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The Real Effects of Shadow Banking: Evidence from China

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Abstract. We provide firm-level evidence on the real effects of shadow banking in terms of technological innovation. Firm-to-firm entrusted loans, the largest part of the shadow banking sector in China, enhance the borrowers' innovation output. The effects are more prominent when the borrowers are subject to severer financial constraints, information asymmetry, and takeover exposures. A plausible underlying channel is capital reallocations from less productive but easily financed lender firms to more innovative but financially less privileged borrower firms. Our paper suggests that shadow banking helps correct bank credit misallocations and thus, serves as a second-best market design in financing the real economy.

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Keywords: shadow banking • corporate innovation • capital reallocation

1. Introduction

Shadow banking, broadly known as the credit intermediation outside of the regulated banking system (Adrian and Ashcraft 2012, Allen and Gu 2021), has been expanding significantly during the last two decades. Meanwhile, concerns are heightened that the shadow banking system could be purely a regulatory arbitrage without benefiting the real economy, leading to problems such as increases in risk spillover, idle funds, firm leverage, and consequently, the outbreak of systemic risk. By far, advantages and disadvantages of shadow banking are still not fully understood by the existing studies, largely because of limitations on data availability (Financial Stability Board 2019).

In China, the second largest economy in the world, the ambiguous effects of shadow banking make it even controversial. On the one hand, China's central government has been restraining the enlargement of the shadow banking sector since 2014 because of the concern of potential outbreaks of systemic risk. On the other hand, scholars argue that the surge of shadow banking in China reflects the deficit of financial resources and thus, could serve as a supplement to bank credit in a financially depressed economy (e.g., Chen et al. 2018, Allen et al. 2019). Although past wisdom supplies substantial evidence and arguments upon the causes of the upsurge of the shadow banking sector (e.g., Buchak et al. 2018, Chen et al. 2020), the pricing of shadow bank credit (Allen et al. 2019, Acharya et al. 2020), and its influences to the financial system (Xiao 2020), there is still a lack of direct micro-level evidence on its consequences for the real economy.[1] In this paper, we attempt to fill this gap by examining the real effects of shadow banking in terms of borrower firms' technological innovation, which has always been considered as a key engine of economic growth (Solow 1956, Romer 1986). Innovation is also claimed by China's central government as the core driving force and key policy target for its future growth.

Another puzzling question in China, documented by the existing literature, is why the vast enlargement of private sectors is able to coexist with the misallocated bank credit given that the country's banking system is disproportionally in favor of the state-owned enterprises (SOEs) because of the government's implicit guarantees (Brandt and Zhu 2000, Song and Xiong 2018, Cong et al. 2019). Shadow banking, as an important source of alternative finance, is expected to help reconcile these seemingly contradicting facts in explaining China's economic growth (Allen et al. 2005, Allen and Gu 2021). For example, Allen et al. (2017) argue that alternative finance in China plays an important role and cooperates with the formal financing sector in promoting the efficiency of resource allocation and thereby, supports the new pattern of innovation-driven growth. Our study goes one step further and offers the first attempt to empirically show that shadow banking in China serves as a capital reallocation mechanism (i.e., it channels capital out of less productive but easily financed firms to more innovative but financially less privileged firms) and thus, improves the efficiency of resource allocation, which ultimately helps promote borrower firms' corporate innovation output.

Entrusted loans, the biggest part out of China's shadow banking sector until 2014 and the second largest thereafter (Elliott et al. 2015), offer a good opportunity to identify the real effects of shadow banking on corporate innovation. Entrusted loans are firm-to-firm loans, of which the lenders and the borrowers determine the loan contract, whereas the banks only serve as the trustees that charge service fees but bear no risk (Allen et al. 2019). In China, direct intercorporate loan is legally banned for nonfinancial firms for a long period, and hence, each transaction must rely on a bank to serve as the agent. Moreover, if the lender is a publicly traded firm, entrusted loan transactions are required to be disclosed in the lender's annual reports, which allows us to observe the concrete information of this major component of shadow banking activities at a micro level.[2]

Unlike routine activities, innovation is subject to a large degree of uncertainty and high failure risk, and hence, it is difficult to be effectively financed and motivated. Although earlier literature generally finds that the use of debt finance is negatively associated with innovation output (Hall and Lerner 2010, Hsu et al. 2014), recent studies show that debt (including bank loans) plays more subtle roles than the literature previously believed (Gu et al. 2017, Hochberg et al. 2018). Specifically, intercorporate loans can help motivate borrowers' innovation for two reasons. First, in China, the depressed and distorted financial system makes external equity, as well as bank credit, a relatively scarce financing resource for most firms in the private sector, whereas the large state-owned enterprises have substantially easier access to a variety of cheap financial instruments, even though they lack good investment opportunities (Song et al. 2011). Because "explicit" banks highly distort the primary allocation of financial resources, shadow banking could reallocate the misplaced capital under the "invisible hand" of markets through intercorporate loans, with the lenders serving as the implicit but more efficient de facto banks. Hence, consistent with the argument by Allen and Gu (2021), an entrusted loan is actually a market-based conduit in favor of those borrower firms that are more productive and innovative but capital deprived, which serves as a second-best market design to mitigate borrowers' financial frictions and hence, ultimately foster borrowers' innovation in a financially distorted market.

Second, there is growing recent evidence emphasizing the role of bank credit and debt finance in supporting innovation (Nanda and Nicholas 2014, Cornaggia et al. 2015). As pointed out by Chang et al. (2019b), debt would be plausible in financing innovation if its compatibility with innovation is enhanced. Following this logic, we argue that several characteristics of entrusted loans could make them more compatible with innovation and even better than traditional bank credit in enhancing innovation. First, the lenders of entrusted loans are typically capital-intensive firms that have easy access to cheap finance but lack investment opportunities. Given that these firms lend with their own assets (i.e., cash in hand) and are not subject to various banking regulations (e.g., capital requirement or risk management), they could have higher failure tolerance, which is important in motivating and financing innovation (Manso 2011, Tian and Wang 2014). Second, Allen et al. (2019) find that the prices of entrusted loans are significantly lower if the transactions are within the same industries, cities, or business groups, suggesting that information plays a crucial role in lenders' decisions about the contracts of entrusted loans. In addition, a considerable proportion of entrusted loan transactions appears in several successive years, similar to staged financing implemented in the venture capital investment, which implies that it is possible for the lenders to learn more about the borrowers through staging (Liu and Tian 2022).[3] Hence, lower informational frictions between lenders and borrowers could potentially make intercorporate loans more suitable in financing borrowers' innovation than traditional bank credit.

To explore the effects of entrusted loans on corporate innovation, we undertake empirical tests that are based on a large sample of firms from the Annual Survey of Industrial Firms (ASIF) between 2005 and 2013. The ASIF has by far the most comprehensive coverage of manufacturing firms in China and has been widely used in the existing literature (e.g., Bai et al. 2016, Huang et al. 2020, etc.). We merge the ASIF sample with manually collected entrusted loan data by the borrower's name. Following Allen et al. (2019), we obtain entrusted loan information from the annual reports and announcements of all listed firms on China's stock market. We then manually check the borrower for each transaction (because occasionally, the disclosed borrower name is incorrect) and standardize the name of the borrower. We identify and term the firms with at least one record of entrusted loan borrowing as entrusted loan firms (EL firms hereafter) and firms without any record of entrusted loan borrowing as nonentrusted loan firms (non-EL firms hereafter).

To measure a firm's technological innovation productivity, we use the number of invention patents granted by the China National Intellectual Property Administration (CNIPA; the patent office of China) as the quantity measure of borrower firms' innovation output and the number of forward citations as the quality measure of borrower firms' innovation output, following Hall et al. (2001). In addition, we follow Kong et al. (2022) to identify explorative patents and use the number of granted explorative invention patents to capture borrower firms' cutting-edge innovation that is likely to cause technological breakthroughs. We then merge innovation output data with the ASIF data by standardized firm names. We manually check for match accuracy and construct the sample. After dropping observations with missing data, we are left with 343,517 unique firms, among which 101 firms have at least one entrusted loan record. Our sample is largely representative in terms of both entrusted loans and corporate innovation in China.

One important observation of our initial sample is, however, that the number of non-EL firms significantly exceeds that of EL firms, and the two groups of firms may not be randomly assigned. Thus, to primarily address the concerns of sample selection and spurious significance (because of *t*-statistic inflation with an unbalanced large sample), we follow previous studies (e.g., Hainmueller 2012) and conduct an entropy balancing matching procedure to assign a continuous weight for each observation, which can promise the balance of each covariate. In our matched sample, the EL firms are statistically and economically more innovative than their matched non-EL counterparts, and EL firms exhibit higher innovation output after borrowing, suggesting that entrusted loans go to those more innovative firms and might be associated with a positive change in terms of patenting activities.

We begin our analyses with the baseline regressions in the spirit of the difference-in-differences (DiD) approach using the matched sample. The estimation captures the comparison of the changes in EL firms' innovation output around entrusted loan borrowing against that of non-EL firms. The main results show that after entrusted loan borrowing, EL firms file 18.1% more patents and 12.5% more explorative patents, and their patents receive 14.2% more citations compared with their non-EL counterparts. Our findings continue to hold in a variety of robustness checks with alternative matching procedures, alternative variable definitions, alternative subsamples, alternative model specifications, and all the applicable tests for patent data recommended in the checklist of Lerner and Seru (2022).

Although the baseline results appear to suggest a positive relation between entrusted loan borrowing and innovation output, the causal interpretation is subject to various potential endogeneity concerns. For example, the decision to do entrusted loan transactions may not be exogenous, and hence, the estimated relation could be because of either the omitted variables driving simultaneously both entrusted loan transactions and innovation output or the higher innovation facilitating entrusted loan borrowing (i.e., the reverse causality argument). We undertake several tests attempting to address these concerns and establish a causal link from entrusted loan borrowing to corporate innovation output.

First, we include in our main specification potential omitted variables that could drive our main results. At the firm level, we include *Change of debt* and *Change of current liability*, accounting for a firm's recent debt issuance, to rule out the probability that the baseline findings resulted from enhanced abilities of debt issuance or other types of borrowing instead of entrusted loans. We also take a firm's mergers and acquisitions (M&A) activity into account because the existing literature shows that innovation is a relevant driving force of mergers and acquisitions (e.g., Bena and Li 2014, Sevilir et al. 2022). At the city level, we include *gross domestic productivity (GDP)*, *Bank loans*, *Government revenue*, and *Government expenditure* to mitigate the concern that city-level characteristics could affect borrower firms' investment in innovation. In addition, we control for city-year and industry-year fixed effects to take out the influence of any city-level or industry-level omitted variables. Our baseline results remain intact with these tests.

Second, we perform two tests to address the reverse causality concern (i.e., the higher patenting output could be considered as a favorable signal or collateral and leads to an easy access to entrusted loan borrowing). Specifically, we include a firm's past innovation success in the baseline regressions and continue to observe the significant positive relation between entrusted loan borrowing and innovation output. In addition, we also follow Bertrand and Mullainathan (2003) to decompose the key explanatory variable, *Entrusted loan*, into a set of time indicators to explore the dynamic effect in years before and after the entrusted loan borrowing. The results show that the significantly positive effects appear only in the years after the entrusted loan borrowing but are absent in the years before the borrowing. These observations reassure that our baseline results are unlikely driven by reverse causality.

Third, we undertake a placebo test with entrusted loan borrowing years artificially assigned. Specifically, we randomize the key explanatory variable (but keep the distribution) and assign the falsified borrowing years to EL firms. We then re-estimate the baseline regression with falsified key variable of interest and repeat it 1,000 times. The results from the Monte Carlo procedures show that randomly falsified entrusted loans have no effect on the borrower firm's innovation output, suggesting that our baseline findings are unlikely driven by event clustering or sample selection induced by unobservable differences between EL and non-EL firms.

Fourth, we construct an instrument based on the house purchase restriction policy imposed by the local government in the lender's city and use an instrumental variable (IV) approach to tackle the identification issue. The instrument captures plausibly exogenous variation in the supply of entrusted loans. Chen et al. (2017) find that the house purchase restriction policy imposed by local governments lowers the price of real estate and consequently, affects the allocation of financial resources within listed firms. Allen et al. (2019) suggest that weakened financing demand in real estate could emancipate considerable capital to be reallocated to the manufacturing firms by entrusted loans. Because the restriction policy in the lender's city is unlikely to be related to the borrower's innovation output, the instrument is relatively exogenous and reasonably satisfies the exclusion restriction. Once again, we find positive and significant effects of (instrumented) entrusted loans on the borrower firm's corporate innovation output.

Finally, we use China's unexpected "back-to-normal" policy (Chen et al. 2018, 2020; Xiao 2020) in 2010 as a quasinatural experiment to disentangle the demand of entrusted loan borrowing from the supply side. We find that the positive effects of entrusted loans on innovation output are more pronounced after the policy-induced rise of shadow banking, further suggesting a causal link between entrusted loans and the borrower's innovation output.

In summary, all the identification attempts produce consistent evidence that entrusted loans positively affect the borrower's innovation output. Although each piece of evidence is open to alternative interpretations, these pieces of evidence collectively are difficult to reconcile with specific alternative arguments. Hence, these identification attempts suggest that the positive relation between entrusted loans and the borrower's innovation output is likely causal.

To better understand how entrusted loans can have an effect on borrowers' corporate innovation, we also explore the effects of entrusted loan characteristics. On the basis of our baseline regression model, we include additional explanatory variables that capture various aspects of entrusted loan characteristics and rerun the baseline regressions. The results suggest that loans with larger sizes and longer maturities that are not dependent on collateral and are contracted as for specific projects (instead of for returning earlier debt) are more likely to be associated with better performance in enhancing borrowers' innovation output, whereas loan interest rates are unlikely to play a role. These findings are consistent with both our conjecture as well as the existing innovation literature, and they are supportive of our main findings in a more nuanced way.

Next, we examine cross-sectional heterogeneity in the effects of entrusted loans on innovation output. We find the baseline results are more prominent when the borrowers are subject to severer financial constraints, information asymmetry, and takeover exposures. Overall, these tests further ensure our causal argument because it is hard to find an omitted variable that biases the results equally in all the cross-sectional dimensions discussed.

