Internet Appendix for

"The real effects of shadow banking: Evidence from China"

(Not to be published)

This Internet Appendix provides supplemental analyses and robustness tests to the main results presented in "The real effects of shadow banking: Evidence from China". Section A provides summary statistics of the final (weighted) sample. Section B presents the results of numerous robustness checks. Section C discusses additional identification attempts. Section D reports the results of heterogeneity tests.

A. Summary statistics of the final (weighted) sample

In Table 2 of the paper, we present the summary statistics of the unweighted sample. To better describe the data that actually work in main analyses, we also report the summary statistics of the post-weighting (i.e., matched) sample in Table A1. Hence, the regressions in this paper can be understood as either weighted regressions on the unweighted sample, or ordinary regressions on the weighted sample.

[Insert Table A1 about here]

B. 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 Lerner and Seru (2022)'s checklist, as robustness checks for the baseline results. For brevity, we only report the coefficient estimates of key variables, in Table A2.

[Insert Table A2 about here]

First, we alter the matching criteria in Section 4.5, including (a) using a 1-to-4 nearest-neighbor propensity score matching (PSM) approach based on Logit model in generating the propensity score; (b) using a 1-to-4 nearest-neighbor PSM approach based on Probit model in generating the propensity score following Rosenbaum and Rubin (1983); (c) matching EL firms with non-EL firms if the two firms are both in the same decile of total assets, leverage, ROA, and age in the latest available year prior to a entrusted loan borrowing. Our results remain robust to these alternative matching procedures.

Second, we test the robustness of our main results to alternative definitions of the key explanatory variable, *Entrusted loan*. Specifically, we use two alternative definitions: (a) using the borrowing years (i.e., the years with new entrusted loan borrowing only) rather than the years before expiration as the entrusted loan year [*Entrusted loan (First year only)* = 1]; (b) using an ante-post definition of the dummy variable that takes the value of one in and after the year of the first/largest entrusted loan transaction and zero otherwise. Our main findings are not altered by these alternative definitions of the key variable.

Third, to allow for a longer gestation period of the innovation process (Manso, 2011), we follow Chang, Chen, Wang, Zhang, and Zhang (2019) to use the number of patents and citations measured in year $t + 2$ as the dependent variable. The main results remain unaltered.

Fourth, we extract self-citations from the number of total forward citations to avoid the inflated citation measure because firms could repeatedly cite their own patents. The result does not change qualitatively.

Fifth, we use the number of citations per patent to measure the intensive margin of innovation quality, which is different from the total-citation measure because a firm might receive a large number of citations in total by just simply accumulating the number of patents, rather than filing patents with higher quality. The results are robust to this alternative citation measure.

Sixth, we exclude the financial crisis period (2007-2008) from our sample and repeat the baseline analysis to address the concern that the presence of global financial crisis and the subsequent 4-trillion-yuan stimulus plan in China could drive increases in both entrusted loan borrowing and corporate innovation output. Our results are robust to this alternative sample period.

Seventh, we follow the recommendation of Petersen (2009) to estimate Eq. (1) with standard errors clustered at both firm and year to mitigate the concern regarding the presence of residual correlation in both dimensions. Our baseline results are robust to the two-way clustering.

Eighth, we run negative binomial regressions with the number of patent and citation counts (instead of taking logarithm) to address the concern that the count of patents and citations is non-negative and discrete, and thus is closer to a Poisson distribution. We also follow Cohn et al. (2022) and conduct Poisson regressions to further mitigate the concern that even the negative binomial regressions can be potentially biased in some cases. Our main findings are unaffected by either of these alternative regression models.

Finally, Lerner and Seru (2022) point out that the use of patent data can be subject to a series of truncation problems that could bias the results, and typical adjustment approaches cannot fully address the concerns. We acknowledge that the problems they point out might also significantly undermine the validity of our results, thus we conduct all the applicable robustness tests according to Lerner and Seru (2022)'s checklist to further ensure that our results are not the production of truncation bias[1]. Specifically, we exclude: a) the last year of sample, b) industries that experienced a surge of patenting or in citations per patent (i.e., computers and electronics and chemicals), c) regions that experienced a surge of patenting or citations per patent (i.e., Beijing, Shanghai, Guangzhou, and Shenzhen, similar to California and Massachusetts for US in terms of the local capability of innovation), d) firms with features that experienced a surge in patenting or citations per patent (i.e., firms above the firm-level median size, leverage or ROA), e) firms that exit over the sample period, f) firms in the sample where the match confidence is low (i.e., the register code in ASIF that is not uniquely defined for a firm identified by its standardized assignee name), and g) firms in the sample that might be engaging in strategic patent and citation assignment practices.[2] We re-conduct the baseline regressions. The main results continue to hold (although not perfectly), suggesting that our findings are unlikely fully driven by the truncation problems pointed out by Lerner and Seru (2022).

