% respectively during May 2010-December 2011.

We analyze the pricing of products issued in the two years around the implementation of Order 10. The implementation was staggered across provinces.[13] We define *RE shock* equal to 1 if the product was issued in the 12 months before Order 10 was implemented in the province where the product proceeds was invested, and 0 if it was issued in the 12 months before. We estimate the following regression:

$$Yield\ spread_{i,t} = \beta_0 + \beta_1 * RE\ shock_t + \beta_2 * RE\ shock_t * IG\ index_{i,t} + \beta_3 * IG\ index_{i,t} + \beta_4 * control\ variables_{i,t} + e_{it} \tag{5}$$

Column 1 of Table 8 presents the regression results. We find that *RE shock* has a significantly positive coefficient, suggesting that following the negative shock to the real estate market, yield spreads of these products increase due to the higher underlying risk. The coefficient on *IG index×RE shock*, however, is significantly negative, suggest-

Table 8
Restrictions on housing as a negative shock to the underlying risk of real estate products.
This table reports the results of regressions examining the impact of "Order 10" (housing purchase restrictions) in April 2010 on the pricing of implicit guarantee in the real estate industry. The implementation of "Order 10" was staggered across provinces. We include real estate products issued two years around the implementation of the rules. *RE shock* is defined as 1 if the product was issued in the 12 months after the restriction was implemented in each province, and 0 if the product was issued within 12 months before. The indicators *Time()* are defined eight 3-month periods around the policy shock in the 2-year period, e.g., *Time(0)* equals to 1 if the product was issued in the first three months after the policy shock, and *Time(-1)* equals to 1 if the product was issued in the three months before the policy shock, and so forth. The dependent variable is the product yield spread. Other controls include *Maturity, Structure, Long Inv Threshold, Collateral, GDP growth* and year fixed effects. All other variables are defined in the Appendix. Standard errors are clustered at the firm and year levels and reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dep. Var. = Product expected yield spread (%)	
	(1)	(2)
IG index	-0.173	-0.0615
	(0.109)	(0.154)
RE shock	0.627***	
	(0.196)	
IG index× RE shock	-0.370***	
	(0.125)	
IG index× Time(-4)		-0.535
		(0.353)
IG index× Time(-3)		-0.0116
		(0.208)
IG index× Time(-2)		-0.221
		(0.143)
IG index× Time(-1)		0.0779
		(0.220)
IG index× Time(1)		-0.716**
		(0.280)
IG index× Time(2)		-0.494***
		(0.184)
IG index× Time(3)		-0.500**
		(0.237)
Hmarket risk	0.0304	0.0207
	(0.0195)	(0.0252)
Cons	YES	YES
Other controls	YES	YES
Time FE	NO	YES
Province FE	YES	YES
Obs	331	331
adj. R-sq	0.185	0.169

[13] Policy attitudes toward real estate switch between the desire to slow down fast price increases and the fear of steep price drops. The regulators eased control on the industry again at the end of 2011. Since many provinces did not implement Order 10 until late 2010, we choose the one-year window after the staggered implementations.

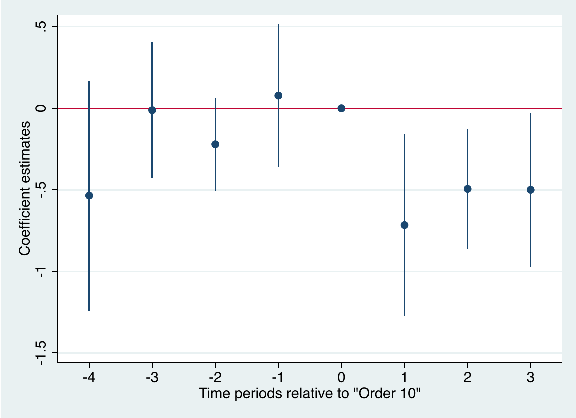

Fig. 6. "Order 10" and yield spreads of trust products.
This figure plots the time trend of the treatment effect estimates around the "Order 10" announced in April 2010, as explained in Section 5.3.1 and reported in Column 2 of Table 8. For each time period, we plot the point estimate (the solid circle) and the 95% confidence interval (the vertical lines intersecting the solid circles). Time indicators are defined eight 3-month periods around the policy shock in the 2-year period, e.g., *Time(0)* denotes the first three months after the policy shock, and *Time(-1)* denotes the three months before the policy shock, and so forth.

ing that the impact of the negative shock is mitigated by strong implicit guarantee.