In the final part of the paper, we explore a plausible underlying economic channel through which entrusted loans promote the borrower's innovation output: capital reallocation from less productive but easily financed lender firms to more innovative but financially less privileged borrower firms, which mitigate the distortion of primary credit allocations by China's traditional banking system. To examine this plausible channel, we first investigate whether the capital lent out through entrusted loans is "redundant" for lender firms. Specifically, because the lenders in our sample are all public firms, we first collect firm-level information of all China's A share-listed firms and compare the characteristics of lenders against those of nonlenders, and then, we explore the effects of lenders' characteristics on our main findings. The results from univariate comparisons show that lenders of entrusted loans are larger, more mature, more profitable, and more likely to be SOEs, relying more on credit loans rather than collateral loans to get financed, but they significantly lack investment opportunities and exhibit poor investment returns. We also observe from entrusted loan characteristics that those lenders, with better access to finance and scarcer investment opportunities, are more likely to make entrusted loans with larger sizes and longer maturities, which could better match the nature of financing innovation. Furthermore, we find that the positive effect of entrusted loans on the borrower's innovation output is more prominent when the lender has easier access to bank credit or lacks investment opportunities, whereas other dimensions of the lender's characteristics (i.e., size, age, return on assets (ROA), state ownership) do not exhibit similar effects in our baseline findings. These observations help explain why entrusted loans can serve as a capital reallocation conduit (i.e., lenders) with easier access to bank credit but fewer good investment opportunities and are willing to lend their "redundant" money in hand through entrusted loans.

Finally, we estimate the effect of entrusted loan lending on the lenders' innovation output, operating performance, and stock market performance. We find no effect of entrusted loan lending on lender firms' innovation output, operating outcome, or stock market return, suggesting that the positive effects of entrusted loans on borrowers' innovation output are not at the cost of lenders' own innovation productivity and performance. Therefore, the capital reallocation between the lender and the borrower is likely economically efficient in terms of promoting innovation output.

In summary, these findings collectively point to a plausible underlying economic channel that the presence of entrusted loan financing, as a way of market-based efficient capital reallocation mechanism, channels funds out of firms with "redundant" money but few good investment opportunities to those financially less privileged but economically more innovative firms, which thereby allows shadow banking to enhance innovation output.

The remainder of the paper is organized as follows. Section 2 discusses the related literature. Section 3 introduces the institutional details of China's entrusted loan market. Section 4 describes the construction of our data, sample, and variables. Section 5 presents the main empirical findings, the robustness checks, a variety of tests on endogeneity, and the investigation on the effects of entrusted loan characteristics. Section 6 investigates the economic channel of capital reallocation. Section 7 concludes.

2. Relation to the Existing Literature

Our paper contributes to three strands of literature. First, it helps reconcile the "China puzzle" documented by the existing studies (i.e., the disproportionally high credit allocation to SOEs (Brandt and Zhu 2000, Cong et al. 2019) coexists with the rapid growth of the private sector in China (Song et al. 2011), which mainly drives the country's vast economic growth). As concluded by Song and Xiong (2018), in spite of the long-standing financial frictions, the private sector has been flourishing over decades, accounting for 80% of China's urban employment and continuing to serve as the vital growth engine. Built on the previous literature, recent studies tend to pay more attention to the role of shadow banking in China because it is an important financial resource for capital-deprived, although more productive, private sector firms. Our paper provided the first direct firm-level microevidence that the shadow banking sector in China could channel capital out of less productive but easily financed firms to more innovative but financially less privileged firms and thus, improve the efficiency of capital allocation. We argue that through the conduit of entrusted loans, capital reallocation by shadow banking is in fact a market-based power to correct highly distorted primary capital allocation in China and thus, sustains the enlarging private sector. Moreover, past literature emphasizes the important role of capital reallocation in enhancing the growth of productivity (e.g., Hsieh and Klenow 2009). We find that, specifically in China, the reallocation can happen in the form of shadow banking activities, such as entrusted loans, between the highly productive borrowers and the lenders that lack investment opportunities. Hence, our study not only helps explain the "China miracle," but it also sheds light on a more generalized inquiry in economics (i.e., capital reallocation and economic growth).[4]

Second, our paper adds to the shadow banking literature. This emerging literature mainly focuses on two lines of inquiries. First, previous studies show that the rise of shadow banking sectors could be mainly attributed to regulatory burden and arbitrage (Plantin 2015, Buchak et al. 2018, Hachem 2018) or the unintended legacy of fiscal stimulus (Chen et al. 2018, 2020; Acharya et al. 2020). Second, theories (Gennaioli et al. 2013, Xiao 2020) and product-level empirical studies (e.g., Allen et al. 2019) focus on the pricing and the related risk features of the shadow banking sector. Nevertheless, it is not clear what the real effects of shadow banking are, and hence, whether shadow banking should be encouraged or restricted remains an unanswered question. Our study extends this literature by offering direct micro-level evidence that documents the bright side of shadow banking (i.e., its role in enhancing borrowers' technological innovation). Our findings are consistent with Allen et al. (2019) and Allen and Gu (2021) in that capital reallocations from entrusted loan lending firms are a second-best market design to finance innovative projects, which could reduce systemic risks ultimately.

Third, our study contributes to the literature on finance and innovation.[5] Although the main stream of innovation literature emphasizes the role of internal financing and external equity in supporting research and development (R&D) investment, recent studies underscore the importance of debt financing (Kerr and Nanda 2015, Gu et al. 2017). This nascent literature, however, is exclusively focused on bank credit (e.g., Nanda and Nicholas 2014, Hochberg et al. 2018, Chang et al. 2019b). We add to this stream of literature by offering evidence on the effect of an alternative debt financing choice (i.e., loans from shadow banking) and further corroborating the crucial role of debt in motivating and financing innovation, especially in a financially distorted economy. As a departure from bank credit, our paper focuses on shadow banking loans, the lenders of which are not even banks but industrial firms. Based on the large sample of (mainly private) manufacturing firms in China, we find that intercorporate loans promote corporate innovation output through an efficient capital reallocation channel. Moreover, unlike the past literature, such as Nanda and Nicholas (2014) who show that better credit access *in total* enhances innovation, we focus on the complementarity of nonbank loans to bank loans, especially under the circumstances of financing constraints. Our paper not only underlines the role of debt financing on innovation but is an attempt to posit the firm-to-firm loans into the "pecking order" for financing corporate innovation.

3. Institutional Background

China's financial system, dominated by state-owned commercial banks, is not easily accessible to most private firms, especially small- and medium-sized firms (Allen and Qian 2014). The country's commercial banks prefer to lend to large SOEs rather than to private firms because SOEs are believed to be (implicitly) guaranteed by the government (Song et al. 2011). As a result, shadow banking arises as a reflection of, as well as a solution to, imperfections and distortions in financial markets (Chen et al. 2018). In China's shadow banking sector, the major origin of capital is known as the wealth management products (WMPs), through which banks can enhance their profitability and avoid various banking regulations compelled by the government (e.g., loan-debt ratio and Basel accords), whereas the use of capital mainly consists of entrusted loans and trust loans (Allen and Gu 2021).

Entrusted loans, one of the most important and dominant components of China's shadow banking system, are intercorporate loans made by a nonbank party (e.g., an industrial firm) to another firm, with a bank as an agent in between. In entrusted loan transactions, banks bear no risk but merely serve as a nominal agent because direct firm-to-firm cash transaction is illegal for a long period in China. Entrusted loans allow financially privileged firms with access to cheap capital to materially act as (implicit) credit intermediaries to provide credit to less privileged firms that bank credit would not typically cover.

Lenders of entrusted loans tend to be large and well-capitalized firms (Allen et al. 2019). Their costs of borrowing are similar to or lower than the official bank loan rates, whereas they can lend out via entrusted loans at similar or higher rates. Moreover, they are more likely to have excess cash but insufficient growth opportunities, and therefore, they have more incentives to use the loans as an alternative investment channel. Notably, entrusted loan lenders seem to keep a quite stable relationship with their borrowers (i.e., almost all of the multirecord borrowers make entrusted loans from only one unique lender (572 of 589 multirecord borrowers in the entrusted loan sample of Allen et al. 2019), whereas those that borrow from multiple lenders (17 of 589 multirecord borrowers) are likely to make entrusted loans that are largely clustering at one lender).

Entrusted loans have experienced a rapid surge in the past two decades. McMahon and Wei (2014) describe the situation: "Loans between companies is the fastest-growing category of shadow banking in China."[6] According to Elliott et al. (2015), outstanding entrusted loans grew from 267 billion renminbi (RMB) in 2002 to 13,970 billion RMB in 2017, which results in a 51.3-fold increase. In contrast, outstanding loans of financing institutions increased only 7.7-fold in the same period of time. Entrusted loans, accounting for 34.3% of shadow banking and 15% of total social financing in 2013 (Elliott et al. 2015), were the largest component of the sector until 2014 and are the second largest since, having been surpassed by WMPs.

At the transaction level, according to our manually collected entrusted loan data (also used previously in Chen et al. 2018 and Allen et al. 2019), the average entrusted loan transaction is 218.4 million RMB but with a wide range from less than 0.5 million to over 80 billion. Roughly 90% of entrusted loans are less than 300 million. The median loan value is 50 million. Thus, entrusted loans in China are generally sizable enough to support firms' innovative activities.

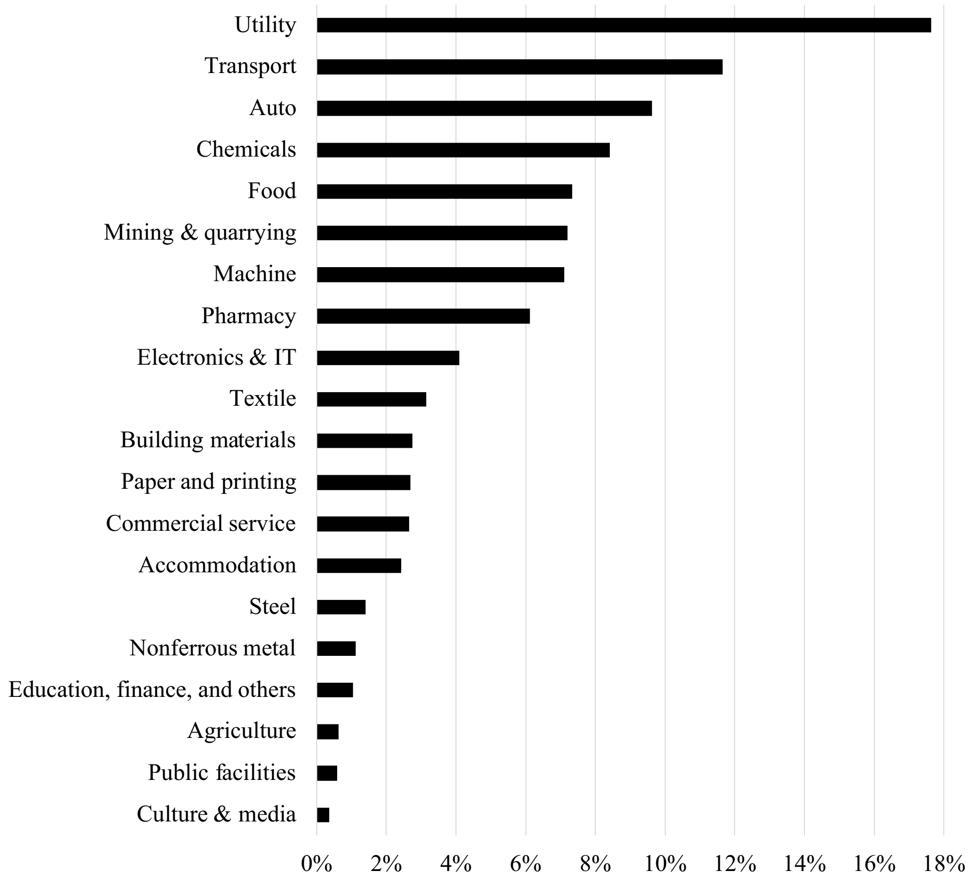
Entrusted loans can be either long term or short term, ranging from 1 to 120 months. The mean maturity of entrusted loans is 16.4 months, and the median maturity is 12 months. Although short-term loans (i.e., maturity no more than one year) are typically used to return other debt (i.e., debt rollover), long-term loans are more likely to reflect real needs (e.g., investment on production facilities or R&D projects).

As for the pricing of entrusted loans, the mean loan interest rate is 8.1%, higher than typical interest rates of bank credit (roughly 5%–6%). Moreover, after netting of bank credit interest rate of the corresponding maturity, the average abnormal interest rate of entrusted loans is 1.89%. In particular, according to Allen et al. (2019), affiliated borrowers borrow roughly at the same rate as the lending firms, which is approximately the same as the official bank loan rate. The loan rates for nonaffiliated loans (average of 13.9%) are about twice the average official bank loan rates, which reflect the market cost of borrowing for small- and medium-sized private firms.

Regarding the industry distribution of borrowers, in terms of dollar value, around 13.5% of the borrowing (20% by the number of loan transactions) comes from the real estate and construction industry. This observation is specific for real estate firms because of related regulations (Allen et al. 2019) and hence, is not the focus of this paper. For non-real estate borrowing, we present the industry distribution in Figure 1. Although utility and transportation take about 30% of the borrowing, industries such as auto, chemicals, food, mining, machine, and pharmacy take a sizable proportion (over 5% for each industry). Notably, the industry of electronics and information technology corresponds to more than 4% of entrusted loan borrowing, ranking between pharmacy and textile. Overall, observations in Figure 1 suggest that most entrusted loans flow into industries that are innovative and patent intensive.

