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Digital Technology, Legal Reforms, and Bank Lending

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ABSTRACT

The introduction of online collateral auctions through legal reform has established a more efficient bankruptcy resolution mechanism. This technology-driven change has enhanced the ex-ante value of secured loans, influencing the supply, demand, and composition of bank lending. Using granular loan-level data and staggered Difference-in-Differences (DiD) estimations, we find a significant shift from unsecured to secured loans, particularly among private firms with greater fixed assets, stronger credit ratings, and higher reliance on external financing. Meanwhile, interest rates on unsecured loans rise, while those on secured loans remain unchanged. The effects are more pronounced in bank branches facing higher competitive pressures, where lenders expand credit to capitalize on the increased value of secured loans. Following the reform, banks increased secured lending, improved risk-adjusted interest earnings, and attracted more private-sector firms.

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I. Introduction

In most economies, except for highly advanced ones like the U.S., bank lending remains the dominant form of financial intermediation. Banks assess borrowers' repayment capacity to guide lending decisions. To mitigate potential losses in the event of default, loans are often secured with collateral. Despite the current trend of using data as collateral in some regions, from a legal perspective, the efficacy of bank loans relies on (i) borrowers' legal ownership and ability to pledge collateral, (ii) the strength of creditors' rights, and (iii) an efficient legal process that allows banks to swiftly and effectively liquidate collateral in bankruptcy proceedings.

This paper examines the third component, which has received less attention in the literature. We argue that enhancing the efficiency of collateral liquidation can increase the value of pledged assets for lenders, thereby boosting ex-ante loan values. When lenders face lengthy judicial proceedings to liquidate collateral, its value can erode significantly—particularly if the insolvent borrower engages in opportunistic behavior.

Comprehensive legal reforms can be slow, thwarted by resistance, and generate unintended consequences. A more practical alternative is to harness digital technology. Modern IT systems enable broad market participation in auctions, making online collateral auctions a viable replacement for traditional offline procedures with just a simple court order. This shift facilitates faster, market-driven collateral sales, shortens bankruptcy proceedings, alleviates court congestion, and reduces potential judicial biases. As a result, collateral is liquidated more efficiently at fair market value, making bankruptcy resolution significantly quicker and less costly. Consequently, the expected value of secured loans increases, driving a shift from unsecured to secured credit. Credit availability may also expand for creditworthy borrowers with pledgeable assets. However, with a more efficient liquidation process, defaulting borrowers will have fewer opportunities to extract value from pledged assets. Anticipating the constraint, high-risk borrowers may self-select to apply for fewer loans.

The reform has far-reaching implications, particularly in China, where bank financing plays a central role in the economy. The country's adoption of online collateral auctions in bankruptcy proceedings is a striking example of how digital transformation can reshape the judicial system. China's broader digital revolution has enhanced access to legal services and equipped judges with advanced electronic search tools.

One of the most significant shifts has been in judicial auctions, which now allow widespread public participation. Platforms like Alibaba—China's equivalent of Amazon or eBay—facilitate court-ordered asset sales, making the process more transparent and efficient. Zhejiang province, home to Alibaba's headquarters, pioneered digital collateral auctions in 2013. With strong public support, this practice quickly spread to Intermediate People's Courts in other provinces. By 2016, the Supreme People's Court issued a nationwide directive mandating the full adoption of online auctions, and by the end of 2017, most cities had transitioned to digital platforms. Today, these auctions cover a wide range of assets, including vehicles, machinery, real estate, and equity or debt rights.

To examine the effects of the reform, we analyze loan-level data from one of the largest state-owned national banks between 2011 and 2017. Leveraging the staggered rollout of online collateral auctions across cities and regions, we uncover a chain of significant outcomes. The reform drives a shift from unsecured to secured loans, primarily led by privately owned enterprises (POEs), which comprise over 90% of borrowers.

We observe that the interest rate spread rises for unsecured loans while remaining unchanged for secured loans. Among POE borrowers, those with higher fixed assets, greater reliance on external financing, and stronger credit ratings are the key drivers of this shift in interest rate dynamics. POE borrowers with low credit ratings obtain fewer loans. Additionally, the default rate on unsecured loans declines, whereas the default rate on secured loans remains stable. Furthermore, these effects are more pronounced in bank branches operating in highly competitive environments, where market pressures push lenders to adjust their loan offerings. Overall, our findings suggest that the simple reform of implementing online collateral auctions enhances the ex-ante value of secured loans, reshaping loan demand and supply. Increased lending competition compels banks to respond strategically, benefiting creditworthy borrowers with pledgeable assets.

The reform also benefits banks. After a city adopts online collateral auctions, local bank branches expand their lending, increase the average loan size, and generate higher interest income—all driven by the growth of secured loans. This expansion is largely fueled by increased lending to creditworthy POEs with higher fixed assets and stronger credit ratings. Furthermore, we find evidence of enhanced financial inclusion: following the reform, more POEs enter the market, suggesting that the improved collateral liquidation mechanisms lower barriers to credit access.

The literature guides our work on the role of legal institutions in shaping credit behavior. Haselmann et al. (2010) examine bank lending in Central and Eastern European economies, finding that while legal reforms generally increase bank credit supply, collateral law plays a more crucial role than bankruptcy law in credit market development. This is because, while bankruptcy law ensures an orderly resolution of conflicting claims in insolvency, collateral law directly strengthens creditors' ability to enforce claims against insolvent debtors. Cerqueiro et al. (2016) find that a legal reform that exogenously reduced collateral values incentivizes banks to tighten credit limits and reduce the intensity of its monitoring of borrowers and collateral. Campello and Larrain (2016) show that the reform in Eastern European economies expanded the pledgeable assets to include movable assets, increased credit access, and investment and employment. Calomiris et al. (2017) find that the LTV of loans collateralized with movable assets is lower in countries with weak collateral laws and that lending is biased toward the use of immovable assets.