In Column 2 of Table 8, we further conduct a dynamic DiD test. Specifically, we replace the *RE shock* dummy with several time period indicators and interact each indicator with *IG index*. The time indicators, *Time(),* are defined for each 3-month window of the two-year period before around the policy shock. For example, *Time(0)* is defined as the first 3 months after the policy shock, and *Time(1)* is defined as the second 3 months after the policy shock and so on. Column 2 shows that the coefficients on the interaction terms are insignificant for all periods before the shock. In contrast, all the interaction terms for periods after the shock have significantly negative coefficients. Fig. 6 depicts the coefficients of these interaction terms and their 95% confidence intervals. This suggests that the parallel trend condition is satisfied before the shock and that the effect of the policy shock is mitigated by strong implicit guarantees. Overall, using the subsample of real estate products, we again find supporting evidence for Hypotheses I and II.

5.3.2. Matched sample tests

We recognize that there might be a selection issue in our sample: it is possible that trusts with a higher strength of guarantee (larger trusts, those backed by central SOEs) or products sold via Big 5 banks tend to invest in safer or higher quality projects. If so, then the relationship we find between yield spread and guarantee strength may be driven by this possible endogeneity issue. We have tried to address this concern by using several shocks to either the guarantee strength or the (perceived) underlying investment risk and conducting DiD tests around the shocks. In this subsection, we redo our analyses using a matched sample that control for the differences in the underlying risk between products with low and high implicit guarantees.

Specifically, we conduct a propensity score matching test as follows. We divide the sample into products with high and low IG index: a product has a high IG index if its *IG index* is greater than or equal to two. The matching begins with a probit regression of the high IG index dummy on *Log borrowersize* and *GDP growth*. We use the propensity scores from the probit regression estimation and perform a nearest-neighbor match without replacement, applying a caliper of 0.01. We also require that the matched products be invested in the same industry. This procedure ensures that each product with high IG index is paired with a product that has similar underlying risk (in terms of industry, GDP growth, borrower size), but has low IG index. Out of the 10,290 products with non-missing data including borrower size information, we end up with a matched sample with 7,864 products (3,932 each with high or low IG index).

Table 9 Panel A compares *Log borrowersize* and *GDP growth* for the matched subsamples (recall that matched products are required to be in the same industry). After being matched, products with high and low IG index have similar borrower size and GDP growth: the difference is close to zero and not significantly different.

We redo our previous analysis using the matched sample, replacing *IG index* with *HIGindex* (a dummy equal to 1 if *IG index* is greater than or equal to 2). Table 9, Panel B reports the results. Column 1 reruns the test in Column 2 of Table 3, Panel B. The results are similar as those in Table 3: the yield spread depends on both the strength of implicit guarantee and the underlying risk. The spread is lower when *HIGindex* is equal to 1, and decreases in borrower size and the province's GDP growth, and increases if the funds are invested in real estate.

Column 2 reruns the test in Column 2 of Table 5. The coefficients on *HIGindex*×*GDP growth, HIGindex*×*i.real estate, HIGindex*×*Log borrowersize* are opposite the signs of those on *GDP growth, i.real estate,* and *Log borrowersize*, respectively and they are all statistically significant with the exception of the coefficient on *HIGindex*×*Log borrowersize*. This supports Hypothesis II, i.e., strong implicit guarantees reduce the spread-to-risk sensitivity.

Column 3 reruns the test in Column 1 of Table 6. We find a positive but insignificant coefficient on *Post default* and a significantly negative coefficient on *HIGindex*×*Post default*. That is, the effect of the first high-profile default case is mitigated by strong implicit guarantees. Column 4 reruns the test in Column 2 of Table 7. For the subsample of real estate products, the coefficient on *Hmarket risk* is significantly positive and that on *HIGindex*×*Hmarket risk* is significantly negative. In other words, yield spreads increase with the housing market risk but less so for products with high guarantee strength.

In summary, analyses using the matched sample produce qualitatively results as before. The evidence again supports Hypotheses I and II.