Compared with bank credit, entrusted loans have a number of advantages in financing firms' innovation activities. First, innovation is subject to a large degree of uncertainty and high failure risk, and hence, it is difficult to be effectively financed by bank credit. This is especially true in China, where small- and medium-sized private firms struggle to obtain external finance. Entrusted loans can serve as a second-best market design to overcome financial frictions (Allen and Gu 2021). For affiliated loans, compared with bank loans, lenders have informational advantages in knowing their affiliates, the ability to control the affiliates, and the incentive to help the affiliates develop. For nonaffiliated loans, lenders

Figure 1. Industry Distribution of Non-Real Estate–Entrusted Loan Borrowers



Notes. The sample contains all of the 2,178 non-real estate–entrusted loans in our entrusted loan data from 2005 to 2013. The data were manually collected following Allen et al. (2019) and manually checked for the ultimate borrower of every loan. IT, information technology.

have incentives to obtain a high interest premium and thus, to take the risk. On the other hand, for entrusted loan borrowers, when they have good investment opportunities but are financially constrained, they are also willing to pay a reasonably higher interest to get the projects financed and launched. In this case, entrusted loans would play a pivotal role in financing value-creating projects, such as innovation activities.

Second, entrusted loan lenders are typically well-capitalized firms with high liquidity ratios, which means that the capital involved in entrusted lending compared with their size is a quite small proportion (about 5.1%) that generally does no harm in waiting for a longer period to get a higher interest. Third, evidence shows that entrusted loans are actually unlikely to pose high risk or liquidity problems to lenders. According to Allen et al. (2019), the loss ratios of affiliated and nonaffiliated loans are both small: 0.57% for nonaffiliated loans and 0.29% for affiliated loans compared with 0.61% for loans from listed banks. These could potentially enhance the lenders' tolerance for failure, which is well accepted as important in motivating innovation (Manso 2011, He and Tian 2013, Tian and Wang 2014).

4. Data, Sample, and Variable Construction

4.1. Data

We manually collected the entrusted loan data from annual reports and public announcements of nonfinancial listed firms in China from 2005 to 2013, following Allen et al. (2019), and then manually checked and standardized the name of the ultimate borrower for each transaction (because occasionally, the formally disclosed borrower is merely nominal, whereas the real borrower that gets the loan is disclosed in the entrusted loan announcement). Because of the mandatory disclosure requirement on listed firms in China, any entrusted loan transaction with a publicly traded lender must be disclosed in the lender's annual reports, which allows us to observe the date of the loans and identify the lender and the borrower of each loan transaction.[7] The entrusted loan sample is broadly representative, which contains 2,874 entrusted loans made by 467 unique lender firms and 1,678 unique borrower firms during the period of 2005–2013, and shows a steady growth trend.[8] Lenders and borrowers are in almost every industry. As mentioned, although the real estate and construction industry receives about 13.5% of the total loans by value (and about 20% by the number of loans), most loans go to the industries that need innovation. Loans are made in all provinces, and most are in relatively developed provinces, such as Beijing, Shanghai, and Zhejiang. The amount, terms, and interest rates of entrusted loans also show reasonable characteristics. Notably, we find that the borrowers with multiple entrusted loans keep a quite stable relationship with their lenders. Only 17 of 589 multiple-loan borrowers in the entrusted loan sample have ever switched to another lender. This characteristic of entrusted loans is to some extent similar to the multistaged financing that typically appears in a venture capital investment (Tian 2011), suggesting that entrusted loans might play a hybrid role of both debt and equity finance in financing the borrower firms in the long run, which could better fit the needs of enhancing innovation than bank credit.

Unlike Allen et al. (2019), who examine the lenders of entrusted loans, we focus on the borrowers. Because the borrowers of over 99% of entrusted loan transactions in our sample are private firms, we use the ASIF database as the source of borrowers' firm-level financial information. The database has been widely used in the existing literature (e.g., Song et al. 2011, Aghion et al. 2015, Bai et al. 2016, Huang et al. 2020) because of its broad coverage of public and private firms in China.

The ASIF covers the universe of above-scale manufacturing firms until 2013, including non-SOE firms with sales revenue of at least 5 million RMB and all the state-owned firms (Brandt et al. 2014).[9] Following Huang et al. (2020), we drop observations with nonpositive total assets or extremely high or low revenue (at the 1% cutoffs) and winsorize all the firm-level variables at the 5th and 95th percentiles of their distributions. In addition, as pointed out by Brandt et al. (2014) and Huang et al. (2020), the 2009 and 2010 waves of the ASIF data either are not available or are poorly reliable in some important variables, such as fixed assets; therefore, our sample does not cover these two years either.

We use a firm's patenting activities to capture its innovation output, following the existing literature (He and Tian 2018, 2020). We obtain patent and citation information from the CNIPA, the patent office of China, and supplement the patent assignee information using the China Stock Market and Accounting Research (CSMAR) patent database.[10] Patents filed at the CNIPA are typically classified into one of the following three categories: invention, utility model, or design. We keep only invention patents that are eventually granted to capture authentic technological innovation.

To merge the three databases and construct our initial sample, we first standardize firms' full names in the three databases and then extract the key identifier as the stem names. Next, we merge the three databases by their standard names and stem names. We then manually check for the matching accuracy. After dropping observations with missing data, we are left with 343,517 unique firms, among which 101 firms have at least one entrusted loan record, and no entrusted loan borrower (of these 101 firms) has ever switched to another lender.

4.2. Entrusted Loans

The key explanatory variable in this paper is *Entrusted loan*, an indicator variable that equals one from the year the firm borrows an entrusted loan until the year the loan expires and zero otherwise. To clarify, we choose this definition over an ante-post variable (i.e., a dummy variable that takes the value of one in and after the year of the first or largest entrusted loan transaction and zero otherwise) because 35.1% of entrusted loan borrowers have multiple borrowing records (589 of 1,678 firms in the original entrusted loan sample), and any single-trigger definition, whether identified by the first or largest borrowing, would be misleading for the years between the former loan expiration and the latter one's initiation. Likewise, we do not use only the initiating year of borrowing as the definition in order to better capture the timing of loan expiration. Nevertheless, our results are robust to the alternative definitions of the entrusted loan variable.

4.3. Measuring Innovation Output

In line with common practice of innovation research, we use three measures of corporate innovation: *Patent*, *Citation*, and *ExplorePat*. *Patent* is the number of granted invention patents in a year. As suggested by Griliches et al. (1987), patent application year is more important than the grant year because it is close to the time of the actual innovation. Hence, we construct the innovation variables on the basis of the year in which the patent applications are filed.[11]

Patent count is well received as a proxy for corporate innovation output, especially for manufacturing firms because patenting is the major form for these firms to materialize their inventions and to protect the corresponding exclusive rights. Nevertheless, patents vary largely with respect to their technological and economic magnitudes, making patent count an imperfect measure of innovation output. Therefore, we follow Hall et al. (2001, 2005) to construct our second measure based on the number of forward citations (i.e., citations received from other patents). One potential concern for this measure is that the count of forward citations may not be comparable across different years and technological classes. To address this issue, we follow Hirshleifer et al. (2012) to partial out time-technology class fixed effects of forward citations. Specifically, we scale the raw citation counts by the average forward citations in the same technology class and filing year, and then, we add up adjusted citation counts for each firm-year to form our second innovation measure, *Citation*.[12]

In addition, we follow Kong et al. (2022) to distinguish explorative patents (i.e., innovation conducted through the exploration of new technologies) from exploitative patents (i.e., innovation conducted through the exploitation of existing knowledge) because whereas patents can reflect firms' innovation output, only explorative ones are likely to drive technological breakthroughs. Specifically, a patent is defined as exploitative if at least 60% of its backward citations are from the firm's existing knowledge (i.e., the firm's existing patents filed in the last five years and the citations to these patents); otherwise, a patent is defined as an explorative one. We then count the total numbers of explorative patents at the firm-year level as our third innovation measure: *ExplorePat*.

4.4. Control Variables

We control for several firm and industry characteristics identified by the past literature as relevant to corporate innovation. First, we include firm size (ln(*Assets*), the natural logarithm of the book value of total assets) and capital intensity (ln(*PPE/Employees*), the logarithm of book value of fixed assets divided by the number of employees, where *PPE* denotes property, plant, and equipment) following Hall and Ziedonis (2001). Second, to account for a firm's life cycle and profitability, we control for firm age (ln(*Age*), the natural logarithm of one plus the number of years since the firm is established), return on assets (*ROA*, operating profit divided by total assets), and *Sales growth* (the logarithm of one plus the sales growth rate). Third, we include *Leverage* (the book value of total debt divided by total assets) and *Current asset ratio* (the ratio of current assets to total assets) to capture the effect of capital structure. Finally, we incorporate industry-level market competition, the Herfindahl–Hirschman index (*HHI*, the sum of squared market shares within the three-digit industry), and its squared term (HHI^2) into the array of control variables because Aghion et al. (2005) show that there is an inverted U-shaped relation between product market competition and corporate innovation.[13] In addition, because state-owned enterprises are largely different from private-owned firms in China's economic system (Song et al. 2011), we include *SOE* (a binary variable that equals one if the firm is a state-owned enterprise in a year and zero otherwise) to account for this specific economic setting.[14]

Unfortunately, we cannot include all the relevant control variables because of data limitations. For example, most firms in our sample are private and hence, have no publicly traded shares; this prevents us from including stock volatility (Chan et al. 2001) and liquidity (Fang et al. 2014) as well as market-to-book ratio as controls (Cornaggia et al. 2015). Likewise, we do not include R&D expenses because information on R&D is not available for most years in the ASIF database. However, we try to include unavailable controls with analogous variables if possible. For example, ASIF does not report firms' cash holdings, and thus, we include the alternative variable, *Current asset ratio*, to account for similar effect.

4.5. Entropy Balancing Matching

One potential concern about our sample is that firms with or without entrusted loan borrowing are not randomly assigned, which makes our results vulnerable to selection bias concerns because the differences between the two groups of firms could systematically affect innovation output. Moreover, because non-EL firms take a large part out of the initial sample, our regression-based estimation could exhibit spurious significance because of *t*-statistic inflations in unbalanced and unweighted large samples.

To address the two concerns, we follow Hainmueller (2012) to conduct an entropy balancing matching. This approach assigns a continuous weight to each observation and thereby, minimizes the differences of all the covariates between treatment and control groups via constrained optimization. Compared with the widely accepted propensity score matching approach (which we use in robustness checks later), entropy balancing is advantageous in at least three important ways. First, it provides better balance between treatment and control groups in terms of not only the covariates' first moments but also, their second and third (or even higher-degree) moments, which further ensures distributional similarity between the two groups. Second, this approach is less subject to various arbitrary choices in the propensity score matching (e.g., replacement, model specification, matching criteria). Third, it can avoid dropping many observations, which undermines the representativeness of the sample. Following standard execution, we set three as the highest degree of moment for balancing (i.e., the approach balances the sample in terms of every covariate's means, variances, and skewness). We also drop those three-digit industries with no firms that have borrowed an entrusted loan (i.e., match within industry) and require a minimum number of observations of seven for each firm to mitigate the concern that some unobservable factors or the occasional appearance of some firms could drive our results.

Table 1 tabulates the results of the diagnostic tests to evaluate the effectiveness of our matching algorithm. Panel A of Table 1 reports the means of the independent variables of EL firms (column (1)) and non-EL firms (columns (2) and (4)) along with the *t*-tests of univariate comparisons with the prematch (column (3)) and postmatch (column (5)) samples. In columns (3) and (5) of Table 1, panel A, the mean differences of all the covariates are largely reduced in terms of both their magnitudes and statistical significance levels. For example, the mean difference in ln(*Assets*) is 1.859, with the *t*-statistic of 10.02, in the prematch sample, whereas it is 0.120 and statistically insignificant (with the *t*-statistic of 0.83) after

Table 1. Diagnostic Tests of the Entropy Balancing Matching

	Panel A: Comparison of firm characteristics prior to borrowing					Panel B: Logit regressions	
		Prematch		Postmatch		Prematch	Postmatch
Variable	(1) EL firms	(2) Non-EL firms	(3) Difference	(4) Non-EL firms	(5) Difference	(1) *Entrusted loan*	(2) *Entrusted loan*
ln(*Assets*)	12.627	10.768	1.859***	12.507	0.120	1.016***	0.047
			(0.18)		(0.14)	(0.17)	(0.19)
Leverage	0.531	0.544	−0.013	0.559	−0.028	−0.637	−0.452
			(0.04)		(0.04)	(0.66)	(0.64)
ln(*Age*)	2.552	2.329	0.224***	2.435	0.117	0.049	0.411
			(0.07)		(0.08)	(0.30)	(0.27)
ln(*PPE/Employees*)	5.263	4.004	1.259***	5.202	0.061	0.030	−0.081
			(0.16)		(0.16)	(0.18)	(0.18)
ROA	0.087	0.144	−0.057*	0.080	0.007	0.119	0.483
			(0.03)		(0.02)	(0.95)	(0.99)
Current asset ratio	0.414	0.522	−0.108***	0.431	−0.016	−1.066	−1.333*
			(0.04)		(0.04)	(0.81)	(0.81)
Sales growth	0.210	0.264	−0.054	0.313	−0.103	−0.062	−0.096
			(0.14)		(0.17)	(0.13)	(0.13)
HHI	0.041	0.036	0.005	0.040	0.0005	3.936	0.863
			(0.01)		(0.008)	(10.07)	(9.11)
HHI^2	0.005	0.006	−0.001	0.005	0.0002	−31.072	−6.051
			(0.003)		(0.002)	(37.50)	(36.48)
SOE	0.479	0.060	0.419***	0.424	0.055	1.665***	0.256
			(0.03)		(0.08)	(0.40)	(0.30)
Industry fixed effects						Yes	Yes
Year fixed effects						Yes	Yes
Observations						260,067	260,067

Notes. This table reports the diagnostic tests of the entropy balancing matching. The sample includes the firms with entrusted loans (EL firms) and all the matched firms without entrusted loans (non-EL firms) in ASIF with enough no missing data observations during 2005–2013. Panel A presents the univariate comparison for the variables included in the matching between EL firms and prematch/postmatch (weighted) non-EL firms. Panel B reports the results of logit regressions with prematch and postmatch samples predicting the probability of a firm having entrusted loans. Other detailed variable definitions are in Table 2. The *t*-tests of the mean differences are conducted for the univariate comparison. The dependent variable, *Entrusted Loan*, equals one in and after the year of entrusted loan borrowing until the loan expires and zero otherwise. Postinitial borrowing years of EL firms are excluded following the existing literature. All the independent variables are lagged by one year. Industry and year fixed effects are included in both regressions in panel B but not tabulated. Standard errors, reported in parentheses, are clustered by firm.