Building on this, Qian and Strahan (2007) show that loans have more concentrated ownership, longer maturities, and lower interest rates in counties with stronger creditor protection. Vig (2013) demonstrates that reforms accelerating creditors' liquidation of defaulting firms' collateral can benefit financially constrained borrowers by improving their access to credit. However, he cautions that some borrowers might reduce their borrowing or pledge less collateral for the same amount of secured debt, fearing that lenders could seize assets prematurely, leading to potential losses. Sautner and Vladimirov (2018) find that financially distressed firms are less exposed to indirect distress costs in the form of reduced access to credit when debt enforcement in bankruptcy is stronger.

Research on bankruptcy law reforms highlights the impact of judicial efficiency on financial access and firm investment. Chemin (2012) in India, Rodano et al. (2016) in Italy, Ponticelli and Alencar (2018) in Brazil, and Iverson (2018) and Muller (2022) in the U.S. demonstrate that improvements in court efficiency enhance credit availability and stimulate business investment. Favara et al. (2017) further emphasize that weak debt enforcement discourages risk-taking and incentivizes investment in distressed firms. Similarly, Brown et al. (2017) extend these insights to externally imposed courts in Native American reservations, showing that stronger legal enforcement improves credit markets and drives better economic outcomes. Schiantarelli et al. (2020) show that firms choose to delay payment to less healthy banks, and the effect is more pronounced when the legal enforcement of collateral recovery is slow.

There is a growing literature studying China's bankruptcy reform. Li and Ponticelli (2022) find that establishing specialized bankruptcy courts improves efficiency, leading to higher local employment and capital productivity. Liu et al. (2022) demonstrate that enhancing court independence and removing local government influence reduces protectionism and encourages cross-regional investment. Additionally, Hotchkiss et al. (2023) provide a comprehensive review of default and bankruptcy resolution practices in China. Liu et al. (2024) demonstrate that increased judicial transparency due to a mandatory online publication of court decisions promotes entry into entrepreneurship.

Our paper contributes to the literature by demonstrating that a straightforward improvement in bankruptcy resolution—adopting online collateral auctions—can significantly enhance access to credit, even without broader legal changes. This reform bypasses the lengthy and cumbersome bankruptcy procedures, avoiding costly competition between conflicting parties to influence judges and government officials. We show that expedited bankruptcy resolution generates downstream effects on the distribution of loan types and interest rate spreads, benefiting both qualified borrowers and banks. Additionally, our findings provide evidence that the reform encourages increased firm entries into the market.

The paper is structured as follows: Section II provides an overview of the online auction reform in China. Section III outlines our data sources. Section IV tests the hypothesis that banks shift their preference toward secured loans following the reform. Section V analyzes the impact of the reform on loan spreads. Section VI examines how market competition drives banks to adjust: the changes in loan interest rate spreads and default rates for secured and unsecured loans are most pronounced in areas with high bank competition. Section VII evaluates the aggregate performance at the branch level. Sections VIII and IX explore the broader implications of the reform, focusing on how both banks and firms benefit. Finally, Section X concludes.

II. Online Auction Reform in China

The judicial auction system is a process in which courts, during the enforcement of civil cases, order public auctions to liquidate a debtor's assets in order to repay creditors. In theory, this system can help bypass the tendency of some bankrupt debtors to conceal assets or delay compliance with court orders to sell assets. China formally established the auction system as part of its bankruptcy enforcement mechanisms under the 1991 Civil Procedure Law. The traditional practice is that courts delegate the auction process to third-party auction companies, which appraise the asset values and then conduct the auctions. This approach had several significant drawbacks, including limited public participation, high operational costs, low transparency, and susceptibility to corruption.

In July 2012, the Primary People's Court of Beilun District and Yinzhou District in Ningbo, Zhejiang Province, partnered with Alibaba Group to conduct the first online auction via the Taobao platform. In August 2012, the Civil Procedure Law was revised to prioritize the use of auctions in enforcing civil cases. This revision also eliminated the mandatory requirement for courts to delegate auctions to third-party companies, granting courts the authority to organize auctions independently. As explained below, the initiative in Ningbo proved popular, especially among lenders. The success of this initiative led to its adoption across Zhejiang and Jiangsu provinces, eventually being implemented nationwide.

In 2016, the Supreme People's Court mandated the full adoption and further refinement of auction procedures across all Intermediate Courts. By the end of 2017, most prefecture-level courts in China had implemented the online auction model. These online auctions cover a wide range of items, including vehicles, machinery, residential and commercial properties, equity, debt rights, mining rights, and more. By October 2024, courts nationwide had conducted 9.73 million online auctions, generating a total transaction value of 29.4 trillion yuan, with a success rate of 63.72%. This transition saved participants an estimated 89.7 billion yuan in commission fees compared to the traditional entrusted auctions.

The reform, which allows judges to directly appoint an online platform for conducting auctions of defaulted borrowers' collateral, provides significant benefits to lenders. First, appointing a known, impartial platform for open-bid auctions eliminates the need for contracting parties with delinquent loans to spend on influence judges or auction companies. The change thus reduces corruption risks for judges and the contracting parties. Second, online auctions streamline liquidation by bypassing traditional bottlenecks, cutting transaction costs, and accelerating compensation recovery. This faster resolution mitigates borrower opportunism—such as neglecting collateral maintenance—thereby preserving asset value. Third, online auctions attract a wider pool of bidders, ensuring fairer, market-driven pricing and reducing reliance on bankruptcy administrators and third-party auction firms.