5.4. Regulations restricting implicit guarantees

On March 28, 2018, the central government announced the guidelines for *"New Regulations on Asset Management"* (*"New Regulations"* henceforth), with one goal of sweep-

Table 9
Matched sample tests.
This table reports the results of robustness checks using the propensity score matched (product) sample. The dependent variable is the product yield spread. *HIGindex* is defined as 1 if the IG index equals 2, 3 or 4; and 0 otherwise. The products with low level of implicit guarantees (when *HIGindex*=0) are matched based on *Log borrowersize, GDP growth* and *industry* using a one-to-one propensity score matching algorithm with the distance of 0.01 (caliper=0.01) but without replacement. Panel A reports the results of two-sample tests; Panel B reports the results of the regressions examining the effect of implicit guarantees and product expected yield spreads using the matched sample. Other controls include *Maturity, Structure, Long Inv Threshold, Collateral* in Columns (1)-(4) and *i.infrastructure, i.securities market, i.fin institutions,* and *i.others* in Column (4). All other variables are defined in the Appendix. Standard errors are clustered at the firm and year levels and reported in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Panel A. Trust product characteristics: matched sample

	HIGindex=0		HIGindex=1		Difference
	Obs.	Mean(std. err.)	Obs.	Mean(std. err.)	Mean(std)
Log borrowersize	3,932	19.535 (0.0273)	3,932	19.517 (0.0271)	0.0175 (0.0384)
GDP growth	3,932	10.027 (0.0927)	3,932	9.934 (0.0943)	0.0935 (0.132)

Panel B. Regression analysis

	Dep. Var. = Product expected yield spread (%)			
	Table 3 (1)	Table 5 (2)	Table 6 (3)	Table 7 (4)
HIG index	-0.427*** (0.0812)	-0.796 (0.564)	-0.209 (0.137)	-2.756*** (0.982)
GDP growth	-0.0204*** (0.00697)	-0.0334*** (0.00895)	0.00527 (0.0325)	-0.0174** (0.00782)
i.real estate	0.271*** (0.0700)	0.381*** (0.0824)	0.168 (0.114)	
Log borrower size	-0.0277* (0.0143)	-0.0331* (0.0197)	-0.0389 (0.0287)	-0.0906*** (0.0337)
HIGindex×GDP growth		0.0233** (0.0100)		0.0103 (0.0109)
HIGindex×i.real estate		-0.210* (0.116)		
HIGindex×Log borrowersize		0.0106 (0.0270)		0.104* (0.0538)
Post default			0.277 (0.381)	
HIGindex×Post default			-0.395** (0.197)	
Hmarket risk				0.0394*** (0.0135)
HIGindex×Hmarket risk				-0.0449** (0.0183)
Cons/Other controls	YES	YES	YES	YES
Year FE	YES	YES	NO	YES
Province FE	YES	YES	YES	YES
Obs.	7,864	7,864	5,317	3,282
adj. R-sq	0.439	0.442	0.234	0.462

ing away implicit guarantees in investment products issued by financial institutions. Shortly after that, the People's Bank of China, together with the Banking and Insurance Regulatory Commission, China Securities Regulatory Commission, and the State Administration of Foreign Exchange all announced specific rules and directions in support of the New Regulations. Financial institutions cannot provide guarantees to any investment product issued afterwards. They are also discouraged from paying losses for previously issued products.

The *New Regulations* is the first official government doctrine to explicitly ban implicit guarantees in all investment products. While there is anecdotal evidence that trust firms still pay up in some cases of product failures, in practice the process has become quite different from before.[14] Consistent with the provision of implicit guarantees becoming more costly, we observe many more defaults for trust products after the announcement of the *New Regulations*.[15] We observe 57 cases of defaults for our sample products between 2002 and March 2018 (based on iFind supplemented by our own web searches). In

[14] As shown in Table A.1 in Online Appendix A, unlike the pre-2018 period when 'explicit recourse'—covering investor losses when products fail—was common practice and no explanations for the arrangements were needed, there were cases in which trust firms were 'ordered' by courts to cover (partial) losses of failed products to investors, for reasons including inadequate disclosure, especially on the uncertainty in payoffs of projects, after the *New Regulations* were announced.

[15] The higher number of defaults may partly be attributed to worsening overall economic conditions in China.