*Significance at the 10% level; ***significance at the 1% level.

matching. These results suggest that EL and non-EL firms are similar and generally comparable before entrusted loan borrowing in the postmatch (weighted) sample.

Notably, according to Table 1, panel A as well as the summary statistics reported in Table A1 in Online Appendix A, some variables exhibit considerable changes after matching. For example, the mean *ROA* of EL firms (0.087), as well as that of the matched non-EL firms (0.080), is much lower than that of unmatched non-EL firms (0.144). This observation suggests that EL firms are likely in their early stages (i.e., although these firms are more innovative, they might be still struggling to realize profits and therefore, might not have enough income to pledge to get access to enough bank credit). Likewise, the mean *current asset ratio* of EL firms is about 20% lower than that of unmatched non-EL firms, suggesting that EL firms are on average more likely to suffer from financial constraints. On the other hand, we find that the postmatching non-EL firms are larger in both total assets and PPE per employee after reweighting. This observation suggests that although EL borrowers are more likely financially less privileged because of their lack of income to pledge, they are still medium-sized firms (instead of small or microfirms), which is consistent with the characteristics of innovative firms because extremely small firms can hardly afford the sizable capital investment of R&D projects.

Column (1) of Table 1, panel B reports the result of the prematch (unweighted) logit regression, in which we regress *Entrusted loan* on all the control variables (lagged by one year) as well as the year and industry fixed effects.[15] We follow Chang et al. (2019b) to exclude observations of the years after an EL firm's initial borrowing.[16] The results suggest that firms with entrusted loan borrowing are significantly larger in size and more likely SOE. On contrary, column (2) of Table 1, panel B shows that the coefficient estimates on all covariates become insignificant in the postmatch (weighted) sample.[17] These observations ensure the effectiveness of our matching procedure.[18]

4.6. Summary Statistics and Validation of the Final Sample

Table 2, panel A presents the summary statistics of the final sample with 581,810 observations. A typical firm in our sample is a medium-sized manufacturing firm according to the classification standard by the China National Bureau of Statistics, with the book value of total assets of 385.2 million RMB (about 59.4 million U.S. dollars), leverage of 56.0%, age of 10 years, and ROA of 5.9%. Firm characteristics in our sample are comparable with the existing literature (e.g., Geng et al. 2022).

Regarding innovation output, a firm in our sample has on average 0.13 invention patents granted, 0.11 future citations, and 0.04 explorative patents granted per year. The innovation output seems relatively low partly because we only consider invention patents because the censoring of utility model patents and design patents is largely loose, and thus, patents of these two types are far from technological innovation.[19] In addition, most of the firms in our sample are private firms, and these private manufacturing firms in the sample period (i.e., during 2005–2013) are not as innovative as those in today's China. Because the distribution of innovation measures is highly skewed, we use the natural logarithm of one

Table 2. Descriptive Statistics

Panel A: Summary statistics

Variable	Mean	Standard deviation	Minimum	25th	Median	75th	Maximum
Patent	0.129	16.676	0	0	0	0	6,802
Citation	0.107	15.650	0	0	0	0	6,501
ExplorePat	0.038	4.432	0	0	0	0	1,766
ln(*Patent*)	0.011	0.160	0	0	0	0	8.825
ln(*Citation*)	0.009	0.144	0	0	0	0	8.780
ln(*ExplorePat*)	0.007	0.104	0	0	0	0	7.477
Entrusted Loan	0.000	0.014	0	0	0	0	1
ln(*Assets*)	10.626	1.270	7.882	9.695	10.559	11.548	12.817
Leverage	0.543	0.255	0.036	0.351	0.560	0.747	0.959
ln(*Age*)	2.236	0.580	0.693	1.792	2.303	2.639	3.178
ln(*PPE/Employees*)	4.004	1.263	1.241	3.173	4.044	4.880	6.367
ROA	0.143	0.214	−0.056	0.012	0.059	0.178	0.817
Current asset ratio	0.525	0.281	0.006	0.336	0.567	0.750	0.957
Sales growth	0.286	0.919	−1.997	−0.073	0.207	0.625	2.422
HHI	0.036	0.065	0.001	0.003	0.009	0.035	0.285
HHI^2	0.006	0.017	0.000	0.000	0.000	0.001	0.081
SOE	0.060	0.237	0	0	0	0	1

Panel B: Univariate comparison on innovation output

	Means			*t*-statistics		
Variable	(1) EL firms before borrowing	(2) EL firms after borrowing	(3) Non-EL firms	(1) − (3)	(2) − (3)	(2) − (1)
ln(*Patent*)	0.319	0.515	0.011	37.62***	34.11***	2.66***
ln(*Citation*)	0.207	0.373	0.009	27.01***	27.48***	2.73***
ln(*ExplorePat*)	0.171	0.290	0.006	2.72***	30.87***	29.46***

Notes. This table reports the summary statistics of the (unweighted) sample for the variables used in our baseline analysis. For each variable, we report the mean, standard deviation, minimum value, 25th percentile, median, 75th percentile, and maximum value. The sample includes the firms with entrusted loans (EL firms) and all the matched firms without entrusted loan (non-EL firms) in ASIF with enough no missing data observations during 2005–2013, and it contains 581,810 firm-year observations of each variable. ln(*Patent*) is the log of one plus the number of granted invention patents applied in the reference year. ln(*Citation*) is the log of one plus the total number of citations adjusted for year and technology class fixed effects. ln(*ExplorePat*) is the log of one plus the number of granted explorative invention patents applied in the reference year. *Entrusted Loan* equals one in and after the year of entrusted loan borrowing until the loan expires and zero otherwise. ln(*Assets*) is the log of a firm's book value of total assets (in thousands). *Leverage* is the book value of total debts scaled by total assets. ln(*Age*) is the log of one plus the number of years since a firm's establishment. ln(*PPE/Employees*) is the log of the book value of fixed assets scaled by the number of employees. *ROA* is the log of one plus operating profit scaled by total assets. *Current asset ratio* is the book value of current assets scaled by total assets. *Sales growth* is the log of sales revenue scaled by lagged sales revenue. *HHI* is the Herfindahl–Hirschman index calculated as the sum of squared market shares in sales of three-digit industry. *SOE* indicates whether a firm is a state-owned enterprise in the reference year.

***Significance at the 1% level.

plus *Patent*, *Citation*, and *ExplorePat* as the dependent variables (i.e., ln(*Patent*), ln(*Citation*), and ln(*ExplorePat*), respectively) in subsequent analysis following the existing literature.

Moreover, we conduct a univariate comparison with both the dependent variables before moving on to the regression analysis. Specifically, we use ln(*Patent*), ln(*Citation*), and ln(*ExplorePat*) to compare the innovative performances of EL firms and non-EL firms as well as that of the periods before and after entrusted loan borrowing. Table 2, panel B reports the results. Regarding the mean of innovation output of both types of firms, we find that EL firms are more innovative than their non-EL counterparts. The pattern appears within EL firms as well; on the intensive margin, the successive innovation output of the EL periods is around 70% higher (from 0.319 before to 0.515 after for ln(*Patent*), from 0.207 before to 0.373 after for ln(*Citation*), and from 0.171 before to 0.290 after for ln(*ExplorePat*)) than that of the years without entrusted loans. The findings here point to that in our final sample, entrusted loans actually go to those more innovative firms and might be associated with a positive change in terms of the borrowers' patenting activities, which is consistent with our conjecture.

Because of missing firm records in the ASIF data set as well as the exclusion of entrusted loans made to real estate firms (because the ASIF only covers manufacturing firms), the number of EL firms in our analysis is relatively small. This is also because of the fact that we rely on the inclusion of all possible control variables proven relevant by the existing literature to primarily validate the causal inference. Because it is not the case that the majority of EL firms in our initial sample always have EL borrowing during the sample period, our final sample is still representative in terms of both entrusted loans and corporate innovation in China, which helps support our interpretation as the real effects.

5. Main Results

5.1. Baseline Results

We begin with examining the effects of entrusted loans on borrower firms' innovation output by undertaking the following regression that is in the spirit of a multivariate DiD framework:

$$Innovation_{i,t+1} = \alpha + \beta \cdot Entrusted\ Loan_{i,t} + \boldsymbol{\gamma}'\boldsymbol{X}_{i,t} + Firm_i + Year_t + \epsilon_{i,t}, \tag{1}$$

where $Innovation_{i,t+1}$ represents the three innovation output measures (i.e., ln(*Patent*), ln(*Citation*), and ln(*ExplorePat*)) for firm i in year $t+1$.[20] The key explanatory variable is $Entrusted\ loan_{i,t}$, which equals one if firm i has entrusted loan borrowing or the loans are undue in year t and zero otherwise. The estimator of the key variable of interest, β, captures the percentage changes in borrowers' innovation output attributed to entrusted loan borrowing. X represents the array of control variables described in Section 4.4. We include firm fixed effects and year fixed effects in the regressions to account for the effect of time-invariant firm characteristics and aggregate time trends, respectively. We cluster robust standard errors by firm.

Columns (1)–(3) of Table 3 report the results of a parsimonious DiD regression (i.e., we regress a firm's innovation output only on the key variable of interest: $Entrusted\ loan_{i,t}$) and firm and year fixed effects. The coefficient estimates are positive and significant at the 1% level, which indicate that the observations within the periods of entrusted loan borrowing witness a higher successive innovation output before taking into account any other firm-level characteristics.

Moreover, in Table 3, columns (4)–(6) present the baseline regression results with all control variables included. The coefficient estimates on *Entrusted loan* are positive and significant at the 5% or 1% levels in both columns, suggesting that EL firms, compared with their non-EL counterparts, exhibit a larger increase in the number of patents, citations, and explorative patents after entrusted loan borrowing. Moreover, the positive β estimator is not only statistically significant but also economically sizable. On average, compared with non-EL firms, patent, citation, and explorative patent counts in EL firms exhibit 18.0%, 14.1%, and 12.4% higher increases, respectively, after entrusted loan borrowing.

The effects of control variables on innovation output are consistent with the previous literature. For example, firms with lower leverage tend to be more innovative. The negative coefficient estimates on *SOE* in columns (4)–(6) in Table 3 suggest that non-SOE firms are more likely to file (explorative) patents and that their patents get more forward citations. Overall, the findings in Table 3 suggest that the presence of entrusted loan borrowing has a positive effect on corporate innovation output measured by the numbers of patents, citations, and explorative patents.

5.2. Robustness Checks

We perform a series of additional tests, including alternative model specifications, alternative variable definition, alternative sample selection, and the recommended tests for patent data in the checklist of Lerner and Seru (2022) to ensure the robustness of our baseline results. We find that our results survive in these tests. For brevity, we report the results in Table A2 in Online Appendix B, with only the coefficient estimates on key variables tabulated, and we present the detailed discussion in Online Appendix B.

5.3. Identification Attempts

Although we observe a positive and robust relation between entrusted loan borrowing and firms' innovation output in the baseline regressions, it only provides

Table 3. Entrusted Loan Borrowing and Corporate Innovation

Variable	(1) ln(*Patent*)	(2) ln(*Citation*)	(3) ln(*ExplorePat*)	(4) ln(*Patent*)	(5) ln(*Citation*)	(6) ln(*ExplorePat*)
Entrusted Loan	0.179***	0.142**	0.124***	0.180***	0.141**	0.124***
	(0.07)	(0.07)	(0.04)	(0.07)	(0.06)	(0.04)
ln(*Assets*)				0.103	0.105*	0.054
				(0.06)	(0.05)	(0.04)
Leverage				−0.213*	−0.186*	−0.138*
				(0.12)	(0.10)	(0.08)
ln(*Age*)				−0.094	−0.087	−0.059
				(0.08)	(0.06)	(0.05)
ln(*PPE/Employees*)				0.021	0.014	0.017
				(0.03)	(0.03)	(0.02)
ROA				0.149	0.033	0.027
				(0.10)	(0.10)	(0.06)
Current asset ratio				0.196**	0.146	0.112*
				(0.10)	(0.10)	(0.06)
Sales growth				0.001	0.001	0.007
				(0.01)	(0.01)	(0.01)
HHI				−2.105	−1.529	−1.251
				(1.51)	(1.33)	(0.97)
HHI^2				7.945	5.730	3.460
				(5.25)	(4.69)	(3.00)
SOE				−0.186***	−0.140**	−0.111**
				(0.07)	(0.06)	(0.04)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	581,810	581,810	581,810	581,810	581,810	581,810
R^2	0.681	0.612	0.636	0.695	0.625	0.649

Notes. This table examines the impact of entrusted loan borrowing on corporate innovation. The sample includes the firms with entrusted loans (EL firms) and all the matched firms without entrusted loan (non-EL firms) in ASIF with enough no missing data observations during 2005–2013. ln(*Patent*) is the log of one plus the number of granted invention patents applied in the reference year measured in year $t+1$. ln(*Citation*) is the log of one plus the total number of citations adjusted for year and technology class fixed effects measured in year $t+1$. ln(*ExplorePat*) is the log of one plus the number of granted explorative invention patents applied in the reference year measured in year $t+1$. *Entrusted Loan* equals one in and after the year of entrusted loan borrowing until the loan expires and zero otherwise. ln(*Assets*) is the log of a firm's book value of total assets (in thousands). *Leverage* is the book value of total debts scaled by total assets. ln(*Age*) is the log of one plus the number of years since a firm's establishment. ln(*PPE/Employees*) is the log of the book value of fixed assets scaled by the number of employees. *ROA* is the log of one plus operating profit scaled by total assets. *Current asset ratio* is the book value of current assets scaled by total assets. *Sales growth* is the log of sales revenue scaled by lagged sales revenue. *HHI* is the Herfindahl–Hirschman index calculated as the sum of squared market shares in sales of three-digit industry. *SOE* indicates whether a firm is a state-owned enterprise in the reference year. Robust standard errors in parentheses are clustered by firm.