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[1] We conduct recommended tests 2 to 8 in Lerner and Seru (2022)'s checklist. The only exception that is not applicable for our analysis is recommended test 1 in their list. We cannot compute patent and citation bias because there is no other applicable patent dataset covering our sample period.

[2] To identify firms that might be engaging in strategic patent and citation assignment practices, we first compute the Herfindahl-Hirschman index at the industry-year level using the number of patents to measure the competing environment to the extent of patenting activity. Firms with the index below median value are considered to be faced with severer patenting competition and thus are more likely to engage in strategic practices. We follow the checklist and exclude these firms for a robustness check.

In addition, to avoid extreme values of innovation output measures driving our results, we set an upper bound to each of the three innovation measures and rerun the baseline model. Specifically, we first obtain the median value for each of the innovation measures within the observations of positive innovation output; then we replace those larger-than-median values with the corresponding median value. Our baseline results continue to hold in this test. The results also remain intact if we alternatively use the top quartile or decile, instead of the median value.

C. Identification attempts: Supplementary evidence

Tables A3 and A4 report supplementary results of identification attempts. All the following tests of supplementary identification attempts 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.

C.1 Addressing omitted variable concerns

First, Bena and Li (2014) and Sevilir et al. (2019) find that corporate innovation is a relevant driving force in M&A deals. A firm could use entrusted loans to increase its patent output merely by acquiring other innovative firms rather than enhancing its own innovation productivity. Thus, we include a firm's M&A activity, measured by the logarithm of one plus the number of M&A bids that the firm has in year *t*, to explore whether our baseline results could be absorbed by variations reflecting M&A activities. We report the results in Panel A of Table A3, and find that our baseline results remain largely intact.

[Insert Table A3 about here]

Second, local conditions could be relevant to both the demand and supply of entrusted loans and firms' innovation output. For example, Huang et al. (2020) find that local governments in China set a number of financing vehicles to cover their expenditures, and consequently crowd out investment of private sector firms. To mitigate the concern that firm local conditions could be a source of omitted variables, we follow Huang et al. (2020) and control for an array of city-level variables, including *GDP*, *GDP per capita*, aggregate size of

Bank loans, *Population*, *Government revenue* and *Government expenditure*.[3] Panel B of Table A3 shows that our main results are robust to including these city-level variables. In addition, the coefficient estimates of the city-level variables are statistically insignificant.

C.1.1 Addressing reverse causality concerns

We follow Bertrand and Mullainathan (2003) to examine the dynamics of corporate innovation output by decomposing the key explanatory variable, *Entrusted loan*, into six indicators: $Year^{-2}$, $Year^{-1}$, $Year^{0}$, $Year^{+1}$, $Year^{+2}$, and $Year^{\geq+3}$. $Year^{j}$ is a set of dummy variables that equals one in the j^{th} year relative to the entrusted loan borrowing year, and zero otherwise. $Year^{\geq+3}$ is a dummy variable that equals one if the year is three or more years after an entrusted loan borrowing for a firm, and zero otherwise. We then regress the innovation output measures of year t on these indicators as well as all the control variables and fixed effects as in Eq. (1). If reverse causality drives our results, we then expect to observe positive and significant coefficient estimates of year dummies that are before entrusted loan borrowing. However, Table A3 Panel C shows that the coefficient estimates of $Year^{-2}$, $Year^{-1}$ are all statistically insignificant, suggesting that the dynamic trend of innovation output before borrowing is parallel between EL and non-EL firms. Moreover, the coefficient estimates of $Year^{+1}$ and $Year^{+2}$ are positive and statistically significant at the 1% or 5% level. This result suggests that EL firms starts to outperform non-EL firms in innovation output from the entrusted loan borrowing year onward, and the effect becomes stronger in the subsequent years. We notice that, while the coefficient estimates of $Year^{\geq+3}$ are all significant at the 5% the level for the three dependent variables, the long-run effect of entrusted loans seems to be smaller economically, which is consistent to the nature of debt, i.e., most of the entrusted loans are contracted with a duration of two years or shorter.