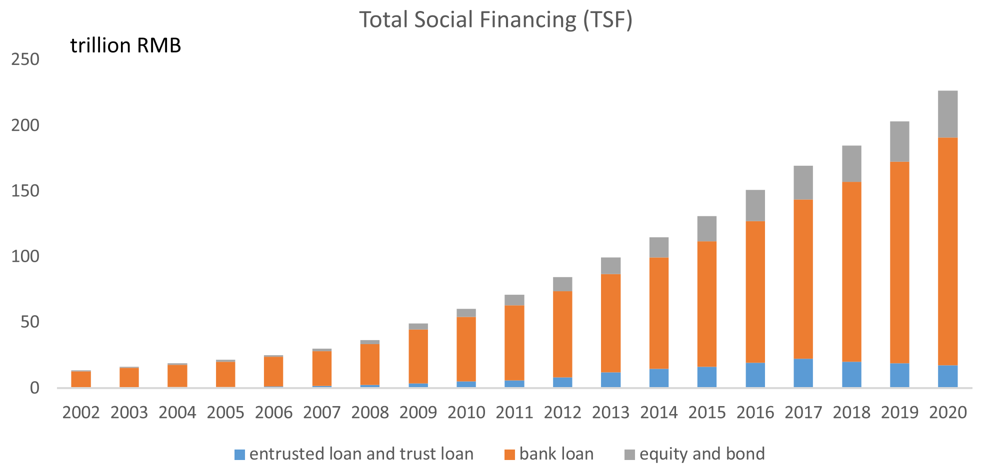

Fig. 7. Components of total social financing in China.
This figure plots the breakdown of total social financing (TSF) in China from 2002 to 2020.

comparison, there were 178 defaults during April 1998-2020. Table A.1 in Online Appendix A also reports whether and how investors are paid in default cases for 62 cases where we can find such information. Investors are fully paid (with principal plus the expected yields) in 74% of default cases prior to *New Regulations* (in most cases the trust firm paid), but the ratio drops to 39% after 2018.

Hypothesis III predicts that following such a regulation restricting implicit guarantees, the size of shadow banking will shrink, and the non-SOE sector will receive less funding as a result of the higher cost in providing guarantees by the trust companies. We find evidence at both the aggregate and dis-aggregated levels consistent with these predictions. Fig. 7 reports by year the breakdown of the total social financing flow (TSF) in China in three large categories: bank loans, equity and bonds (i.e., direct financing), and entrusted loans and trust loans (i.e., shadow banking).[16] The figure shows that the sector of shadow banking steadily increases until 2018 and has been decreasing since then. Moreover, entrusted loans and trust loans each follow the same trend. The total amount of outstanding trust loans decreases from RMB 8.5 trillion in 2017 to 7.9 trillion in 2018 and to 7.4 trillion in 2019. Similarly, the size of the outstanding entrusted loans decreases from RMB 14.0 trillion in 2017 to 12.4 trillion in 2018 and 11.4 trillion in 2019. In contrast, bank loans and direct financing has increased steadily since 2018. There are other components of shadow banking that are not included in TSF. Fig. A.3 in Online Appendix A reports by year the total size of shadow banking and its various components according to Moody's. This figure shows the same pattern: the sector of shadow banking has been increasing till 2018 and has been declining since then.

Fig. 8 reports by year the fraction of capital funded by our sample trust products going to non-SOE projects. To identify the ownership type of borrowers, we match our sample with firms' registration information in State Administration for Industry and Commerce (SAIC) and China Economic Census Data. Consistent with Hypothesis III, the percentage of funds going to non-SOEs declined after 2018: from 66% in 2018 to 49% in 2019 and 43% in 2020.[17]

We perform two sets of tests at the product- and trust-loan levels. First, with regulatory restrictions on implicit guarantees, the relationship between product pricing and our measures of implicit guarantee strength (which capture the ability to honor guarantees) will become weaker. We examine whether and how this relationship changes around the implementation of *New Regulations* by estimating the following regression.

$$\begin{aligned} Yield\ spread_{i,t} = {} & \beta_0 + \beta_1 * Post\ regulation_t * IG\ index_{i,t} \\ & + \beta_2 * IG\ index_{i,t} \\ & + \beta_3 * Control\ variables_{i,t} + e_{it} \end{aligned} \tag{6}$$

where *Post regulation* equals to 1 if the product was issued after the announcement of the policy (i.e., March 28, 2018), and 0 otherwise. We include year fixed effects in the model.