*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level.

some suggestive evidence on the causal effect of entrusted loans on the borrower's innovation output. In this section, we attempt to address identification concerns by using two sets of empirical strategies. The first set of tests explicitly describes the endogeneity issues (i.e., omitted variable, reverse causality, and sample selection) and presents the results of corresponding tests that rule out the possibility that our results are driven by these endogeneity concerns. In the second set of attempts, we tend to mitigate any remaining endogeneity concerns with two identification designs: an IV approach and a policy-based quasinatural experiment. All the following tests in this section include the control variables and firm and year fixed effects as in Table 3, but their coefficient estimates are not tabulated for brevity.

5.3.1. Addressing Omitted Variable Concerns. The first endogeneity concern is omitted variables (i.e., our baseline results are driven by firm unobservables that are correlated with both entrusted loan borrowing and innovation output). To address this concern, we first include three sets of variables in the baseline regressions. First, one may be concerned that the presence of entrusted loan borrowing could be a reflection of a firm's greater financing capacity, which is related to firm unobservables (e.g., changes in political connections). Thus, the reported enhancement of innovation output could be attributed to any type of borrowing rather than entrusted loans per se. To address this concern, we include *Change of debt*, the logarithm of one plus the growth rate of total nonentrusted loan debt, and *Change of current liability*, the logarithm of one plus the growth rate of nonentrusted loan current liabilities, to partial out the influence of recent issuance of any other types of long-term and short-term debt. We report the results in panel A of Table 4 and find that our baseline results remain unaffected in terms of both the size and the significance level of the coefficient estimates. Likewise, we also attempt to mitigate omitted variable concerns by including a firm's M&A activity, which is found relevant to corporate innovation by Bena and Li (2014) and Sevilir et al. (2022), and city-level local conditions following Huang et al. (2020). As shown in Table A3, panel A in Online Appendix C and discussed in Online Appendix C, we find that our baseline results remain largely intact.

To further rule out the effects of any city characteristics on innovation output, we control for city-year fixed effects in Table 4, panel B. Likewise, we also control for industry-year fixed effects to account for the effect of any industry-level variation. The positive effect of entrusted loan borrowing on corporate innovation output remains unchanged. Taken together, evidence in panels A and B of Table 4 suggests that our baseline results are unlikely driven by these firm-level, city-level, or industry-level omitted variables.

5.3.2. Addressing Reverse Causality Concerns. We conduct two tests to address the reverse causality concern (i.e., the enhancement in innovation output could make the firm easier to get financed through entrusted loans). To this end, we directly include firms' *Past innovation success* into the baseline regression. Following Chang et al. (2019b), *Past innovation success* is calculated as the rolling average number of patents or citations from year $t-1$ to $t-5$. Our baseline results remain unchanged, and the coefficient estimates on *Entrusted loan* in Table 4, panel C are comparable with those in Table 3 both statistically and economically. We also follow Bertrand and Mullainathan (2003) to examine the dynamics of corporate innovation output by decomposing the key explanatory variable. The results in Table A3, panel C in Online Appendix C (discussed in detail in Online Appendix C) suggest that the dynamic trend of innovation output before borrowing is parallel between EL and non-EL firms.

Overall, the analyses suggest that the causal link seems to be from entrusted loan borrowing to firms' innovation output, not the other way around.

Table 4. Addressing Endogeneity

Variable	(1) ln(*Patent*)	(2) ln(*Citation*)	(3) ln(*ExplorePat*)
Panel A: Controlling for omitted variables (other types of loan)			
Entrusted loan	0.178***	0.140**	0.124***
	(0.07)	(0.06)	(0.04)
Change of debt	0.107**	0.067	0.036
	(0.04)	(0.04)	(0.03)
Change of current liability	−0.026	−0.016	−0.009
	(0.04)	(0.04)	(0.03)
Controls	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	581,810	581,810	581,810
R^2	0.697	0.626	0.650
Panel B: Controlling for city-year and industry-year fixed effects			
Entrusted loan	0.201***	0.233***	0.102**
	(0.07)	(0.07)	(0.04)
Controls	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
City-year fixed effects	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes
Observations	581,792	581,792	581,792
R^2	0.840	0.812	0.798
Panel C: Including past innovation success			
Entrusted loan	0.158**	0.132**	0.110***
	(0.06)	(0.07)	(0.04)
Past innovation success	0.303***	0.127*	0.196***
	(0.08)	(0.08)	(0.06)
Controls	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	581,810	581,810	581,810
R^2	0.723	0.632	0.680

Notes. This table contains a number of empirical attempts to address potential endogeneity issues (i.e., omitted variables and reverse causality). The sample includes the firms with entrusted loans (EL firms) and all the matched firms without entrusted loan (non-EL firms) in ASIF with enough no missing data observations during 2005–2013. ln(*Patent*) is the log of one plus the number of granted invention patents applied in the reference year measured in year $t+1$. ln(*Citation*) is the log of one plus the total number of citations adjusted for year and technology class fixed effects measured in year $t+1$. ln(*ExplorePat*) is the log of one plus the number of granted explorative invention patents applied in the reference year measured in year $t+1$. *Entrusted Loan* equals one in and after the year of entrusted loan borrowing until the loan expires and zero otherwise. In panel A, *Change of debt* is the natural logarithm of one plus the growth rate of total nonentrusted loan debts measured in year t. *Change of current liability* is the natural logarithm of one plus the growth rate of nonentrusted loan current liability measured in year t. In panel C, *Past innovation success* is the logarithm of the rolling average of the innovation measures from year $t-1$ to year $t-5$. All regressions include the same control variables as those in Table 3. Robust standard errors in parentheses are clustered by firm.

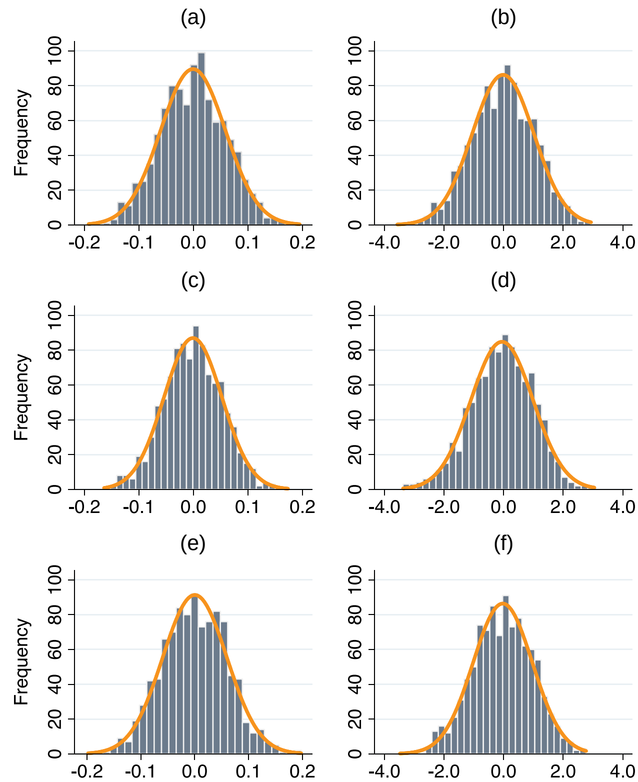
*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level.

5.3.3. Placebo Test with Randomly Assigned Borrowing Years. We are aware that our entropy balancing matching procedure is based on observable firm characteristics. Thus, a reasonable concern is that unobservable differences between EL and non-EL firms could drive our main results.

To mitigate this concern, we conduct a Monte Carlo analysis as a placebo test following Bekaert et al. (2005). Specifically, we first randomly assign borrowing years to EL firms but preserve the distribution of the actual time of entrusted loan borrowing, and then, we re-estimate the baseline model. We repeat the procedures 1,000 times. If our baseline results were driven by any unobservable difference between the treatment group and the control group, many replications would capture the effects statistically close to those in our results, regardless of whether the estimates are obtained from the randomly assigned falsified borrowing years or the actual ones.

Figure 2 plots the distributions of the coefficient estimates (the left three panels) and the corresponding *t*-statistics (the right three panels) of the randomized key explanatory variable. The distributions in all six panels of Figure 2 exhibit normal distributions with the mean of zero, suggesting that placebo borrowing years are not likely to yield any statistically or economically significant effect on corporate innovation output. More importantly, the coefficient estimates (0.181, 0.142, and 0.125) reported in Table 3 are far out in the right tail of the distribution in the placebo test (i.e., larger than the corresponding 99th percentiles in panels (a), (c), and (e) of Figure 2, respectively), suggesting that our main results are unlikely driven by a statistical artifact induced by sample selection or a consequence of event clustering.

Figure 2. (Color online) Placebo Test with Randomly Assigned Time of Borrowing (1,000 Replications)



Notes. The sample contains all EL firms and matched non-EL firms with no missing data in ASIF during 2005–2013. *Patent* is the number of granted invention patents applied in the reference year. *Citation* is the total number of citations adjusted for year and technology class fixed effects. *PatExplore* is the number of granted explorative invention patents applied in the reference year. Histograms in panels (a), (c), and (e) (panels (b), (d), and (f)) report the distribution of coefficient estimates (*t*-statistics) of the randomized *Entrusted loan*. The number of the borrowing years ($Entrusted\ loan_{random}$ = 1, randomly assigned to EL firms) is the same with that of the actual ones. The specification of all the regressions is the same as that in Equation (1) and Table 3 except for replacing the key variable of interest, *Entrusted loan*, with the randomized one. The curves in the panels show comparable normal distributions with the same means and variances as the simulation results. (a) Coefficients ($Y = \ln(1 + Patent)$). (b) *t*-statistics ($Y = \ln(1 + Patent)$). (c) Coefficients ($Y = \ln(1 + Citation)$). (d) *t*-statistics ($Y = \ln(1 + Citation)$). (e) Coefficients ($Y = \ln(1 + PatExplore)$). (f) *t*-statistics ($Y = \ln(1 + PatExplore)$).

5.3.4. Further Identification Attempts. In our second set of tests to address endogeneity concerns, we execute an IV approach as a further identification attempt. Specifically, we use the house purchase restrictions in the entrusted loan lenders' cities (*Lender HP Restriction*) as an instrumental variable for entrusted loan transactions. China has experienced a real estate boom since 2003 (Fang et al. 2016, Glaeser et al. 2017, Liu and Xiong 2020). To prevent the housing bubble from triggering a systematic crisis, local governments across the country have been adopting a variety of housing purchase restriction policies. An important feature of this quasinatural experiment is that the timing of policy implementation decided by local governments is different across cities, mainly because local governments have to keep a balance weighing the benefits of stability in the real estate market against the costs of impeding local GDP growth because of the restriction, as pointed out by Liu and Xiong (2020). Hence, it represents multiple shocks that affect different firms at exogenously different times, which avoids a common identification difficulty faced by studies with a single shock, namely the existence of potential omitted variables coinciding with the shock that directly affects borrower firms' innovation output.

Furthermore, Chen et al. (2017) show that the house purchase restriction policy negatively affects real estate prices, and thus, it affects the financial resource allocations of listed firms by weakening their incentives for speculating in the real estate market triggered by China's long-lasting dramatic housing boom. Given that a large part of the money borrowed from entrusted loans goes to the real estate industry (and related industries, such as construction) to yield a higher interest rate (Allen et al. 2019), the house purchase restriction policy represents a positive shock to the supply of entrusted loans flowing to manufacturing firms (i.e., the real economy) because of its negative effect on real estate market returns.

Based on the intuition, we construct the instrumental variable, *Lender HP restriction*, that takes the value of one if the city implements a housing purchase restriction policy from Q4 of year $t-1$ to Q3 of year t and zero if there is no restriction in the year or the policy is cancelled.[21] Because we investigate the innovation output of EL borrowers, whereas the instrument is defined based on the lender side, *Lender HP restriction* is not likely to directly drive or be driven by firm-level innovation output, especially that of borrower firms. The exclusion restriction, in particular, is likely satisfied by the fact that we use the policy in lenders' cities as the instrument, and the lenders are likely from other cities instead of the same city where the borrowers locate. The "foreignness" of this instrument helps partial out the possibility that the lower real estate prices caused by the restrictions could affect local governments' revenues from the land sale, which in turn, affects local government investments and local fiscal policies (e.g., taxation). Therefore, our instrumental variable is likely to be exogenous and reasonably satisfies the exclusion restriction.

Table 5 presents the instrumental variable regression results.[22] To further ensure that the exclusion condition is satisfied, we first conduct the tests with the full sample (reported in columns (1)–(3) in Table 5), and then, we exclude firms located in the same province (reported in columns (4)–(6) in Table 5) with their lenders. In the first stage, *Entrusted loan* is regressed on the instrumental variable along with all the controls and fixed effects in our baseline regression. The coefficient estimates on *Lender HP restriction*, the instrumental variable, are all statistically significant at the 1% level and economically sizable (ranging from 0.295 to 0.525).

Additionally, the *F*-statistics of the weak instrument test are significantly larger than 10, and the *p*-values of the underidentification test are less than 0.01. Taken together, the relevance condition of the instrumental variable approach is satisfied. In the second stage, we use the instrumented entrusted loan variable in the regressions estimating Equation (1) and observe that the coefficient estimates on the instrumented entrusted loan variable are all positive and significant, consistent with our main results.

Besides the instrumental variable approach, we make use of a quasinatural experiment based on the "back-to-normal" policy (see Online Appendix C.1.2). The results, reported in Table A4 in Online Appendix C, support our conjecture consistently.

To summarize, we undertake a battery of tests, trying to address various endogeneity concerns and establish a causal link between entrusted loans and the borrower firm's innovation output. We fully acknowledge that no empirical tests can perfectly rule out all possible endogeneity concerns. However, although each test alone might be subject to various criticisms, these pieces of evidence taken together are difficult to reconcile with specific alternative arguments, and hence, they suggest that the positive relation between entrusted loan borrowing and borrowers' innovation output is likely to be causal.