Additionally, adopting online auctions accelerates bankruptcy proceedings. In China, when a debtor (an enterprise legal person) defaults on its debts, creditors may file an application with the court for reorganization or liquidation (for details, see Li and Ponticelli (2022)). The court is typically located where the debtor is domiciled. Upon accepting a bankruptcy application, the court designates a bankruptcy administrator, which may be a liquidation group from relevant departments or a social intermediary agency such as a law firm, accounting firm, or bankruptcy liquidation firm. The committee then determines whether to order reorganization, liquidation, or both. The swift and competitively valued collateral recovery through online auctions empowers both judges and committees to resolve cases more quickly, helping to reduce the buildup of backlog cases.

Thus, integrating online collateral auctions into bankruptcy proceedings accelerates resolution, reduces corruption risks, lowers transaction costs, and increases recovery value. The implications are wide-reaching. First, higher recovery values enhance the ex-ante value of secured loans, encouraging lenders to favor secured over unsecured lending. Second, this benefits borrowers, allowing them to secure larger loans or lower interest rates based on the same tangible assets. Borrowers with pledgeable assets – especially those previously constrained – will gain greater financial access, promoting financial inclusion. These changes will likely shift loan compositions, interest rate spreads, and bank lending strategies, effects that the following empirical analysis will explore.

III. Data

Our primary analysis is based on loan-level data from one of China's five major state-owned commercial banks, covering loan issuance from 2011 to 2017. We obtained a random 10 percent sample of the bank's manufacturing loans, which is representative of the broader Chinese market. The dataset spans firms across all thirty-one provinces, encompassing a diverse range of sizes, ownership types, and industries. It includes comprehensive details on each loan, such as loan type, credit spread, loan amount, maturity, default status, and information on the borrowing firms' names, locations, and credit ratings.

To obtain information on firm financial conditions, we merge the bank loan data with the Annual Survey of Industrial Firms (ASIF), a comprehensive and widely used dataset maintained by the National Bureau of Statistics of China (NBSC). The ASIF provides detailed data on various aspects of firms, including ownership structure, employment, gross output, industry, and firm identification (e.g., company name and organization code). Additionally, it includes information from the three primary financial statements—balance sheets, profit and loss accounts, and cash flow statements—allowing for a thorough analysis of the firms' financial health.

Our data on online reform auctions is manually collected from the Taobao court auction platform, owned by Alibaba Group. Alibaba was the first online platform to partner with Chinese courts to facilitate digital auctions, and as of 2020, it dominates the market with an 85% share among the seven platforms authorized by the Supreme People's Court of the People's Republic of China. Given its market leadership, we rely on the Taobao court auction platform as our primary source for determining the reform adoption dates. Alibaba maintains a comprehensive list of all courts conducting online auctions through the platform, categorized by their hierarchical levels: the High People's Court (provincial level), the Intermediate People's Court (prefectural level), and the Primary People's Court (county level).

Our study focuses on prefecture-level cities, which represent the second tier in China's local government hierarchy, as most legal cases are adjudicated at this level. For each court, we identify the date of the first online auction based on records of announcements. We prioritize the actual date when a court first conducted an online auction, rather than the date when the court publicly announced its partnership with Alibaba through media channels. In the case of directly-administered municipalities (Beijing, Chongqing, Shanghai, and Tianjin), each of which has multiple Intermediate People's Courts, we select the earliest online auction date across all courts within the municipality. Our data encompasses 357 courts, including 333 prefecture-level courts, 4 directly-administered municipalities, and 20 counties governed directly by provincial authorities.

The Taobao online court auction platform was launched in in Zhejiang Province, the home of Alibaba Group, which became the first region to implement online auctions. As illustrated in Figure A1 in the appendix, the adoption of online court auctions expanded gradually from 2013 to 2017. By the end of 2013, all prefectures in Zhejiang, some in Jiangsu Province, and Kunming city in Yunnan Province had started conducting online auctions. The reform subsequently spread to other prefectures, especially in eastern China. By the end of 2017, the online auction system had been adopted in the majority of prefectures nationwide.

Table I provides a summary of our variables. The final sample spans from 2011 to 2017. To mitigate the impact of extreme values, we winsorize the key loan characteristics at the bottom and top 1 percent. Since the ASIF data have not been updated after 2013, we report the Producer Price Index (PPI) adjusted financial variables averaged over 2007 to 2012 as the baseline firm conditions before the reform.

Table II presents the summary statistics for the loan-level data. After merging the loan data with the ASIF dataset, the final sample consists of approximately 174,000 loans. Over 90% of the borrowers in our sample are privately owned enterprises (POEs), while state-owned enterprises (SOEs) account for less than 10%. The average loan spread is 0.61, with the median at 0.56. Loan sizes exhibit a left-skewed distribution, with the mean of the logarithm of loan amounts at 1.171 and the median at 1.281. The non-performing loan (NPL) ratio stands at 4%, which is relatively low compared to the national average of 5.2% in 2017, reflecting the fact that large banks typically experience lower NPL rates.

IV. Loan Composition Analysis

We begin our empirical analysis by investigating whether banks are more inclined to favor secured loans over unsecured loans following the implementation of the online auction system. To achieve this, we aggregate the loan-level data to the branch level and analyze how the composition of each branch's loan portfolio evolves over time. We hypothesize that, after the reform, there will be an increase in the proportion of secured loans within banks' portfolios.

The model specification is the following:

$$Y_{bt} = \alpha + \beta Online_{bt} + \gamma X_{bt} + \eta_b + \phi_t + \varepsilon_{bt} \qquad (1)$$

where b indicates bank branch and t indicates year.