Table 10 shows the regression results. We include a full set of control variables including *Log borrower size* and *Log Shrld size*. Results are qualitatively the same if excluding one or both variables. Column 1 includes each dimension of implicit guarantees as well as their interactions with dummy *Post Regulation*. The coefficients on *Central SOE* and *Log Reg cap* are all significantly negative and that on *Sale bank big5* is negative but less significant. This is consistent with our Hypothesis I, i.e., implicit guarantees reduce product yield spreads. The three interaction terms, *Central SOE*×*Post regulation, Log Reg cap*×*Post regulation, Sale*

[16] In addition to these categories, TSF also includes "undiscounted bankers' acceptances" and "others."

[17] The percentage of funds going to non-SOEs also declined after 2011, possibly due to the RMB 4 trillion stimulus in 2009-2010. The stimulus-driven credit expansion (2009-2010) disproportionately favored SOEs in the banking system (Cong, Gao, Ponticelli, and Yang, 2019), and many of these loans were subsequently rolled over in the shadow banking sector including trust products (hence following the stimulus, with much of the shadow banking capital going to support SOEs).

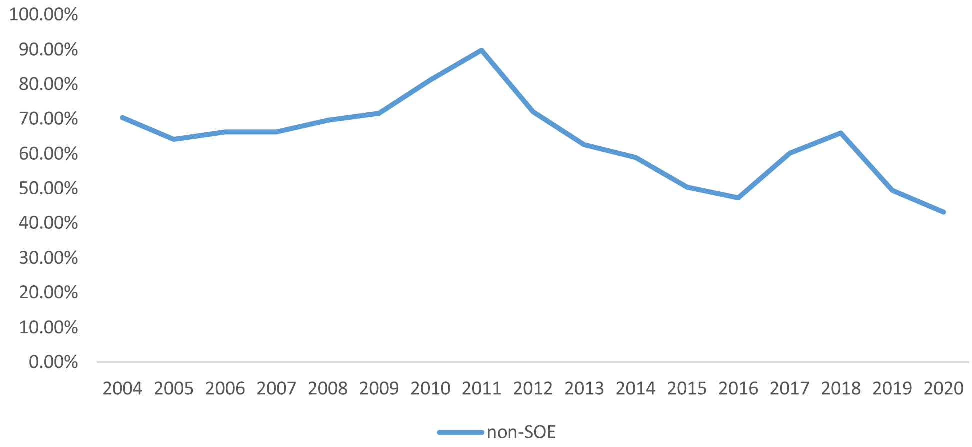

Fig. 8. Percentage of trust loans for non-SOEs.
This figure plots the percentage of capital funded by our sample trust products going to non-SOE borrowers from 2004 to 2020. To identify whether the borrower of trust products is an SOE, we match with the registration data originated from the State Administration for Industry and Commerce (SAIC) and China Economic Census Data.

Table 10
Policy shock to implicit guarantees: *New Regulations on Asset Management in 2018*.
This table reports the results of the regressions examining the effects of a policy change on implicit guarantees, the "New Regulations on Asset Management" announced in March 2018. *Post regulation* is defined as 1 if the product is issued after March 28, 2018, and 0 otherwise. The dependent variable is the product yield spread. Columns (1) and (2) use the full sample and Column (3) uses the propensity-score-matched sample, which follows the same matching criterion as those in Table 9. Other controls include *Maturity, Structure, Long Inv Threshold, Collateral.* All other variables are defined in the Appendix. Standard errors are clustered at the firm and year levels and reported in parentheses.