Table 5. Further Identification Attempt: Instrumental Variable Approach

	Full sample			Same-province excluded		
Variable	(1) ln(*Patent*)	(2) ln(*Citation*)	(3) ln(*ExplorePat*)	(4) ln(*Patent*)	(5) ln(*Citation*)	(6) ln(*ExplorePat*)
Entrusted loan	1.070**	0.725*	0.767**	1.390***	1.152***	0.907***
	(0.48)	(0.42)	(0.34)	(0.48)	(0.45)	(0.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	489	489	489	241	241	241
First-stage coefficient of IV	0.294***	0.294***	0.294***	0.520***	0.520***	0.520***
	(0.08)	(0.08)	(0.08)	(0.11)	(0.11)	(0.11)
Weak IV test ($F^{\text{1st-stage}}$)	18.576	18.576	18.576	25.607	25.607	25.607
Underidentification test (*p*-value)	0.0009	0.0009	0.0009	0.0005	0.0005	0.0005

Notes. This table presents estimates on the two-stage least square panel regressions using the housing purchase restriction in the lender's city as an instrumental variable. The sample includes the firms with entrusted loans (EL firms) in ASIF with enough no missing data observations during 2005–2013. ln(*Patent*) is the log of one plus the number of granted invention patents applied in the reference year measured in year $t+1$. ln(*Citation*) is the log of one plus the total number of citations adjusted for year and technology class fixed effects measured in year $t+1$. ln(*ExplorePat*) is the log of one plus the number of granted explorative invention patents applied in the reference year measured in year $t+1$. *Entrusted Loan* equals one in and after the year of entrusted loan borrowing until the loan expires and zero otherwise. The instrumental variable *Lender HP restriction* equals one if there is any local housing purchase restriction policy in the lenders' cities and zero otherwise. All regressions include the same control variables as those in Table 3. Robust standard errors in parentheses are clustered by firm.

*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level.

5.4. Further Analyses on the Effect of Entrusted Loan Characteristics

So far, our analysis mainly focuses on the effects of the presence of entrusted loan borrowing on corporate innovation; to enrich the analysis, we go a step further to explore how the effect of entrusted loans on corporate innovation varies with loan characteristics. Specifically, on the basis of our baseline empirical model, we further include six extra explanatory variables: *Entrusted loan* × *Loan size*, *Entrusted loan* × *Long maturity*, *Entrusted loan* × *Loan interest*, *Entrusted loan* × *Abnormal interest*, *Entrusted loan* × *For project*, and *Entrusted loan* × *For return*.[23] Although the key explanatory variable, *Entrusted loan*, still captures the difference between EL and non-EL firms in terms of the changes in innovation output around entrusted loans, each of the six newly included explanatory variables further accounts for the heterogeneous effects of the specific entrusted loan characteristic, conditional on the presence of entrusted loans.

Table 6 reports the results after taking entrusted loans' size, maturity, spreads, and contract terms into account. First, columns (1)–(3) of Table 6, panel A include *Entrusted loan* × *Loan size* that equals the logarithm of the amount of an EL firm's largest entrusted loan and zero for non-EL firms. The coefficient estimates on the newly included variable are all positive and significant at the 1% level in the regressions in which patent and explorative patent counts are the dependent variables. These results suggest that larger entrusted loans are associated with even better performance in motivating firms to file more (explorative) patents, yet no significant result shows that these loans are different from those smaller ones in their effect on patent quality. One plausible explanation of the finding is that although larger loans can help finance more innovative projects, the quality of a firm's innovation output (measured by ln(*Citation*)) might need a longer gestation period to get enhanced.

Second, columns (4)–(6) of Table 6, panel A include *Entrusted loan* × *Long maturity* that equals one if an entrusted loan's maturity is over one year and zero otherwise. The coefficient estimates on *Entrusted loan* × *Long maturity* are all positive and significant, suggesting that long-term entrusted loan borrowing (i.e., longer than one year) plays a more important role in enhancing corporate innovation, which is consistent with the existing innovation literature (e.g., Manso 2011, Tian and Wang 2014).

Third, panel B of Table 6 considers the effects of entrusted loan interests and reliance on collateral. We include *Entrusted loan* × *Loan interest* (the interest rate of a firm's entrusted loan borrowing for EL firms and zero for non-EL firms) and find that the coefficient estimates on the newly added explanatory variable are statistically insignificant and economically close to zero.[24] This finding suggests that the effect of entrusted loans on borrowers' innovation output is not likely to vary with loan interests and spreads, which is consistent with Allen et al. (2019) that borrowers' risks are largely priced in the market, and thus, interest rates are not likely differentiate the effects of entrusted loans on corporate innovation.

Columns (4)–(6) of Table 6, panel B include *Entrusted loan* × *No collateral* that equals one if an entrusted loan does not require any type of collateral and zero otherwise. We find that the coefficient estimates on *Entrusted loan* × *No collateral* are positive and significant at the 1% or 5% level. This observation suggests that entrusted loan lenders rely more on their relation with borrowers (and thus, informational advantages) instead of tangible collateral, consistent with our conjecture that entrusted loans can be advantageous in motivating innovation (compared with bank credit) because of possible informational advantages.

Finally, Table 6, panel C takes entrusted loan contract terms into consideration. As mentioned, part of the entrusted loan contracts would pin down the use of loans. For example, some of the loans are exclusively designated to be invested in certain projects in the contract, and others can be used for returning debt. We include *Entrusted loan* × *For project* (equals one if an entrusted loan is disclosed specifically for some project(s) and zero otherwise) and *Entrusted loan* × *For return* (equals one if an entrusted loan is disclosed specifically for returning the borrower firm's other loans and zero otherwise), respectively. The results show that although the coefficient estimates on *Entrusted loan* × *For project* are positive and significant for patent and explorative patent counts, those of *Entrusted loan* × *For return* are negative, close to zero, and largely insignificant. This finding is consistent with our conjecture that the loans contracted for specific projects (i.e., real business) are more likely to better help enhance corporate innovation, whereas those simply borrowed to return other debt are unlikely to have effects on firms' innovation activities.

Put together, the results of exploring the heterogeneous effects of entrusted loan characteristics suggest that loans with larger size, loans with longer maturity, and loans that are contracted for specific projects (rather than for returning earlier debt) are more likely to play a bigger role in enhancing borrowers' innovation output, whereas loan interest rates and spreads do not appear to play a role. These findings are consistent with both our conjecture and the existing literature, and they are supportive of our main findings in a more nuanced way. The evidence can also help better understand how entrusted loans can have an effect on borrowers' corporate innovation.

5.5. Heterogeneity Tests

On top of the evidence, we also provide evidence on heterogeneity of our main findings to further

Table 6. Entrusted Loan Characteristics and Corporate Innovation

Variable	(1) ln(*Patent*)	(2) ln(*Citation*)	(3) ln(*ExplorePat*)	(4) ln(*Patent*)	(5) ln(*Citation*)	(6) ln(*ExplorePat*)
			Panel A: Loan size and maturity			
Entrusted loan × *Loan size* (× 1,000)	0.383***	0.053	0.254***			
	(0.12)	(0.19)	(0.07)			
Entrusted loan × *Long maturity* (>1 year)				0.171**	0.151*	0.117*
				(0.07)	(0.09)	(0.06)
Entrusted loan	0.110	0.132	0.078*	0.012	−0.012	0.010
	(0.08)	(0.08)	(0.04)	(0.10)	(0.10)	(0.07)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	581,810	581,810	581,810	581,810	581,810	581,810
R^2	0.699	0.625	0.653	0.695	0.625	0.649
			Panel B: Loan interest and collateral			
Entrusted loan × *Loan interest*	0.003	−0.001	0.007			
	(0.02)	(0.02)	(0.01)			
Entrusted loan × *No collateral*				0.203***	0.155**	0.136***
				(0.07)	(0.07)	(0.04)
Entrusted loan	0.167	0.146	0.096	−0.235	−0.138	−0.118
	(0.11)	(0.10)	(0.06)	(0.17)	(0.18)	(0.11)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	581,810	581,810	581,810	581,810	581,810	581,810
R^2	0.695	0.625	0.649	0.696	0.625	0.650
			Panel C: Loan terms—for project/for return			
Entrusted loan × *For project*	0.447***	−0.022	0.243*			
	(0.09)	(0.11)	(0.13)			
Entrusted loan × *For return*				−0.067	−0.082	−0.061
				(0.08)	(0.09)	(0.05)
Entrusted loan	0.164**	0.142**	0.116***	0.181***	0.142**	0.125***
	(0.07)	(0.07)	(0.04)	(0.07)	(0.06)	(0.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	581,810	581,810	581,810	581,810	581,810	581,810
R^2	0.697	0.625	0.650	0.695	0.625	0.649

Notes. This table examines the effects of entrusted loan characteristics on corporate innovation by including new explanatory variables (on the basis of the baseline model) that account for various characteristics of entrusted loans shown in their contracts. The sample includes the firms with entrusted loans (EL firms) and all the matched firms without entrusted loan (non-EL firms) in ASIF with enough no missing data observations during 2005–2013. ln(*Patent*) is the log of one plus the number of granted invention patents applied in the reference year measured in year $t + 1$. ln(*Citation*) is the log of one plus the total number of citations adjusted for year and technology class fixed effects measured in year $t + 1$. ln(*ExplorePat*) is the log of one plus the number of granted explorative invention patents applied in the reference year measured in year $t + 1$. *Entrusted Loan* equals one in and after the year of entrusted loan borrowing until the loan expires and zero otherwise. In panel A, *Entrusted loan* × *Loan size* equals the size of a firm's biggest entrusted loan for EL firms and zero for non-EL firms; *Entrusted loan* × *Loan maturity* equals one if an entrusted loan's contracted maturity is longer than 12 months and zero otherwise. In panel B, *Entrusted loan* × *Loan interest* (*Entrusted loan* × *Abnormal interest*) equals a borrower firm's typical entrusted loan interest rate (abnormal interest rate) for EL firms and zero for non-EL firms. In panel C, *Entrusted loan* × *For project* equals one if an entrusted loan is contracted and used for investment in some specific projects and zero otherwise; *Entrusted loan* × *For return* equals one if an entrusted loan is contracted and used for returning the borrower firm's other debt and zero otherwise. All regressions include the same control variables as those in Table 3. Robust standard errors in parentheses are clustered by firm.

*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level.

understand the effect of entrusted loans on the borrower's innovation output. For brevity, we only tabulate the results with the key variables of interest in Table A5 in Online Appendix D and present the detailed discussion in Online Appendix D. The results suggest that the effects of entrusted loans are more prominent when the borrowers are subject to severer financial constraints, information asymmetry, and takeover exposures, consistent to our conjecture.

6. Plausible Underlying Channel: Capital Reallocation

Thus far, we have shown that entrusted loans improve borrowers' innovation output. In this section, we attempt to explore a plausible underlying channel through which entrusted loans promote borrowers' innovation output. As we have discussed before, the primary credit allocation through the traditional banking system is highly distorted in China. Given that shadow banking is less regulated and more market based (Allen et al. 2019), it is reasonable to expect that the shadow banking sector, as a conduit, could help correct distortions in China through reallocating misplaced capital from less productive but easily financed firms to capital-deprived but more productive firms.

To explore the plausible underlying channel, we go a step further and focus on the relation between entrusted loan borrowers and their typical lenders, especially how the lenders' characteristics can affect the borrowers' innovation output.[25] The logic behind this is that capital reallocation denotes the "redundant" money out of one side (i.e., entrusted loan lenders) to be redeployed to the other side (i.e., entrusted loan borrowers) that lacks capital. Whether an entrusted loan reflects the "redundant" money depends on the lenders' characteristics. Hence, we expect that the entrusted loans that better enhance borrowers' innovation should be from those lenders that are more likely to have the "redundant" money in hand.

Along this line of inquiry, we first compare entrusted loan lenders with those that do not lend entrusted loans (i.e., nonlenders) to explore whether the lenders are more likely to have "redundant" money. Then, we use the sample of EL firms and run formal tests on the heterogeneous effects of lenders' characteristics on borrowers' innovation output, expecting that the positive effect of entrusted loans on borrowers' innovation output should be more pronounced if the lender is more likely to have "redundant" money in hand.[26] Moreover, we use the sample of listed firms and compare lenders with nonlenders to examine whether lenders are sacrificed in innovation, operating, or stock market performance because capital reallocation can be validated only when entrusted lending is not at the cost of the lenders. We expect that the balance of these pieces of evidence together could point to the role of entrusted loans as an efficient tool of capital reallocation.

6.1. Entrusted Loan Lenders' Characteristics and Borrowers' Innovation Output

We start with lender firms' characteristics by comparing lenders with nonlenders in the sample of A share-listed firms obtained from CSMAR. Panel A of Table 7 reports the results of univariate comparisons between entrusted loan lenders and nonlenders. We find that entrusted loan lenders are larger, older, more profitable, and more likely to be SOEs. Regarding the structure of loans, lenders hold a significantly larger proportion of credit loans, whereas nonlenders rely more on collateral to get bank finance. These observations suggest that entrusted loan lenders are more likely to have easier access to bank credit because of their better operating performance and state-owned status. Meanwhile, entrusted loan lenders' return on investment and *Tobin's Q* (a firm's market value divided by its asset replacement cost) are much lower than nonlenders, which indicates that lender firms have limited growth potential and poor investment opportunities and returns. All of these findings suggest that entrusted loan lenders are advantageous in getting cheap and abundant finance but suffer from a lack of promising investment opportunities and poor investment returns. Given that Allen et al. (2019) document that interest rates of entrusted loans are typically higher than those of bank deposits, lending it out through entrusted loans could be an appealing way to use the "redundant" capital for these firms.

We then compare loan characteristics across lenders with different levels of access to finance and investment opportunities. Table 7, panel B shows (although not with perfect significance) that firms with better access to bank credit (i.e., a lower collateralized loan ratio and a higher credit loan ratio) but scarcer investment opportunities (i.e., a lower return on investment and *Tobin's Q*) are more likely to make larger and longer-maturity entrusted loan lending. This observation suggests that lenders that are financially privileged but lack investment opportunities are more likely to provide entrusted loans that can better fit the requirement for financing innovation.