C.1.2 Further identification attempt: quasi-natural experiment

Besides instrumental variable approach, we also use a quasi-natural experiment based on the “back-to-normal” policy that is detailed described and investigated by Chen et al.

[3] We take logarithms for all these continuous city-level variables.

(2018). They show that, after a two-year fiscal stimulus amount to 4 trillion RMB (for the sake of stabling the negative shock by the 2008 global financial crisis), China's central government decides to terminate the unconventional expansion and compel the bank credit back to normal. As an unintended consequence, the suddenly suspended credit expansion leaves substantial funding deficit and thus originates a soaring shadow banking sector in China.[4] Moreover, Chen et al. (2018) directly document that a tightened monetary policy leads to more prevalent entrusted loan lending. Following this logic, firms rely more on shadow banking to meet their financing needs due to the precipitous drop of bank credit after the "back-to-normal" policy, which represents a plausibly exogenous shock to the demand of shadow banking.

To make use of the back-to-normal policy, we interact *Entrusted loan* with the dummy variable, *Back-to-normal*, which equals one if the observation is after 2010 when the policy was implemented, and zero otherwise. The interactions between *Back-to-normal* and all other variables are included in the regressions as well to account for the different effects of all other control variables across groups. Table A4 reports the results of the identification test with the policy shock. The coefficient estimates of the interaction term, *Entrusted loan* × *Back-to-normal*, are positive and significant (except for the second column), suggesting that the benefits of shadow banking is augmented during the period of bank credit tightening. This finding also supports Chen et al. (2020)'s argument that shadow banking in China plays a role that is complementarity to the banking sector in terms of financing the real economy.

D. Heterogeneity tests

In this section, we provide evidence on heterogeneity of our main findings to further 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.

[Insert Table A5 about here]

D.1 Financial constraints

[4] Chen et al. (2020) and Xiao (2020) report similar findings.

Motivating innovation, a long-term process with high uncertainty and high risk of failure (Manso, 2011), requires persistent capital investment, which is hardly satisfied completely by firms' internal financing. Thus, as an important part of debt financing in China, entrusted loans could play critical roles that finance firms' innovation activities by relaxing their financial constraints. As a result, we expect that the effect of entrusted loans on innovation output to be more pronounced for firms suffering more from binding financial constraints.

To examine how financial constraints alter our main results, we construct a firm-level financial constraint measure (i.e., *FC score*). Following Howell (2016), our financial constraint score is based on the estimation on a Euler equation that links a firm's characteristics (e.g., size, age, and industry) and cash flow to its investment, and is calculated as adding up the productions of the estimated coefficients multiplied by the corresponding firm characteristics. [5] Since a firm's *FC score* is generated from its time-varying characteristics, the score is time-varying as well. A higher *FC score* denotes a severer level of financial constraints. We then interact the score with *Entrusted loan*, as well as all the control variables following standard execution.

We present the results in Table A5 Panel A. The coefficient estimates of *Entrusted loan* × *FC score* are positive in all columns and significant at the 5% level when *Ln(Patent)* and *Ln(ExplorePat)* are the dependent variables, suggesting that the positive effect of entrusted loans in financing innovation is more pronounced for firms with severer financial constraints.

D.2 Informational asymmetry

Technological innovation is typically hard to understand and evaluate by outside investors. Thus, it is important for firms to effectively communicate with outside investors for

[5] Compared to Hadlock and Pierce (2010)'s SA index, which is estimated based on US firms, Howell (2016)'s Euler equation approach in measuring financial constraints is more suitable for firms in China, especially those non-publicly-traded firms. In addition, we are aware of the wide usage of other measures of financial constraint (e.g., Kaplan and Zingales, 1997; Cleary, 1999; Almeida et al., 2004; Whited and Wu, 2006), as well as the modified version of these indexes (e.g., Cull et al., 2015; Guariglia and Yang, 2016; Xiao and Wang, 2020). However, unfortunately we do not have access to observe some key components in constructing these measures (e.g., credit rating, dividend payment, or external finance), which limits our use of other credit constraint measures. We thank an anonymous referee for suggesting these financial constraint measures.