	Dep. Var.=Product expected yield spread (%)		
	(1) Full sample	(2) Full sample	(3) Matched sample
Central SOE×Post regulation	0.427* (0.231)		
Log Reg cap×Post regulation	0.0418* (0.0245)		
Sale bank big 5×Post regulation	0.503** (0.242)		
IG index×Post regulation		0.195** (0.0859)	0.196** (0.0855)
Central SOE	-0.292** (0.146)		
Log Reg cap	-0.175** (0.0693)		
Sale bank big 5	-0.0619 (0.0794)		
IG index		-0.259*** (0.0551)	-0.237*** (0.0555)
Log Shrld size	-0.0911*** (0.0308)	-0.0872*** (0.0268)	-0.0764*** (0.0275)
GDP growth	-0.00631 (0.00748)	-0.00718 (0.00710)	-0.0221** (0.0111)
i.real estate	0.239*** (0.0805)	0.240*** (0.0826)	0.209** (0.0828)
Log borrower size	-0.00809 (0.0164)	-0.0146 (0.0166)	-0.0264 (0.0182)
i.infrastructure	-0.00127 (0.0638)	-0.0113 (0.0595)	0.0237 (0.0673)
i.securities market	0.496* (0.254)	0.490** (0.247)	-2.165 (1.623)
i.fin institutions	-1.065*** (0.137)	-1.050*** (0.139)	-0.848*** (0.185)
i.others	0.0331 (0.111)	0.0320 (0.112)	0.110 (0.108)
Cons/Other controls	YES	YES	YES
Year FE	YES	YES	YES
Province FE	YES	YES	YES
Obs	5,810	5,810	4,409
adj. R-sq	0.482	0.469	0.407

Table 11
The effect on issuance size of trust loans: *New Regulations on Asset Management*.
This table reports the results of the regressions examining the effect of the “New Regulations on Asset Management” announced in March 2018 on the issuance size of the trust loans. *Post regulation* is defined as 1 if the product is issued after March 28, 2018, and 0 otherwise. *Borrower non-SOE* is defined as 1 if the underlying borrower is a non-SOE, and 0 otherwise. The dependent variable is the natural logarithm of the issuance size of trust loans. The sample covers the product lending to real estate and Commercial and Industrial (C&I) firms. Other controls include *Maturity, Structure, Long Inv Threshold, Collateral.* All other variables are defined in the Appendix. Standard errors are clustered at the firm and year levels and reported in the parentheses.

	Dep. Var.=Log Loan size	
	(1)	(2)
Borrower non-SOE×Post regulation	-1.548***	-2.327**
	(0.471)	(0.904)
Central SOE× Borrower non-SOE×Post regulation	2.101***	
	(0.712)	
IG index × Borrower non-SOE×Post regulation		1.073**
		(0.425)
Central SOE×Borrower non-SOE	0.196	
	(0.274)	
Central SOE×Post regulation	0.109	
	(0.793)	
Log Reg cap×Post regulation	-0.00222	
	(0.108)	
Sale bank big 5×Post regulation	2.183***	
	(0.753)	
IG index×Post regulation		0.0292
		(0.195)
IG index ×Borrower non-SOE		-0.0932
		(0.124)
Central SOE	-0.0400	
	(0.311)	
Log Reg cap	0.0563	
	(0.146)	
Sale bank big 5	-0.488***	
	(0.182)	
IG index		0.0906
		(0.100)
Borrower non-SOE	0.0486	0.158
	(0.105)	(0.194)
Log Shrld size	0.0593	0.0561
	(0.0494)	(0.0443)
GDP growth	0.0240	0.0339
	(0.0210)	(0.0226)
i.real estate	0.167*	0.222**
	(0.0881)	(0.0859)
Log borrower size	0.169***	0.186***
	(0.0282)	(0.0397)
Cons/Other controls	YES	YES
Year FE	YES	YES
Province FE	YES	YES
Obs	1,100	1,100
adj. R-sq	0.229	0.216

bank big 5×Post regulation are all significantly positive, suggesting that the *New Regulations* reduce the effect of implicit guarantees from the perspective of investors. Column 2 uses IG index instead. The coefficient on IG index is significantly negative and the interaction *IG index×Post regulation* is significantly positive, again suggesting that the effect of implicit guarantees is mitigated after the regulation shock. Column 3 uses the propensity-score-matched sample instead of the full sample in Columns 1 and 2. Consistently, the coefficient on *IG index* is significantly negative and that on the interaction is significantly positive.[18] These results suggest that after the announcement of *New Regulations*, the effect of implicit guarantees on yield spreads of trust products becomes weaker, reflecting lower expectation on the provision of guarantees in case of product failure.