Next, we undertake a multivariable test to explore the heterogeneity in our main findings based on lenders' investment opportunities. Specifically, on top of the baseline model of which borrowers' innovation output measures are still the dependent variables, we interact *Entrusted loan* with the lender's access to bank credit (i.e., whether the firm has a low proportion of collateralized loans or a high proportion of credit loans) and investment opportunities proxies (i.e., return on investment and *Tobin's Q*), respectively. Based on the capital reallocation conjecture, we expect that what drives our baseline results are the entrusted loans lent out from firms that are more likely to have "redundant money" (i.e., have better access to bank credit but scarcer investment opportunities). We report the results in panels C and D of Table 7.[27]

As shown in Table 7, panels C and D, the key variables of interest are *Entrusted loan* × *Easy access to bank credit*, *Entrusted loan* × *Tobin's Q*, and *Entrusted loan* × *ROI*. The coefficient estimates on *Entrusted loan* × *Easy access to bank credit* are positive and significant for both measures. The coefficient estimates on *Entrusted loan* × *ROI* in panel D in Table 7 are negative and significant at the 5% or 1% level, and the coefficient estimates on *Entrusted loan* ×

Table 7. Capital Reallocation Channel

Panel A: Univariate comparison between entrusted loan lenders and nonlenders

Variable	Mean (1) Nonlender	Mean (2) Lender	Mean difference (2) − (1)	*t*-statistic
Lender's characteristics				
Total assets (billion RMB)	5.178	16.762	11.584	19.86***
Firm age	8.269	9.291	1.022	3.94***
ROA (%)	3.836	4.661	0.825	3.10***
SOE	0.401	0.529	0.128	5.91***
Lender's access to bank credit				
Collateralized loan ratio	0.361	0.248	−0.114	−7.97***
Credit loan ratio	0.434	0.520	0.086	5.89***
Lender's investment opportunities				
Return on investment (ROI)	0.379	0.238	−0.141	−1.86*
Tobin's Q	2.515	1.926	−0.589	−7.82***

Panel B: Comparing loan characteristics based on lenders' characteristics

Variable	*Loan size (million RMB)* High − low	*t*-statistic	*Loan maturity (>1 year)* High − low	*t*-statistic
Lender's access to bank credit				
Easy access to bank credit (small collateralized loan ratio)	163.099	3.00***	0.046	0.77
Easy access to bank credit (large credit loan ratio)	66.531	0.68	0.125	1.21
Lender's investment opportunities				
Return on investment (ROI)	−13.566	−0.67	−0.077	−2.30**
Tobin's Q	−123.432	−6.54***	−0.008	−0.24

Panel C: Testing the capital reallocation channel based on the lender's access to bank credit

Variable	(1) ln(*Patent*)	(2) ln(*Citation*)	(3) ln(*ExplorePat*)
C1: Measuring access to bank credit with the ratio of collateralized loans			
Entrusted loan × Easy access to bank credit	0.473***	0.367*	0.307***
	(0.18)	(0.19)	(0.11)
Easy access to bank credit	0.138	0.197	0.488
	(1.09)	(0.96)	(0.69)
Entrusted loan	−0.276*	−0.348**	−0.151
	(0.15)	(0.17)	(0.11)
Controls	Yes	Yes	Yes
Firm-year fixed effects	Yes	Yes	Yes
Observations	275	275	275
R^2	0.799	0.755	0.797
C2: Measuring access to bank credit with the ratio of credit loans			
Entrusted loan × Easy access to bank credit	1.042**	0.926**	0.572***
	(0.46)	(0.36)	(0.21)
Easy access to bank credit	6.184	4.556	−0.019
	(5.05)	(4.51)	(2.48)
Entrusted loan	0.129	−0.051	0.100**
	(0.09)	(0.08)	(0.05)
Controls	Yes	Yes	Yes
Firm-year fixed effects	Yes	Yes	Yes
Observations	244	244	244
R^2	0.808	0.775	0.809

Panel D: Testing the capital reallocation channel based on the lender's investment opportunity

Variable	(1) ln(*Patent*)	(2) ln(*Citation*)	(3) ln(*ExplorePat*)
D1: Measuring investment opportunity with the return on investment			
Entrusted loan × ROI	−0.034**	−0.045***	−0.023**

Table 7. (Continued)

Panel D: Testing the capital reallocation channel based on the lender's investment opportunity			
Variable	(1) ln(*Patent*)	(2) ln(*Citation*)	(3) ln(*ExplorePat*)
	(0.01)	(0.01)	(0.01)
Return on investment (ROI)	−0.138	0.161	−0.124
	(0.22)	(0.15)	(0.17)
Entrusted loan	0.127	0.110	0.102*
	(0.09)	(0.08)	(0.06)
Controls	Yes	Yes	Yes
Firm-year fixed effects	Yes	Yes	Yes
Observations	534	534	534
R^2	0.822	0.787	0.825
D2: Measuring investment opportunity with *Tobin's Q*			
Entrusted loan × *Tobin's Q*	−0.126**	−0.128***	−0.070*
	(0.05)	(0.05)	(0.04)
Tobin's Q	−0.452	0.155	−0.437
	(0.59)	(0.68)	(0.48)
Entrusted loan	0.251**	0.233**	0.163**
	(0.11)	(0.10)	(0.08)
Controls	Yes	Yes	Yes
Firm-year fixed effects	Yes	Yes	Yes
Observations	544	544	544
R^2	0.828	0.791	0.826

Notes. This table tests the capital reallocation channel by exploring the heterogeneous effects of lender-side characteristics, especially access to bank credit and investment opportunities. The lender-side sample in panels A and B contains all nonfinancial A share-listed firms during 2005–2013 obtained from CSMAR. The sample in panels C and D contains all EL firms with no missing data in ASIF during 2005–2013. *Collateralized loan ratio* is a firm's amount of collateralized loan divided by the total amount of loans. *Credit loan ratio* is a firm's amount of credit loan divided by the total amount of loans. *ROI* is the lender's rate of return on investment in year *t* calculated as the return of investment divided by the firm's total investment; *Tobin's Q* is the lender's market value divided by the book value of total assets. In panels B and C, *Easy access to bank credit (collateralized loan ratio)* equals to one if *Collateralized loan ratio* is less than 30% and zero otherwise; *Easy access to bank credit (credit loan ratio)* equals to one if almost all the firm's loans (over 90%) are credit loans. The dependent variables in panels C and D are borrowers' innovation output measures, the same as those in Table 3. All the newly included variables in panels C and D capture the focal borrower's typical lender's firm characteristics. All the regressions include the control variables and firm and year fixed effects, the same as those in Table 3, as well as their interactions with the newly included variables, but they are not tabulated. Robust standard errors in parentheses are clustered by firm.

*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level.

Tobin's Q are negative and significant. All these findings suggest that the positive effects of entrusted loans on borrowers' innovation output are more pronounced when the lenders have easier access to bank credit or poor investment opportunities and returns.

One plausible concern of our test, however, is that our loan structure proxies and investment opportunity proxies are merely a reflection of the lender's characteristics, such as their life cycles (i.e., larger and more mature lenders are more likely to have better credit conditions and weaker investment returns). If this is the case, one cannot claim that entrusted loans serve as a channel of efficient capital reallocation. To address this concern, we re-estimate the tests but replace the key variables of interest with the interaction terms between *Entrusted loan* and alternative lender characteristics (i.e., size, age, ROA, and SOE) that capture lenders' life cycles or state ownership status, and we report the results in Table 8, panels A–D, respectively. The coefficient estimates on the interaction terms, *Entrusted loan* × *Lender's* ln(*Assets*), *Entrusted loan* × *Lender's ROA*, *Entrusted loan* × *Lender's age*, and *Entrusted loan* × *SOE lender*, are all statistically insignificant, suggesting that our findings in Table 7 are unlikely driven by lender characteristics that are related to their life cycles and ownership.

Together, the results in this subsection suggest that the shadow banking sector in China helps channel funds out of firms that have considerable "redundant" money but lack good investment opportunities.[28]

6.2. Ruling Out Alternative Channels

Although the evidence is consistent with the capital reallocation channel, an alternative interpretation of the results, however, is that firm-to-firm entrusted loans could be a result of agency problems (i.e., tunneling documented in Jiang et al. 2010, which argues that controlling shareholders of listed firms in China exploit minority shareholders by siphoning funds to their own affiliates without requiring any interest through intercorporate loans (typically reported as part of "other receivables")). Although both capital reallocation and tunneling could benefit the borrowers, their influences on the lenders should be largely different. Specifically, the capital reallocation channel suggests that entrusted loans should not negatively affect the lender's performance; the tunneling channel, however, suggests that because of conflicts of interest between controlling and minority shareholders, entrusted loans should hurt the lender's innovation output. To examine whether our channel test results are because of tunneling, we consider the effects of entrusted loan lending on EL lenders in terms of their innovation output.

We first identify all EL lenders in ASIF corresponding to the EL firms in our final sample and directly examine whether (at the lender side) the enhancement of the borrower's innovation output is at the expense of the lender's own innovation output. To elaborate, the key variable of interest, *Entrusted loan*, is a binary variable that equals one if a firm has an entrusted loan that is lent out and undue in a reference year and zero otherwise. Hence, we now compare the lender's innovation output before and after entrusted loan lending.[29] Table 9, panel A, columns (1)–(3) present the results. We observe that the coefficient estimates on the key variable of interest, *Entrusted loan*, are close to zero and statistically insignificant, suggesting that the innovation output of entrusted loan lenders is not reversely affected by their decisions of lending money out through entrusted loans.

To ensure that the results are not driven by the exclusion of EL lenders that fail to find a borrower match in ASIF, we extend the sample to all 467 EL lenders documented in the entrusted loan sample (described in Section 4.1) and reconduct the analysis. Once again, columns (4)–(6) of Table 9, panel B show that the coefficient estimates on *Entrusted loan* are close to zero and statistically insignificant, further assuring that lenders' innovation output is not sacrificed because of entrusted loan lending.

We then go a step further and test whether lenders' operating and stock market performances are affected around entrusted loan lending. We construct two variables to measure a firm's operating performance following previous studies (e.g., Giannetti et al. 2015). (a) The total factor of productivity (*TFP*) is defined as the residual of the regression of the production function following Schoar (2002), which is widely used to probe the productive efficiency of firms and economies. (b) The return on equity (*ROE*), defined as the net profit over the total equity, captures the capability of lenders to increase value for their shareholders. We also use 12-month averaged *Stock return* to capture a lender's stock market performance. As expected, the coefficient estimates on *Entrusted loan* lending in Table 9, panel B are all close to zero and largely insignificant, suggesting that entrusted loan lending does not affect lenders' operating performance or stock market performance.[30]

Taken together, the results in this subsection show that the enhancement of entrusted loan borrowers' innovation output is not at the expense of lenders' innovation output, operating performance, or stock market performance, suggesting that the tunneling argument is not an underlying channel through which entrusted loans affect borrowers' innovation output.

Overall, the evidence reported in this section suggests that capital reallocation from less productive but easily financed firms to more innovative but financially less privileged firms is a plausible underlying economic channel through which entrusted loans promote borrowers' innovation output.

7. Conclusion

In this paper, we have investigated the real effects of shadow banking in the case of technological innovation. Using manually collected entrusted loan data and examining a large sample of manufacturing firms, we find that firm-to-firm entrusted loans, once the largest part of the shadow banking sector in China, enhance borrowers' innovation output. The effects are more pronounced when the borrower firms are subject to severer financial constraints, informational asymmetry, and takeover threat. A plausible underlying economic channel is the improvement in capital reallocation efficiency, which allows entrusted loans to promote innovation. Our paper sheds new light on a bright side of shadow banking in China (i.e., it helps correct bank credit misallocations and thus, serves as a second-best market design in financing the real economy). Although it goes beyond this paper's scope to discuss the social welfare effect of the shadow banking sector in China, entrusted loans appear to be an efficient tool of capital reallocation. No matter how the economy runs, with distorted or frictionless markets, the "invisible hand" is always there in one form or another.

Although the positive effects of entrusted loans on corporate innovation are likely to be causal and robust, we point out two important caveats in interpreting or generalizing our findings. First, because of data limitations, we can only undertake our analysis on the sample of entrusted loans and corresponding manufacturing firms. Although our final sample is still representative in terms of both entrusted loans and corporate innovation in China, this limitation prevents us from examining the effects of other components of shadow banking (e.g., trust loans or wealth management products) or the other part of entrusted loans that flows into the real estate industry. We also acknowledge that entrusted loans are a specific type, although once the largest component, of shadow banking activities. Hence, we do not tend to draw any conclusion on the topics under the framework of general equilibrium, including net benefit, aggregate risks, and social welfare. In other words, our findings provide micro-level evidence on a (instead of the only one) bright side of shadow banking.

Table 8. Testing Alternative Explanations

Variable	(1) ln(*Patent*)	(2) ln(*Citation*)	(3) ln(*ExplorePat*)
Panel A: Interacting entrusted loan with the lender's size			
Entrusted loan × *Lender's* ln(*Assets*)	−0.020	−0.026	−0.030
	(0.07)	(0.06)	(0.04)
Lender's ln(*Assets*)	0.682	0.229	0.410
	(1.06)	(0.78)	(0.66)
Entrusted loan	0.545	0.685	0.761
	(1.71)	(1.45)	(1.01)
Controls	Yes	Yes	Yes
Firm-year fixed effects	Yes	Yes	Yes
Observations	561	561	561
R^2	0.825	0.773	0.823
Panel B: Interacting entrusted loan with the lender's profitability			
Entrusted loan × *Lender's ROA*	0.342	0.716	−0.041
	(1.53)	(1.31)	(0.95)
Lender's ROA	−11.849	−7.112	−2.675
	(15.82)	(15.05)	(10.15)
Entrusted loan	0.079	0.055	0.083
	(0.10)	(0.09)	(0.07)
Controls	Yes	Yes	Yes
Firm-year fixed effects	Yes	Yes	Yes
Observations	544	544	544
R^2	0.808	0.753	0.798
Panel C: Interacting entrusted loan with the lender's age			
Entrusted loan × *Lender's age*	0.082	0.150	0.013
	(0.20)	(0.18)	(0.13)
Lender's age	0.755	−0.894	0.975
	(2.42)	(1.83)	(1.64)
Entrusted loan	−0.109	−0.304	0.040
	(0.54)	(0.48)	(0.36)
Controls	Yes	Yes	Yes
Firm-year fixed effects	Yes	Yes	Yes
Observations	561	561	561
R^2	0.817	0.771	0.819
Panel D: Interacting entrusted loan with the lender's state ownership			
Entrusted loan × *SOE lender*	0.025	0.118	0.016
	(0.14)	(0.13)	(0.09)
SOE lender	−3.029	0.609	−2.005
	(1.89)	(1.55)	(1.26)
Entrusted loan	0.099	0.032	0.066
	(0.10)	(0.09)	(0.07)
Controls	Yes	Yes	Yes
Firm-year fixed effects	Yes	Yes	Yes
Observations	561	561	561
R^2	0.821	0.781	0.819

Notes. This table examines the validity of the alternative explanations instead of the capital reallocation channel (i.e., whether the alternative lender-side characteristics capturing a firm's life cycle or state ownership can account for the heterogeneous effects of investment opportunities). The sample contains all EL firms with no missing data in ASIF during 2005–2013. ln(*Patent*) is the log of one plus the number of granted invention patents applied in the reference year measured in year $t + 1$. ln(*Citation*) is the log of one plus the total number of citations adjusted for year and technology class fixed effects measured in year $t + 1$. ln(*ExplorePat*) is the log of one plus the number of granted explorative invention patents applied in the reference year measured in year $t + 1$. *Entrusted Loan* equals one in and after the year of entrusted loan borrowing until the loan expires and zero otherwise. *Lender's* ln(*Assets*) is the log of the focal borrower's typical lender's total assets. *Lender's ROA* is the focal borrower's typical lender's ROA. *Lender's age* is the focal borrower's typical lender's age since its listing year. *SOE lender* denotes whether the focal borrower's typical lender is a state-owned enterprise. All the regressions include the control variables and firm and year fixed effects, the same as those in Table 3, as well as their interactions with the newly included variables, but they are not tabulated. Robust standard errors in parentheses are clustered by firm.