their innovation efforts (Bhattacharya and Ritter, 1983; Aboody and Lev, 2000). As an alternative way of debt financing, the most prominent characteristics of entrusted loans that distinguish them from traditional bank credit is that they are loans from firms to firms, which allows easier information production by lender firms and hence are less subject to information asymmetry, compared to bank loans. As a result, Allen et al. (2019) find that entrusted loans within the same cities and industries exhibit a much lower interest rate and ex-post probability to default. In particular, they show that affiliated loans (i.e., entrusted loans of which the lenders and the borrowers are within the same business group or have ownership connections) are close to a pass-through loan, with the interest rate for EL borrowers roughly the same as the rate that EL lending firms borrow from banks. These observations at the transaction level suggest that information asymmetry affects the pricing of entrusted loans. Given that information asymmetry is also critical to finance corporate innovation, entrusted loans should better enhance innovation output for the borrowers who suffer from severer informational frictions.

To examine this conjecture, we consider high-tech industries that are typically considered with severer informational frictions. Aboody and Lev (2000) document that technology and science based high-tech firms are subject to severer information asymmetry. Thus, we follow Loughran and Ritter (2004) to construct a dummy variable, *High-tech*, that equals one if a firm is in a high-tech industry, and zero otherwise.

Table A5 Panel B presents the results in which the key variable of interest is the interaction term between *High-tech* and *Entrusted loan*. The coefficient estimates of *Entrusted loan* × *High-tech* are positive and significant at the 1% level in all three columns, suggesting that the positive effect of entrusted loans on corporate innovation is more pronounced for high-tech firms. The results support the conjecture that entrusted loans could better promote innovation for firm s that are subject to a larger degree of information asymmetry.

One concern is that the evidence reported in Table A5 Panels A and B could also suggest that the baseline effects are more pronounced for firms with more investment opportunities. While this is a reasonable concern, investment opportunities are by no means on contrary to the financing constraint and informational asymmetry arguments in our setting.

Note that entrusted loans are a second-best way of finance given their higher pricing and costs (Allen et al., 2019; Allen and Gu, 2021), and then, intuitively, why does a firm that is richer in investment opportunities still reach out to a second-best finance with higher costs? It is hardly to find alternative explanations that could reconcile these seemingly contradicting characteristics of borrower firms, except for the absence of first-best finance ways due to financial constraints and informational asymmetry. In Section 6, we attempt to reveal that entrusted loans can channel funds out of firms lacking investment opportunities to firms with more opportunities, through which capital re-allocation between the "old" and the "young" can improve the efficiency of the real economy.

D.3 Takeover exposures

As any other type of risk-taking activities, innovation is by nature a counter of short-termism (Manso, 2011; Tian and Wang, 2014). If a firm is exposed to the pressure of being acquired, managers would have to cut off long-term investment in technological innovation to enhance short-term performance and prevent the firm from being hunt resulted from funding shortage. With an entrusted loan borrowing, a firm could more easily satisfy its financing needs, and thus there would be no need for those "safer" managers to liquidate long-term innovative projects. Therefore, entrusted loans should better enhance innovation output for the borrowers that are subject to a larger degree of ex ante exposure to being targeted in M&A deals.

To examine this conjecture, we interact our key variable of interest, *Entrusted loan*, with *M&A exposure* that reflects M&A threats. Using data from the WIND M&A database, *M&A exposure* is calculated as the mean value of the number of M&A bids that the firm receives before entrusted loan borrowing (i.e., M&A bids with *Entrusted loan* = 1 are excluded from the calculation).

Table A5 Panel C presents the results. We observe that the coefficient estimates of *Entrusted loan* × *M&A exposure* is positive and significant at the 1% level when *Ln(Patent)* and *Ln(ExplorePat)* are the dependent variables. Notably, however, while the results for the number of (explorative) patents is consistent with our conjecture above, the effects of entrusted loans on the number of patent citations do not show significant difference between firms with high and low M&A threats, suggesting that borrowers with high takeover exposure do not benefit more from entrusted loans in terms of promoting their innovation quality compared to entrusted loan borrowers with low takeover exposure.

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Table A1 Descriptive statistics of the final (weighted) sample

This table reports the summary statistics of the final (weighted) 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, which 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 thousand). *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.