The dependent variables in our analysis are as follows: (1) the share of secured loans relative to total loans, (2) the share of secured and unsecured loans for private-owned enterprises (POEs) relative to total loans, and (3) the share of secured and unsecured loans for state-owned enterprises (SOEs) relative to total loans. The primary independent variable of interest is the "online" dummy, which takes a value of one if the city where the branch is located has adopted the online auction reform.

To control for branch size, we include the logarithm of the total lending volume for each branch. We also account for unobserved heterogeneity across branches and years by including branch-fixed and year-fixed effects, respectively. Additionally, we cluster standard errors at both the city and year levels to account for potential correlations in errors within these units.

Our identification strategy hinges on the assumption that the decision to adopt online judicial auctions at the prefecture-level city level is exogenous to both current and anticipated future economic conditions in the region. We justify this assumption by emphasizing that the decision is primarily driven by senior judicial officials at the provincial level (High People's Court) or the national level (Supreme People's Court) as part of broader judicial reforms mandated by the central government. These reforms aim to increase the transparency and openness of judicial enforcement processes, with no explicit economic considerations cited as a determining factor. This exogeneity is further supported by Zhao et al. (2022), who demonstrate that the judicial reform – including the establishment of interprovincial circuit tribunals – shows no correlation with local economic indicators such as GDP per capita or the ratio of government expenditure to GDP.

Table III presents the regression results. Column 1 examines the share of secured loans relative to total loans. As expected, the share of secured loans significantly increases following the online reform. The magnitude of this effect is economically meaningful, rising by approximately 6 percent relative to the mean. In Columns 2 through 4, we further decompose the loan data into four categories: POE secured, POE unsecured, SOE secured, and SOE unsecured. The results show that the increase in the share of secured loans is primarily driven by a rise in POE secured loans and a decline in POE unsecured loans. In contrast, the changes in SOE secured and unsecured loans, while in the same direction, are marginal and statistically insignificant. This pattern aligns with the notion that POE firms, which are more likely to face financial constraints, are more sensitive to changes in collateral value. Additionally, since SOEs benefit from government ownership and connections, we expect that legal reforms impact lending to POEs more than to SOEs.

Additionally, we perform an event study to examine the shift in loan composition around the reform year. We define the first year of the online auction system's introduction as $T = 0$, with the year preceding the reform serving as the benchmark. Figure 1 (a) illustrates the dynamics of loan composition over time, confirming our regression findings. The share of secured loans rises sharply following the reform, continuing to increase before stabilizing after about two years. Figure 1 (b) further confirms that the share of POE secured loans increased, while the share of POE unsecured loans declined immediately after the reform.

Our results are robust in two senses. First, we find qualitatively identical results if we aggregate the unit of analysis from the branch level to the city-level.

Second, we examine and account for heterogenous treatment effects. Recent studies highlight that in a staggered difference-in-differences (DID) setting, the two-way fixed effects model may yield biased estimates if treatment effects vary across time periods (Sun and Abraham (2021); Callaway and Sant'Anna (2021); Goodman-Bacon (2021)). To address this, Sun and Abraham (2021) introduced the Interaction-Weighted (IW) Estimator, which uses "never-treated" or "not-yet-treated" samples as controls, avoiding the use of groups that were treated earlier and mitigating the problem of negative weights. Additionally, Borusyak et al. (2024) proposed the Imputation

Estimator to better account for treatment effect heterogeneity in staggered DID settings. In light of this, we re-estimate Equation (1) and plot the dynamic effects, utilizing the methods proposed by Sun and Abraham (2021) and Borusyak et al. (2024). As shown in Figure A2 in the appendix, after accounting for heterogeneous treatment effects, the online reform significantly increased the share of secured loans. Moreover, there is no notable difference between the treatment and control groups prior to the reform.

V. Loan Interest Rate Spread Analysis

This section examines the reform's impact on loan interest rate spreads. We apply the difference-in-differences (DID) regression controlling for firm-, branch- or city-, and year-fixed effects. This approach enables us to compare the changes in interest rate spreads for secured and unsecured loans within the same branch before and after the reform, while controlling for firm-specific and local economic conditions. The model specification is as follows:

$$R_{ijbt} = \alpha + \beta Online_{bt} + \theta Online_{bt} * Secured_{ijt} + \kappa Secured_{ijt}$$
$$+\gamma X_{ijt} + \zeta Z_j * \phi_t + \delta_j + \eta_b + \phi_t + \varepsilon_{ijbt} \qquad (2)$$

where i indicates loan, j indicates firm, b indicates bank branch, and t indicates year.

The dependent variable is the loan spread in the basis point, which is the difference between the loan's interest rate and the benchmark interest rate set by the People's Bank of China. The central bank sets the benchmark rate, a reference rate for financial sectors, to define the country's credit price. For example, when a firm borrows at a spread of 100 basis points, and the benchmark interest rate is 5% pa, the firm pays the lending bank 6%, pa. The online dummy ($Online_{bt}$) equals one if the city where the branch is located adopted the online auction reform, and zero otherwise. The secured dummy ($Secured_{ijt}$) equals one for mortgage- and pledge-type loans, and zero for unsecured loans. The variables of interest are the online dummy and the interaction term between the online and secured dummy. The online dummy captures the reform's effect on the spread of unsecured loans, while the sum of the coefficients for the online dummy and the interaction term reflects the reform's impact on the spread of secured loans.

To account for other loan characteristics, X_{ijt}, we include several control variables that capture key aspects of a loan contract, such as the loan amount and maturity (both in logarithmic form) and loan type fixed effects.