Finally, we examine at the product level, how the terms of trust loans extended to risky projects and private borrowers change after the implementation of *New Regulations*. As stated above, we manually collect data on con-

[18] In Columns 2 and 3, the sum of the coefficient on *IG index* and that on *IG index*post regulation* is negative, suggesting that guarantee strength overall is still associated with *lower* yields post regulation, although the effect is much weaker. In Column 1, the sum of coefficients for each individual guarantee measure and its interaction term is negative for *Log Reg Cap* and positive for *Central SOE and Sale bank big 5*, suggesting that post regulation, the effect of each guarantee variable is not always negative on yields, possibly due to the restrictions on implicit guarantees.

tract terms of a subset of products that funded 'real' (non-financial) sectors. Complete information on actual (with all expenses included) loan interest rates are sporadic, while prior literature (e.g., Stiglitz and Weiss, 1981; Qian and Strahan, 2007) show that in environment with asymmetric information, the effect of using interest rate as the tool to control borrower risk is limited, while non-pricing terms, such as loan size, can be more effective. Specifically, we look at the size of trust loans extended to real estate projects and commercial and industrial (C&I) firms, as these are deemed riskier compared to other industries and SOE borrowers in our sample. We incorporate an indicator, *Borrower non-SOE*, and estimate the following regression:

$$\begin{aligned} &Log\ Loan\ size_{i,t} \\ &= \beta_0 + \beta_1 * Post\ regulation_t * IG\ index_{i,t} \\ &\quad + \beta_2 * Post\ regulation_t * Borrower\ nonSOE \\ &\quad + \beta_3 * Post\ regulation_t * IG\ index_{i,t} * Borrower\ nonSOE \\ &\quad + \beta_4 * IG\ index_{i,t} + \beta_5 * control\ variables_{i,t} + e_{it} \qquad (7) \end{aligned}$$

Table 11 reports the regression results. Column 1 includes each dimension of implicit guarantees, their interactions with dummy *Post Regulation*, as well as the triple interaction of dummies *Central SOE, Post Regulation* and *Borrower non-SOE*. The coefficient on *Borrower non-SOE* ×*Post regulation* is significantly negative, suggesting that the size of trust loans to non-SOE borrowers shrinks after the regulation shock. The coefficient on the triple interaction, *Central SOE*× *Borrower non-SOE*×*Post regulation*, is significantly *positive*, suggesting that the reduction in the size of trust loans is largely mitigated for central SOE trusts, which remain the loan issuers with the strongest guarantee strength. Column 2 uses the IG index. The coefficient on *Borrower non-SOE*×*Post regulation* remain significantly negative, consistent with that in Column 1. The coefficient on *IG index* × *Borrower non-SOE*×*Post regulation* is significantly positive, again suggesting that when trust firm's strength in providing implicit guarantees is stronger, the reduction in loan size is smaller.

These results show that trust firms with greater guarantee strength, or with a lower (regulatory) cost in the provision of guarantees as stated in Corollary 2, are less adversely affected by the New Regulations, and they impose less credit rationing on the non-SOE borrower. The results continue to hold if we include products in infrastructure in addition to real estate and C&I.[19] In terms of economic magnitude, Column 2 estimates suggest that when the trust lender's guarantee strength is weak (*IG index* equals 1, the sample median), the loan size of non-SOE borrowers is reduced by 71% [= exp (-2.327 + 1.073) −1] post regulation, whereas the reduction in loan size is 17% when the *IG index* equals 2.

Overall, the evidence in this subsection is consistent with our model predictions, and in particular, Hypothesis III. At the macro level, restrictions on implicit guarantees result in declines of shadow banking including the size of the trust products, as well as the funding of the non-SOE sector. At the micro level, the relationship between yield spread and measures of implicit guarantee strength becomes weaker, and there is more credit rationing toward non-SOE borrower firms, especially for loan issuers with weaker ability to provide guarantees.

6. Conclusions

We study a central feature in the rise of China's shadow banking, i.e., the prevalence of implicit guarantees provided by financial intermediaries to the investors. Our theoretical model shows that it can be a second-best solution when the financial intermediary is expected to screen the underlying investment projects and the social benefits of screening are high relative to costs. Implicit guarantees on the one hand incentivize the intermediaries to screen projects and on the other hand control risk as the intermediaries are required to cover investor losses in case of project failure (unless an economy-wide bad state occurs). We also demonstrate that shadow banking with implicit guarantees can mitigate capital misallocation in China's economy and provide more funding to non-SOE projects and firms. Restricting implicit guarantees therefore will result in declines of both shadow banking and funding to the non-SOE sector.