Variable	Mean	Standard deviation	Minimum	25^{th}	Median	75^{th}	Maximum
Patent	0.863	15.180	0	0	0	0	6802
Citation	0.595	14.110	0	0	0	0	6501
ExplorePat	0.288	4.093	0	0	0	0	1766
Ln(Patent)	0.217	0.588	0	0	0	0	8.825
Ln(Citation)	0.151	0.493	0	0	0	0	8.780
Ln(ExplorePat)	0.120	0.358	0	0	0	0	7.477
Entrusted Loan	0.117	0.321	0	0	0	0	1
Ln(Assets)	12.510	0.982	7.538	11.900	12.840	13.320	14.620
Leverage	0.560	0.227	0.036	0.406	0.577	0.731	0.959
Ln(Age)	2.359	0.607	0.693	1.946	2.398	2.833	3.178
Ln(PPE/Employees)	5.247	1.075	1.241	4.583	5.368	6.367	6.367
ROA	0.078	0.130	-0.056	0.005	0.044	0.107	0.817
Current asset ratio	0.428	0.273	0.006	0.185	0.446	0.644	0.957
Sales growth	0.318	1.096	-1.997	-0.066	0.171	0.660	2.422
HHI	0.041	0.054	0.001	0.008	0.020	0.049	0.285
HHI^2	0.005	0.013	0.000	0.000	0.000	0.002	0.081
SOE	0.431	0.495	0	0	0	1	1

Table A2 Robustness checks

This table contains a number of checks testing the robustness of the relationship between entrusted borrowing and corporate innovation to alternative matching procedures, variable definitions, subsamples, and model specifications, as well as robustness checks recommended by Lerner and Seru (2022). The sample includes the firms with entrusted loans (EL firms) and all the matched firms 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 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. Each row in the table reports the key result of a corresponding regression. All the report the coefficient estimates of *Entrusted Loan* measured at year *t*, except for Panel B where the explanatory variables are altered (described in Appendix B). All regressions include the same control variables as those in Table 3, but they are not tabulated. Robust standard errors in parentheses are clustered by firm. The symbols ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

Panel A: Alternative matching procedures

Matching procedure	*Ln(Patent)*	*Ln(Citation)*	*Ln(ExplorePat)*
PSM based on Logit model (N = 2,366)	0.149**	0.109*	0.103***
	(0.06)	(0.06)	(0.04)
PSM based on Probit model (N = 2,257)	0.146**	0.102*	0.099***
	(0.06)	(0.06)	(0.04)
Decile matching (N = 2,437)	0.194***	0.130**	0.125***
	(0.07)	(0.06)	(0.04)

Panel B: Alternative definitions of the key explanatory variable (N = 581,810)

Variable	*Ln(Patent)*	*Ln(Citation)*	*Ln(ExplorePat)*
Entrusted loan (First year only)	0.242***	0.115*	0.138***
	(0.07)	(0.06)	(0.04)
Post first entrusted loan	0.242***	0.115*	0.138***
	(0.07)	(0.06)	(0.04)
Post largest entrusted loan	0.218***	0.100*	0.128***
	(0.07)	(0.06)	(0.04)

Panel C: Measuring innovation output in year t + 2 (N = 581,810)

Variable	*Ln(Patent)*	*Ln(Citation)*	*Ln(ExplorePat)*
Entrusted loan	0.157**	0.126*	0.158**

	(0.07)	(0.07)	(0.07)

Panel D: Excluding self-citations (N = 581,810)

Variable		*Ln(Citation)*	
Entrusted loan		0.130*	
		(0.07)	

Panel E: Using citations per patent as the innovation quality measure (N=581,810)

Variable		*Ln(Citation)*	
Entrusted loan		0.069*	
		(0.04)	

Panel F: Excluding 07-08 financial crisis period (N = 380,521)

Variable	*Ln(Patent)*	*Ln(Citation)*	*Ln(ExplorePat)*
Entrusted loan	0.220***	0.146*	0.157***
	(0.08)	(0.08)	(0.05)

Panel G: Two-way clustering (N = 581,810)

Variable	*Ln(Patent)*	*Ln(Citation)*	*Ln(ExplorePat)*
Entrusted loan	0.181**	0.142*	0.125**
	(0.06)	(0.07)	(0.04)

Panel H1: Negative binomial regressions (N = 7,788)

Variable	*Ln(Patent)*	*Ln(Citation)*	*Ln(ExplorePat)*
Entrusted loan	0.591***	0.532***	0.699***
	(0.16)	(0.19)	(0.19)

Panel H2: Poisson regressions (N = 7,788)

Variable	*Ln(Patent)*	*Ln(Citation)*	*Ln(ExplorePat)*
Entrusted loan	0.527***	0.489**	0.713***
	(0.18)	(0.23)	(0.19)