We use borrowing firm fixed effects (δ_j) to control for borrower firm-specific invariant factors that may affect loans. Additionally, we want to control for the variation in demand driven by firm-specific characteristics over time. Due to data limitations, we lack information on the time-varying firm balance sheet over the sample period. Instead, we create interactions between year dummies and firm-level initial characteristics (Z_j), such as firm size, leverage, and the ratio of fixed assets to total assets, to proxy for firm-specific factors that may affect loan terms. This approach allows us to control for the variation in demand driven by firm-specific characteristics over time.

Additionally, we incorporate city-fixed and, more robustly, branch-fixed effects (η_b) to control for unobserved heterogeneity at city or branch levels, such as location-specific economic conditions or branch-specific supply-side characteristics.

Finally, we include year-fixed effects to account for any macroeconomic or temporal trends that could influence loan terms. We employ two-way clustering at the city and year level to ensure robust standard errors.

Table IV presents our benchmark regression results. Column 1 includes only the online reform dummy and its interaction with the secured loan dummy, along with city, firm, and year fixed effects. The results show that the interest rate spread of unsecured loans increases, but the spread of secured loans does not change significantly after the reform. Column 2 adds loan characteristics such as ln(loan amount) and ln(loan maturity). In Column 3, we replace city-fixed effects with branch-fixed effects to account for additional unobservable characteristics at the branch level. We also add the borrower firm fixed effects. In Column 4, we add the interactions between the year dummies and firm-level initial characteristics (such as firm size, leverage, and the ratio of fixed assets to total assets), which leads to the dropping of year fixed effects to avoid collinearity. This specification mitigates concerns regarding potential changes that might be correlated with firm characteristics. All columns show qualitatively similar coefficients for the online dummy and the cross-term of the online and secured dummy. In both Columns 3 and 4, while the coefficients change slightly from those in Columns 1 and 2, their signs and significance levels remain. Also, the sum of the two coefficients in both columns remains statistically insignificant.

Thus, the columns in Table IV show a robust pattern: after the reform, the interest rate spread for unsecured loans increases while the interest rate spread for secured loans remains flat. The increase in the spread of unsecured loans is consistent with the shift of bank credits from unsecured to secured loans. The reform increases the ex-ante value of secured loans, necessitating a higher spread for the marginally retained unsecured loans.[1] The lack of change in the spread of secured loans is consistent with the observation that, after the online reform, both the demand for and supply of secured loans increased with an offsetting effect on the equilibrium interest rate.

Traditionally, SOEs and POEs in China are treated differently in the capital market. SOEs enjoy preferential treatment because of state ownership and backing. The impact of online collateral auction reform on SOEs is unclear. With or without the reform, few lenders take SOEs to court to press for bankruptcy hearings. However, that does not mean that SOEs are unaffected by the reform because the interest rate spread SOEs face is tied to the equilibrium spread that POEs face. Hence, we repeat

[1] The marginally retained unsecured loan may also have a lower default risk. We shall show later that is the case.

the DID regressions in Table IV Column 4, using split samples: SOEs and POEs. Table IV Columns 5 and 6 report these results. Column 5 is based on the SOEs, and column 6 is based on POE subsamples. The patterns of coefficients in both columns are qualitatively identical to those in Table IV, Column 4.

Given that any reforms in bankruptcy law are likely more applicable to POEs and that the ratio of POEs to SOEs in our sample is greater than 10 to 1, we restrict our attention to POE firms from hereon in investigating the drivers for the observed changes in interest spreads. We begin by analyzing how POE firms' characteristics are associated with the changes in interest rate spreads. Specifically, we examine the role of asset structure, external finance dependence, and creditworthiness in influencing the reform's impact.

We use historical measures to capture firm characteristics to avoid endogeneity. Asset structure is measured by the ratio of fixed assets to total assets at the firm level, averaged over 2007 to 2012. Firms in the top third of this ratio are classified as "high fixed asset ratio" firms, while those in the bottom third are categorized as "low fixed asset ratio" firms. External finance dependence is assessed at the four-digit industry level, using the ratio of capital expenditures minus own funds to capital expenditures. The measure is constructed using 2012 data from the Statistical Yearbook of the Chinese Investment in Fixed Assets. A firm is classified into "high external finance dependence" or "low external finance dependence" groups based on its industry's position in the top and bottom thirds of the sample. Creditworthiness is determined by credit ratings, with firms rated AA- or above classified as "high rating" and those rated BBB+ or below as "low credit ratings." The rating scores were assigned to each firm by the bank over the sample periods of 2007 and 2012.[2] Although we could pool the full sample for regression analysis, this would result in numerous cross-term interactions that are difficult to interpret. Instead, we run specifications using sub-samples based on the groupings above, allowing for clearer and more intuitive comparisons.

Table V compares firms with high versus low fixed asset ratios and adopts the specification as in Table IV, Column 4. Columns 1 and 2 present the results for firms with high and low fixed asset ratios. The results clearly show that POEs with high fixed assets drive the results in Column 4 Table IV. Column 1 indicates that, following the online auction reform, POEs with high fixed assets experience a significant increase in the interest rate spread of their unsecured loans, while the interest rate spread on their secured loans remains unchanged. Column 2 shows that for POEs with low fixed assets, the key coefficients for *online* and the *online x secured* variables exhibit a similar pattern as in Column 1 but attain a much smaller magnitude. Both the t-test and Fisher Permutation

[2] The rating scores do not change over the period. We can classify firms into high or low credit rating groups according to their one-year lagged ratings. The results do not change because the ratings turn out to be very stable. Only 0.05% of the ratings changed.

test confirm that the two key coefficients in Columns 1 and 2 are statistically significantly different. These results highlight that the reform, which raises only the value of secured loans, affects interest spread in lending to POEs with more fixed assets.