Table 9. Lender Analysis

Panel A: Entrusted loan lending and lenders' innovation output

	Sample: Lenders of the borrowers in the final sample			Sample: All lenders in the entrusted loan sample		
Variable	(1) ln(*Patent*)	(2) ln(*Citation*)	(3) ln(*ExplorePat*)	(4) ln(*Patent*)	(5) ln(*Citation*)	(6) ln(*ExplorePat*)
Entrusted loan	−0.061	−0.031	−0.061	−0.055	−0.032	−0.049
	(0.08)	(0.07)	(0.06)	(0.04)	(0.04)	(0.03)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	691	691	691	3,423	3,423	3,423
R^2	0.841	0.862	0.806	0.837	0.792	0.753

Panel B: Entrusted loan lending and lenders' performance

Variable	(1) *TFP*	(2) *ROE*	(3) *Stock return*	(4) *TFP*	(5) *ROE*	(6) *Stock return*
Entrusted loan	0.008	0.010	0.088	−0.003	0.001	−0.014
	(0.04)	(0.01)	(0.07)	(0.01)	(0.00)	(0.03)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	599	600	600	2,951	2,960	2,950
R^2	0.694	0.501	0.760	0.637	0.299	0.715

Notes. This table examines the effect of entrusted loan lending on the lender's innovation output, operating performance, and stock market performance. In columns (1)–(3), the sample contains the 94 unique EL lenders of the EL borrowers in the final sample during 2005–2013. In columns (4)–(6), the sample contains all the 467 EL lenders documented in the entrusted loan data (described in Section 4.1) during 2005–2013. In panel A, ln(*Patent*) is the log of one plus the number of granted invention patents applied in the reference year measured in year $t+1$. ln(*Citation*) is the log of one plus the total number of citations adjusted for year and technology class fixed effects measured in year $t+1$. ln(*ExplorePat*) is the log of one plus the number of granted explorative invention patents applied in the reference year measured in year $t+1$. In panel B, *TFP* is the lender's firm-level total factor of productivity following Schoar (2002) in year $t+1$. *ROE* is lender's net profit over total equity in year $t+1$. *Stock return* is the lender's 12-month stock returns in year $t+1$. *Entrusted Loan* equals one in and after the year of entrusted loan lending until the loan expires and zero otherwise. All the regressions include the control variables and firm and year fixed effects, the same as those in Table 3 (but at the lender side). Robust standard errors in parentheses are clustered by firm.

Second, it is well established in the existing literature that debt is inferior to equity when financing and motivating corporate innovation. Our findings are by no means contradicting to the past wisdom. To elaborate, although our results are consistent with the positive effect of entrusted loans and suggest that entrusted loans have advantages compared with traditional bank loans, firm-to-firm debt is still a second-best arrangement compared with equity when financing corporate innovation.

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Endnotes

[1] Allen et al. (2019) examine the real effect by looking at the stock market reactions and investments at the lenders' side. Focused on the borrowers, our paper contributes to the literature by revealing a capital reallocation channel at the micro level, which is frequently discussed in the existing macro literature.

[2] Entrusted loan data were previously used by Chen et al. (2018) and Allen et al. (2019) to investigate the rise, pricing, and risk of the shadow banking sector in China.

[3] The proportion is above 1/3 (589 of 1,678) in our initial sample of entrusted loans described in Section 4.

[4] Using a dynamic stochastic general equilibrium model, Chang et al. (2019a) show that banks' off-balance-sheet activities, in response to the reserve requirement adjustment, reallocate bank credit between SOE loans and private sector credit, which results in greater macroeconomic stability and potential welfare gains. Our paper is different from Chang et al. (2019a) in two important dimensions. First, we focus on intercorporate reallocation activities that entrusted loan lender firms pass through the so-called "SOE loans" to more innovative industrial firms rather than the reallocation within banks' balance sheet. Second, our setting allows us to observe the real effect of entrusted loans in terms of innovation output of borrower firms, which is absent in Chang et al. (2019a).

[5] This literature explores the link between financial tools and corporate innovation as well as the link between innovation output and

capital markets (e.g., Manso 2011; Hirshleifer et al. 2012; Acharya et al. 2013; Cohen et al. 2013, 2019; Levine et al. 2017; Lin et al. 2021). He and Tian (2018, 2020) provide a survey of this literature.

[6] See the first sentence of "A partial primer to China's biggest shadow: Entrusted loans" in the *Wall Street Journal* (McMahon and Wei 2014).

[7] See Allen et al. (2019) for detailed procedures of data collection and a description of entrusted loan data.

[8] Although the number of firms making entrusted loans seems to be small, the market behind is large. As mentioned, the total market size of entrusted loans is over 10 trillion RMB. At the lender side, because there are a total of 2,498 nonfinancial public firms in our sample period, 467 unique lenders suggest that almost 20% of nonfinancial public firms have ever been entrusted loan lenders during the sample period. At the borrower side, our entrusted loan data, as well as the data of Chen et al. (2018) and Allen et al. (2019), are not the full coverage (although the best coverage so far) of the entrusted loan market but only those with public lenders. According to Hachem (2018), this data set covers about 10% of the entrusted loan market. Additionally, the number of EL firms drops to 101, likely because of the coverage of the ASIF data. ASIF only covers China's manufacturing firms that are above scale (i.e., firm size larger than the designated thresholds), which may lead many nonmanufacturing or below-scale firms to remain uncovered. Unfortunately, we could merely rely on this data set to construct causal links that require detailed firm-level financials as the control variables. Caution needs to be exercised when interpreting or generalizing our results.

[9] The designated threshold for being included in the database is until 2011 and 20 million RMB thereafter.

[10] The CNIPA is also known as the State Intellectual Property Office. In the China Patent Data Project (see https://sites.google.com/site/sipopdb/cpdp-home), which is analogous to the widely used National Bureau of Economic Research patent project (but a China patent office version), He et al. (2018) merge patent data from the State Intellectual Property Office to ASIF, yet their data end in 2010. In this paper, we follow the method of He et al. (2018) to first obtain patent data from the China patent office CNIPA (merged with the CSMAR's assignee information) and then standardize the name of the assignee and firm name in ASIF. Finally, we merge the two data sets by firm/assignee name with the sample period of 2005–2013. We also follow He et al. (2018) in firm name standardization in Chinese.

[11] We are aware of the truncation problem in patent counts pointed out by Hall et al. (2001) (i.e., there is, on average, a two-year lag between patent application and grant). Our measure, however, is less vulnerable to this problem because our patent sample ends in 2018, five years later than 2013, the last available year of ASIF. However, we also acknowledge that wider coverage of our patent data cannot fully address all of the truncation concerns, as pointed out by Lerner and Seru (2022). Thus, we also conduct the robustness checks according to the checklist of Lerner and Seru (2022) to mitigate the possibility that truncation biases drive our results.

[12] Although the patent and citation counts are well accepted in the existing innovation literature (He and Tian 2018, 2020), we fully acknowledge the limitations of patenting-based measures. For example, some firms with inventions do not file patents for the sake of keeping business secrets or other strategic reasons, whereas others do not apply for patents because their inventions can hardly meet the criteria for patenting.

[13] We do not include the initial public offering (IPO) variable (i.e., whether a firm goes/is public in the focal year) as a control variable accounting for the effect of trading status on innovation because the number of firms going public/delisting in our sample is small, and thus, the IPO variable is largely absorbed (if not completely) by firm fixed effects. A robustness check that includes the IPO variable in the baseline model does not alter our results.

[14] Similar to the previous literature (e.g., Huang et al. 2020), we determine firms' ownership status by their ownership structure reported in ASIF.

[15] Many observations in ASIF data do not have firms' industry classification. For some firms that are occasionally subject to missing industry classification issues in some years, we use the mode number of a firm's industry classification to supplement the missing information; for other firms without any industry information, the issue causes loss of observations in the tests of Table 1, panel B but does not affect other tests in the rest of this paper. Because the industry information is only used in the two diagnostic tests of Table 1, panel B, we do not exclude these observations with missing industry classification in order to avoid loss of much data.

[16] Except for the exclusion of postinitial borrowing years, in Table 1, panel B, the number of observations is smaller than that of the final sample described in Section 4.6 mainly for two other reasons. (a) Following the existing literature, the tests in panel B use various firm characteristics to predict entrusted loan borrowing; thus, all the independent variables are lagged by one year, which sacrifices observations in 2005 (the first year of sample period). (b) Industry information of many firms in ASIF is missing.

[17] However, the current asset ratio is merely marginally significant ($p = 0.99$).

[18] Although the matching designs are widely implemented in the existing literature (e.g., Chemmanur et al. 2014 among others), we fully acknowledge the limitation of this methodology (i.e., matching (in any form) can only partial out the observable confounded variables to mitigate selection biases). Thus, we do not use the matching procedure to establish causality but mainly rely on it to avoid the t-statistic inflation issue.

[19] For example, even a blackboard that helps one to memorize the content of Marxism philosophy as well as a vacuum cleaner with a Music Player 3 (MP3) for playing music (named "happy vacuum") can be granted a utility model patent. Our main results, however, remain intact if we consider all types of patents.

[20] We measure innovation output in year $t + 1$ to allow for a gestation period of innovation projects, which is a typical practice in the innovation literature (e.g., He and Tian 2018, 2020). In addition, because our patent data end in 2018 and firm-level data end in 2013, the regression specification can avoid loss of sample compared with measuring innovation in year t and lagging all explanatory variables.

[21] Because the proportion of local restriction policies implemented in Q4 is considerable, we define the year of policy implementation from Q4 of year $t - 1$ to Q3 of year t in order to allow for a delay of the effectiveness of the policies, but the results are not altered if we use the exact years of implementation.

[22] Because we rely on the policy of lenders' cities for identification, the sample of IV estimation is actually zoomed in on the treated firms.

[23] The newly added explanatory variables are different subsets (or subsets multiplied by continuous measures of loan characteristics) of *Entrusted loan*, the key variable of interest. As such, the coefficient estimates of these variables actually denote on the basis of the positive effects of entrusted loans on corporate innovation, how different characteristics of entrusted loans could alter the size and significance of the positive effects. We name these variables as interaction terms to more easily interpret the results.

[24] For *Loan interest* of the borrowers with multiple borrowing records, we use a firm's most frequent interest rate (i.e., the interest rate that appears for the most times). Notably, in our entrusted loan

sample, interest rates merely limitedly vary within a firm, and the differences of interest rates are mainly interfirm.

[25] We define a borrower's typical lender by the frequency of a borrower's borrowing from a lender. Specifically, if a borrower has only borrowed entrusted loan(s) from one lender, then this lender would be the typical lender for the focal borrower. Otherwise, if the borrower has made entrusted loans from multiple lenders, the lender that makes the biggest number of entrusted loan transactions to the focal borrower would be the typical lender. Notably, because no firm has ever switched to another lender in the 101 EL firms involved in the regressions, this definition is merely for rigorousness but would not affect any of the results.

[26] In this set of tests, we focus on the sample of EL firms to make use of the richness of lender-side information given that the lenders in our sample are all publicly traded firms and that non-EL firms do not have corresponding lender firms. Notably, some of the tests can be subject to loss of observations because of missing data of lender-side information.

[27] Notably, because in this section, we are aimed at investigating the lender-borrower link (i.e., the "reallocating venue") instead of comparing borrowers and nonborrowers, we use all the EL firms in the text sample (i.e., all the tests in Table 7, panels B and C use the sample of all EL firms). The only reason for observation number inconsistency across the tests of this part is observation losses because of data limitations on the lender side. For example, the reason why Table 7, panel B has only 275 observations is that some borrowers' lenders have missing values of collateralized loan ratio.

[28] One might be concerned that two (of the six) coefficient estimates of *Entrusted loan* in Table 7, panel C are negative and significant, which seemingly contradicts to our conjecture. However, this seemingly counterresult is not robust to all the six regressions in panel C. In addition, note that by no means can the suggestive evidence in this subsection per se perfectly support the capital reallocation channel. The interpretation of an underlying channel of capital reallocation still needs to be based on both these pieces of evidence and the finding in Section 6.2 that lenders' innovation output is not sacrificed because of entrusted loan lending.

[29] There are 97 unique EL lenders in this test. We thank an anonymous referee for suggesting the empirical design of this test.

[30] Note that the differences in sample sizes between panels A and B of Table 9 are because of the execution that the dependent variables are measured one year ahead, whereas the patent data already cover one year after the sample period and thus, are not subject to observation loss under this execution; the differences in sample sizes between columns of panel B are because of occasionally missing data.

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