Panel I: Lerner and Seru (2022)'s checklist

Checklist item	*Ln(Patent)*	*Ln(Citation)*	*Ln(ExplorePat)*
a) exclude the last year of sample	0.177**	0.157**	0.111***
(N = 513,867)	(0.07)	(0.07)	(0.04)
b) exclude computers and electronics and chemicals (N	0.156**	0.163**	0.107**
= 495,437)	(0.07)	(0.07)	(0.04)
c) exclude Beijing, Shanghai, Guangzhou and	0.183**	0.083	0.133***
Shenzhen (N = 520,947)	(0.08)	(0.07)	(0.05)

d1) exclude firms above median size (N = 520,986)	0.184*	0.236**	0.099*
	(0.10)	(0.10)	(0.06)
d2) exclude firms above median leverage (N = 282,567)	0.252**	0.271**	0.129**
	(0.12)	(0.12)	(0.07)
d3) exclude firms above median ROA (N = 266,843)	0.144*	0.114	0.122**
	(0.08)	(0.08)	(0.05)
e) exclude firms that exit over the sample period (N = 540,280)	0.184***	0.118**	0.127***
	(0.07)	(0.06)	(0.04)
(f) exclude firms in the sample where the match confidence is low (N = 564,644)	0.181***	0.141**	0.124***
	(0.07)	(0.06)	(0.05)
(g) exclude firms in the sample that might be engaging in strategic patent and citation assignment practices (N = 347,524)	0.182**	0.219***	0.121***
	(0.08)	(0.08)	(0.04)

Panel I: Setting upper bounds to extreme values in innovation output (N = 581,810)

Variable	*Ln(Patent)*	*Ln(Citation)*	*Ln(ExplorePat)*
Entrusted loan	0.149***	0.131**	0.088***
	(0.05)	(0.05)	(0.02)

Table A3 Addressing endogeneity: supplementary evidence

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, *M&A* is the logarithm of one plus the number of M&A bids that the firm has in year *t*. In Panel B, *GDP* is the total RMB value of gross domestic product. *Bank loans* is the sum of total value of bank loans. *Population* is size of population. *Gov. revenue* and *Gov. expenditure* are total revenue and total expenditure of the municipal government, respectively. All the newly added control variables in Panel B are reported in the *China yearbook of statistics* at city level, taken logarithms, and measured in year *t*. In Panel C, $Year^{-1}$ ($Year^{-2}$) is a dummy variable that equals one if the year is one (two) year(s) ahead of an entrusted loan borrowing for a firm, and zero otherwise. $Year^{0}$ is a dummy variable that equals one at the borrowing year, and zero otherwise. $Year^{+1}$ ($Year^{+2}$) is a dummy variable that equals one if the year is one (two) year(s) after an entrusted loan borrowing for a firm, and zero otherwise. $Year^{\geq+3}$ is a dummy variable that equals one if the year is three or more years after an entrusted loan borrowing for a firm, and zero otherwise. All regressions include the same control variables as those in Table 3. Robust standard errors in parentheses are clustered by firm. The symbols ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

Panel A: Controlling for omitted variables (M&A)

	(1)	(2)	(3)
Variable	*Ln(Patent)*	*Ln(Citation)*	*Ln(ExplorePat)*
Entrusted loan	0.180***	0.141**	0.124***
	(0.07)	(0.06)	(0.04)
M&A	0.020	-0.007	0.014
	(0.05)	(0.04)	(0.03)
Controls and fixed effects	Yes	Yes	Yes
Observations	581,810	581,810	581,810
R-squared	0.695	0.625	0.649

Panel B: Controlling for omitted variables (city-level)

	(1)	(2)	(3)
Variable	*Ln(Patent)*	*Ln(Citation)*	*Ln(ExplorePat)*
Entrusted loan	0.201***	0.166**	0.136***
	(0.07)	(0.07)	(0.04)
GDP	0.286	0.302*	0.153

	(0.22)	(0.18)	(0.16)
GDP per capita	-0.002	0.051	-0.016
	(0.10)	(0.10)	(0.07)
Bank loans	0.063	0.059	-0.000
	(0.14)	(0.11)	(0.08)
Population	0.175	-0.126	0.078
	(0.25)	(0.17)	(0.12)
Gov. revenue	-0.003	-0.011	0.006
	(0.12)	(0.10)	(0.07)
Gov. expenditure	-0.074	-0.038	-0.051
	(0.10)	(0.08)	(0.06)
Controls and fixed effects	Yes	Yes	Yes
Observations	565,156	565,156	565,156
R-squared	0.699	0.635	0.652