Table VI examines how the impact of the online reform varies based on POEs' external finance dependence. Columns 1 and 2 present the regression results for POEs in high and low external finance dependence industries. The findings reveal that high external finance dependence POEs experience a significant increase in the interest rate spread on unsecured loans, while the spread on their secured loans remains unaffected. For low external finance dependence POEs, although the *online x* secured variable attracts a positive and significant coefficient, both secured and unsecured loans show economically minimal and statistically insignificant changes in interest rate spreads. Both the t-test and Fisher Permutation test show that the two key coefficients in Columns 1 and 2 are statistically significantly different. These results highlight that the reform impacts interest rate spread in lending to external finance-dependent POEs.

Table VII investigates the heterogeneous effects of the reform based on the creditworthiness of POEs. Columns 1 and 2 present the regression results for high- and low-credit rating POEs. As in previous tables, the findings show that high credit rating POEs largely drive the results observed in Table IV. Specifically, after the online auction reform, the interest rate spread on unsecured loans for high credit rating POEs increases significantly, while the interest rate spread on their secured loans remains unchanged. In contrast, the interest rate spreads for both unsecured and secured loans of low credit rating POEs exhibit minimal change after the reform. Both the t-test and Fisher Permutation test affirm that the two key coefficients in Columns 1 and 2 are statistically significantly different. These results highlight that the reform impacts interest rate spread in lending to POEs with high creditworthiness.

Results in Tables V to VII are robust in two senses. First, we aggregate the units of analysis from branches to cities and find qualitatively similar results. Second, we re-estimate the regressions and examine the dynamic effects using the methods proposed by Sun and Abraham (2021) and Borusyak et al. (2024). After accounting for heterogeneous treatment effects, the online reform still significantly increased the interest spread of unsecured loans while the sum of the coefficients of online and online x secure remain insignificant. Moreover, there is no notable difference between the treatment and control groups prior to the reform.

Figure 2 Panels a, b, and c provide a more detailed visualization of the heterogeneous effects based on Fixed Asset Ratio, External Finance Dependence, and Credit Rating. The vertical axis represents the change in interest rate spread, while the horizontal axis captures the levels of Fixed Asset Ratio, External Finance Dependence and Credit Rating for secured loan borrowers in panels a, b, and c, respectively. The blue dotted line illustrates the increasingly negative impact of the interaction term between the online reform and secured loan dummy on the interest rate spread, highlighting how the reform's effects vary across different borrower characteristics.

The results in this section align closely with those presented earlier. Following the adoption of online auctions for bankrupt borrowers' assets, we observe a substitution of secured loans for unsecured loans, as the reform enhances the ex-ante value of secured loans. This leads to an increase in the interest rate spread on unsecured loans, reflecting that unsecured loans have to pay higher interest rates to match the increase in the ex-ante value of secured loans post-reform. Given that our sample consists mainly of POEs, which are more affected by the reform than SOEs, we focus on POEs in our analysis. We find that the changes in interest rate spreads between secured and unsecured loans are primarily driven by POEs with high fixed assets, high external finance dependence, and strong credit ratings. Conversely, POEs with low fixed assets, low credit ratings, and low external finance dependence show little to no significant changes in the interest rate spreads of either secured or unsecured loans.

The distinct impact of the reform suggests that credit markets are segmented along key dimensions, including borrower fixed assets, reliance on external finance, and creditworthiness. This segmentation is puzzling if lendable funds are truly fungible within a branch, across clusters of branches in a city, or throughout the entire banking network. A deeper investigation is warranted.

VI. Lending Market Competition, interest rate spread, and default risk

The changes observed above can be attributed to that adopting online auctions for bankrupt borrowers' assets enhances the ex-ante value of secured loans. This, in turn, triggers shifts in both the demand and supply of secured and unsecured loans. A more detailed analysis based on a structural equilibrium model could provide further insights, which will be explored in future research.

In this section, we present two helpful observations. Our analysis is grounded in the idea that competition in the lending market significantly influences bank behavior. In less competitive environments, banks are better positioned to fully benefit from the heightened ex-ante value of secured loans due to the reform. However, in more competitive markets, banks may be compelled to pass on some of the benefits to qualified borrowers. Therefore, we first examine whether a bank branch's competition pressure affects the post-reform interest rate spreads of the loans the branch grants. We then examine whether the competition affects the quality of the loans a branch grants after the reform.

Table VIII presents the regression results for interest rate spreads, following the specification in Table IV, Column 4. We assess a bank branch's level of competition based on the number of commercial bank branches within a 5-kilometer radius. To standardize the data, we normalize each observation using the formula: (own count – minimum count) / (maximum count – minimum count). To avoid overly complex and non-intuitive displays involving multiple cross-terms, we perform a tertiary split of the sample instead of using the full sample. Columns 1 and 2 of Table VIII report the results for the highest and lowest competitive pressure subgroups, respectively. Column 1 shows that branches facing high competition drive the results observed in Table IV: specifically, after the reform, unsecured loan interest rate spreads increase, while secured loan spreads remain largely unchanged. In contrast, Column 2 shows that branches with low competition experience only marginal changes: the reform's impact on interest rate spreads is insignificantly positive for unsecured loans and insignificantly negative for secured loans.