Using a comprehensive set of investment products issued by all licensed trust companies, we test the model's predictions. We first examine the effect of implicit guarantees on these products' ex ante pricing. Unlike the too-big-to-fail problem where the government guarantee is extended to the largest banks, in our setting implicit guarantees are offered by financial firms whose guarantee strengths vary. We measure the guarantee strength based on the sponsoring trust firm's financial health, its ownership type, and the sales channel. Consistent with the model predictions, we find that the product yield spreads increase with the underlying investment risk and decrease with the strength of the guarantee. In addition, strong guarantees reduce the spread-to-risk sensitivity.

Further, a set of new regulations announced in 2018 imposed cost on trust companies in their provision of implicit guarantees. As a result, the relationship between product yields and our measures of guarantee strength becomes weaker after 2018, reflecting revised investor perception on product risks. Also consistent with the model's predictions, we find that the aggregate size of shadow banking, trust products and the capital flow to non-SOE firms all decline, with the extent of credit rationing toward private firms and projects heightened when the trust company's strength in providing guarantees are weaker.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Jun "QJ" Qian reports financial support was provided by National Natural Science Foundation of China (Project number 71972051).

[19] We also examine the maturity of trust loans, but did not find any significant changes before or after the announcement of the *New Regulations* in 2018.

Data availability

The authors do not have permission to share data.

Implicit Guarantees and the Rise of Shadow Banking: the Case of Trust Products (Original data) (Mendeley Data)

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfineco.2023.04.012.

The code and pseudo-data for this article can be found at http://doi.org/10.17632/78d5pc7f7w.2

Appendix. Variable definitions

Variable	Definition
Borrower size	= registered capital of borrower (in millions)
Borrower non-SOE	=1 if borrower is a non-SOE; 0 otherwise
Central SOE	=1 if the controlling shareholder of the trust company is a central SOE; 0 otherwise
Collateral	=1 if the issue is based on collateral; 0 otherwise
Expected yield	= expected yields marketed in the product prospectus
GDP growth	= GDP growth rate of the borrower's headquartered province
HIGindex	=1 if IG index equals to two, three or four; 0 otherwise
Hmarket risk	= residual of the regression of housing price (adjusted by disposable income per capita) on GDP growth by province
IG index	= summation of SOE (=2 for Central SOEs, =1 for Local SOEs or =0 for non-SOEs), Sale bank big5, and Large tfirm
Inv threshold	= minimum investment amount of the trust product (in thousands)
Larget tfirm	=1 if issuing trust company has the upper 33% registered capital, 0 otherwise
Local SOE	=1 if the controlling shareholder of the trust company is a local SOE; 0 otherwise
Log borrowersize	= natural logarithm of borrowers' registered capital (in yuan)
Log Inv threshold	= natural logarithm of the minimum investment amount of the trust product (in thousands)
Log Loan size	=natural logarithm of the issuance amount of trust products (in thousands)
Log Reg cap	= natural logarithm of registered capital of trust companies (in millions)
Log Shrld size	= natural logarithm of the total assets of the controlling shareholders of trust firms (in millions)
Maturity	= maturity of the trust product (in months)
Post default	=1 if the product is issued after the first high-profile default case in the trust industry in the end of January 2014; 0 otherwise
Post regulation	=1 if the product is issued in or after March 28, 2018 when the "*New Regulations on Asset Management*" was announced and 0 otherwise
RE shock	=1 if the product is issued in the 12 months after the implementation of "Order 10" in each province, and 0 if the product was issued within 12 months before

(*continued on next column*)

Variable	Definition
Reg cap	= amount of registered capital of trust companies (in millions)
Sale bank big5	=1 if the product is sold by a Big-5 bank; 0 otherwise
Post crash	=1 if the product is issued between July 1, 2015 to December 31, 2016 (in the 18 months after the stock market crash) and 0 if the product is issued between December 1, 2013 to May 31, 2015 (in the 18 months before the stock market crash)
Structure	=1 if the product is structured; 0 otherwise
Yield spread	= the difference between the expected yield of the product and the yield of a matched Treasury bond based on the month of the product issuance and maturity.

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