Panel C: Test on reverse causality

	(1)	(2)	(3)
Variable	Ln(Patent)	Ln(Citation)	*Ln(ExplorePat)*
$Year^{-2}$	-0.038	0.009	0.017
	(0.09)	(0.08)	(0.06)
$Year^{-1}$	-0.034	0.106	-0.014
	(0.09)	(0.08)	(0.06)
$Year^{0}$	0.123	0.189*	0.085
	(0.11)	(0.11)	(0.07)
$Year^{+1}$	0.178**	0.188**	0.126**
	(0.08)	(0.08)	(0.05)
$Year^{+2}$	0.347***	0.312***	0.229***
	(0.10)	(0.10)	(0.06)
$Year^{\geq+3}$	0.273**	0.125**	0.114**
	(0.12)	(0.05)	(0.05)
Controls and fixed effects	Yes	Yes	Yes
Observations	581,810	581,810	581,810
R-squared	0.700	0.634	0.653

Table A4 Further identification attempt: quasi-natural experiment

This table reports the results of the identification attempt with the *Back-to-normal* policy shock as a quasi-natural experiment. 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. *Back-to-normal* is a dummy variable that equals one if the year is after the year of 2010, and zero otherwise. All regressions include the same control variables as those in Table 3, as well as interaction terms between *Back-to-normal* and all other variables, but they are not tabulated. Robust standard errors in parentheses are clustered by firm. The symbols ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
Variable	*Ln(Patent)*	*Ln(Citation)*	*Ln(ExplorePat)*
Entrusted loan × *Back-to-normal*	0.255**	0.075	0.117*
	(0.10)	(0.11)	(0.06)
Entrusted loan	0.036	0.109	0.061
	(0.08)	(0.10)	(0.05)
Controls and interactions	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	581,810	581,810	581,810
R-squared	0.709	0.636	0.663

Table A5 Heterogeneity tests

This table examines the heterogeneity in our baseline results based on the borrower's financial constraints, informational asymmetry, and takeover threat. 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. *FC score* is Howell (2016)'s firm-year-level financial constraint score calculated based on Euler equation approach. The dummy variable *High-tech* equals one if the firm belongs to a high-tech industry in year *t*, and zero otherwise. *M&A exposure* is the mean value of the number of M&A bids that the firm receives before borrowing an entrusted loan during the sample period. All regressions include the same control variables as those in Table 3, as well as their interactions with the newly added variable, but they are not tabulated. Robust standard errors in parentheses are clustered by firm. The symbols ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

Panel A: Financial constraints

	(1)	(2)	(3)
Variable	*Ln(Patent)*	*Ln(Citation)*	*Ln(ExplorePat)*
Entrusted loan × FC score	0.319**	0.060	0.204**
	(0.15)	(0.17)	(0.10)
FC score	-3.472*	-1.666	-2.513**
	(1.90)	(1.53)	(1.24)
Entrusted loan	-0.154	0.075	-0.087
	(0.17)	(0.20)	(0.11)
Controls and interactions	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	581,810	581,810	581,810
R-squared	0.710	0.638	0.664

Panel B: Informational asymmetry

	(1)	(2)	(3)
Variable	*Ln(Patent)*	*Ln(Citation)*	*Ln(ExplorePat)*
Entrusted loan × High-tech	1.375***	1.362***	0.647***
	(0.10)	(0.07)	(0.05)
High-tech	1.154	0.446	0.533
	(0.73)	(0.27)	(0.52)
Entrusted loan	0.164**	0.124*	0.116***
	(0.07)	(0.06)	(0.04)
Controls and interactions	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes

Year fixed effects	Yes	Yes	Yes
Observations	581,810	581,810	581,810
R-squared	0.700	0.632	0.653

Panel C: Takeover threat

	(1)	(2)	(3)
Variable	Ln(Patent)	Ln(Citation)	Ln(ExplorePat)
Entrusted loan × M&A exposure	0.698***	-0.137	0.539***
	(0.15)	(0.12)	(0.10)
Entrusted loan	0.168**	0.146**	0.115***
	(0.07)	(0.07)	(0.04)
Controls and interactions	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	581,810	581,810	581,810
R-squared	0.695	0.624	0.651