We use the regression specification from Equation 1 to analyze loan default risks. In this case, the dependent variable is a binary indicator for default risk, which takes the value of one if a loan is classified as "special mention," "substandard," "doubtful," or "loss" at the end of the issue year, and zero otherwise. The regression follows the same structure as Column 4 in Table IV, controlling for time-varying firm conditions by including interactions between year dummies and initial firm characteristics such as firm size, leverage, and the fixed asset ratio. Given the large number of fixed effects in the model, we estimate a linear probability model instead of a logit or probit model.

Table IX, Column 1 presents the regression results for the full sample. The coefficient of the online reform dummy indicates a significant decrease in the probability of default for unsecured loans following the reform. However, there is no significant change in the probability of default for secured loans, as the sum of the coefficients for the online dummy and the interaction term between the online dummy and the secured dummy is not statistically different from zero.

We replicate the regression from Table IX, Column 1, to examine loan default risk across high- and low-bank competition sub-samples. Column 2 shows that branches facing high competition experience an increased default risk for unsecured loans after their domicile cities adopt the online reform, while the default risk for secured loans remains unchanged. In contrast, Column 3 reveals that branches facing low competition show minimal changes in default risk for both secured and unsecured loans following the adoption of the online auction reform in their domicile cities. Both the t-test and Fisher Permutation test confirm that the two key coefficients in Columns 2 and 3 are statistically significantly different.

In summary, this section demonstrates that when a location adopts online collateral auctions, market competition compels bank branches to adapt to the changes brought about by the reform. The reform enhances the ex-ante value of secured loans, driving increased demand for these loans. Competitive pressure pushes branches to respond, leading to some shift from unsecured to secured lending. As a result, remaining unsecured loans booked on these branches have higher interest rate spreads and reduced default risk. In contrast, secured loans experience minimal changes in both interest rate spreads and default risk, indicating offsetting shifts in demand and supply. The reform does not seem to affect branches facing low competition.

VII. Impact on Bank Branches

This section examines the impact of the reform on the lending business of bank branches. We use the following model specification:

$$Y_{bt} = \alpha + \beta Online_{bt} + \gamma X_{bt} + \eta_b + \phi_t + \varepsilon_{bt} \qquad (3)$$

where Y_{bt} can be branch-level total loan amount, average loan size, and interest income. We include branch- and year-fixed effects and cluster the standard errors at the city and year levels.

Panel A of Table X shows the total loan amounts issued at the branch level, revealing a noticeable increase in total lending following the online reform. We then break down the results by loan type: Column 2 focuses on secured loans, and Column 3 on unsecured loans. The data indicate that while total secured lending rises, the volume of unsecured loans remains stable. These results suggest that the growth in total lending was primarily driven by the increase in secured loans, further supporting the earlier finding of a shift in loan composition toward secured loans.[3]

Panel B of Table X examines the average loan amounts for all loans, secured loans, and unsecured loans. The coefficients for the online dummy are positive and statistically significant in both the "all" loans and "secured" loans columns but not in the "unsecured" loans column. This pattern suggests that, following the reform, branches issued larger secured loans, driving up the observed average loan size. Previously, we found that secured loans showed no significant changes in interest rate spreads or default risk after the reform. The current result, therefore, aligns with the idea that lenders became more willing to grant larger loans for the same pledged assets post-reform.

Panel C of Table X examines interest income at the branch level following the online reform. The results show that interest income increases in tandem with the rise in lending volume and average loan size. This pattern is evident for all loans and secured loans, but not for unsecured loans. These findings suggest that the reform significantly increases bank lending in secured loans, leading to larger average loan sizes and higher interest earnings for banks.

Having established that a city's adoption of the online auction reform benefits its branches

[3] We acknowledge that our findings differ from those in highly advanced economies like the U.S. Benmelech (2024), in his literature review, notes that in the U.S. credit market, listed firms with low credit ratings are more likely to use secured debt. This suggests that U.S. listed firms preserve collateral slack as a form of insurance or untapped liquidity for difficult times. In contrast, credit behavior in bank-dominant economies may follow a different pattern. In China, secured loans are often the preferred choice due to their lower funding costs. Thus, demand for them increases after the online auction reform for collateral increases the ex-ante value of collateral loans.

through increased secured lending, we now examine which types of firms are receiving these loans. Specifically, we analyze lending patterns based on POE firm classifications by fixed asset ratio (Panel A), external finance dependence (Panel B), and credit rating (Panel C). At the branch level, total lending increased for POE firms with both high and low fixed asset ratios, though the increase is insignificantly smaller for the latter subgroup. The contrast is more pronounced when comparing firms by credit rating—secured lending rises significantly for high credit rating POE firms, while the change for low credit rating firms was negligible. Interestingly, we find no significant difference in secured loan volumes between POE firms in high or low external finance-dependent industries.

These patterns suggest that branches benefit from the adoption of online collateral auctions. Following the reform, they have issued more secured loans, both in terms of average loan size and total volume. Consequently, overall interest earnings have increased due to the rise in secured lending. Branches have also been able to cherry-pick, primarily granting larger secured loans to POEs with higher fixed assets and stronger credit ratings, but not necessarily to those in external finance-dependent industries. Since earlier sections show no change in default rates for these secured loans, we can infer that the reform benefits the bank.

VIII. Impact on Firm's Credit Access and General Firm Entry

POE Firms' Credit Access

This section completes our investigation into the impact of adopting online auctions of collaterals on borrowers. Our empirical results support that the reform raises the ex-ante value of secured loans. We find that after the reform, there has been a shift from unsecured to secured loans and an increase in overall secured lending. Lending to POEs primarily drives the change. Furthermore, after the reform, POEs have gained greater access to secured bank loans, particularly for those with good credit ratings; they secure larger loan amounts without incurring higher interest spreads.

To provide a more comprehensive perspective, we turn our attention to firms with lower credit ratings. By expediting the liquidation of pledged assets in the event of delinquency, the reform enhances creditor rights by restricting a defaulting borrower's ability to extract value from collateral. As a result, the reform lowers the ex-ante value of loans for high-risk borrowers, who may then choose to borrow less (Vig 2013). In this context, reduced credit access for higher-risk borrowers could represent an efficient market outcome.

We conduct a logit regression examining how the reform affects POEs' access to bank loans. We particularly pay attention to POEs that are more likely to have reduced access to bank credit after the reform: firms with low fixed assets and credit ratings. Table XII reports these logit regression results. The sample includes all POE firms ever included in our bank's sample from 2011 to 2017[4]. The dependent variable is LoanDummy, which equals one if a firm received a loan in a given year. There are two key independent variables besides the online reform dummy: (i) LowFA equals one if a firm's fixed asset ratio is in the lowest third and its industry is in the highest third for external finance dependence, and (ii) LowRating equals one if a POE firm's credit rating is BBB+ or below and its industry is in the highest third for external-finance dependence. The regressions include firm- and year-fixed effects, and standard errors are clustered by year and firm.

The coefficient for the online dummy in Columns 1 to 3 consistently indicates that POEs are more likely to obtain bank loans following the online auction reform. This finding supports the idea that the reform enhances the value of secured loans, potentially leading to an overall increase in bank lending to POEs.

Column 1 further shows that while the interaction term online × LowFA is negative and insignificant, the sum of the coefficients for online and online × LowFA is positive and significant. This result aligns with the findings in Table IX, demonstrating that even POEs with low fixed assets secure more loans after the reform. Column 2 reveals that the interaction term online × LowRating is negative and significant, and the sum of the coefficients for online and online × LowRating is also negative and highly significant. These findings suggest that POEs with low credit ratings face reduced access to bank credit post-reform. Similarly, Column 3 reinforces this pattern: post-reform POEs with low credit ratings have less access to bank credit, while POEs with low fixed assets – but not poor credit ratings – do experience greater access to bank credit.

These results from Columns 1 to 3 of Table XII suggest a possible improvement in credit allocation efficiency: following the reform, bank loans shift from riskier borrowers to those with stronger creditworthiness.

However, caution is warranted: a decline in credit access, even through self-selection, could negatively impact firms in industries that heavily rely on external finance. To examine this, we extend the regressions in Columns 1 to 3 by incorporating additional explanatory variables.

First, we introduce the interaction term online × HighEFD, where HighEFD is a binary variable equal to one if a POE's industry falls within the top third of the external finance dependence measure. Next, we add the triple interaction term online × LowFA × HighEFD to the regression in Column 1, presenting the results in Column 4. Similarly, we introduce the triple interaction term online × LowRating × HighEFD in Column 2, with results reported in Column 5. Finally, Column 6 includes all interaction terms. These regressions aim to determine whether POEs in highly finance-dependent industries experience a disproportionate reduction in access to bank credit following the

[4] We admit that the sample excludes borrowers who apply for a loan but are never granted a loan. However, within this sample, we can capture the change in a sample member's probability of getting a loan from the bank.

reform.

We first observe that the interaction term online × HighEFD is negative but entirely insignificant. This suggests that the increase in POEs' access to loans following the reform, as reflected in the positive and significant coefficient on the online dummy, is not influenced by their external finance dependence.

Moreover, the core findings from Columns 1 to 3 remain unchanged after introducing interaction terms to account for HighEFD. Specifically, all POEs experience a higher probability of obtaining a loan, except for those with low credit ratings, which face a decline. An additional insight is that HighEFD status exacerbates the drop in loan access for low-rated POEs, highlighting a potential constraint on credit availability for riskier firms in finance-dependent industries.

Firm Entry

In developing economies, financial inclusion is crucial for fostering entrepreneurship. Financial constraints—such as limited access to credit, insufficient collateral, and high borrowing costs—can severely hinder business creation and growth. Many entrepreneurs struggle to start or expand their ventures due to inadequate financial support.

The results in Table XII indicate that while adopting online collateral auctions improves firm access to bank credit, firms in highly external finance-dependent industries with low credit ratings continue to face significant financial constraints. This raises an important question: does the reform facilitate firm entry, recognizing that firm entry serves as a key indicator of financial inclusion?

To proceed, we examine administrative data on firm registrations, which provides a reliable measure of new business creation. We proceed with the following regression:

$$Y_{ct} = \alpha + \beta Online_{ct} + \gamma X_{ct} + \eta_c + \phi_t + \varepsilon_{ct} \qquad (4)$$

The dependent variable is the number of firm registrations in a city c and year t. City- and year-fixed effects are included in the regression, and standard errors are clustered at the provincial level.

Table XII examines the number of firm registrations for SOEs in Column 1 and POEs in Column 3, respectively. The results indicate that POE firm registrations increase significantly after the online reform, while SOE registrations show no such change. This is not surprising, as SOEs typically have greater access to financing and are less constrained by capital limitations than POEs. As a robustness check, we advance the reform year by two years and re-estimate the regression using a "false reform" dummy. None of the coefficients from this regression are statistically significant, suggesting that the observed effects are not driven by confounding factors unrelated to the reform.

IX. Conclusion

The rapid advancement of technology is transforming various facets of society and the economy. With the rise of online platforms, individuals now rely on digital tools for everyday activities—ranging from purchasing goods and services to making doctor appointments, paying utility bills, and participating in financial markets. Drawing on these technological advancements and user experiences, courts can adopt online auction platforms to liquidate a defaulting borrower's collateral, efficiently compensating creditors. This shift requires no changes to the existing legal framework; it simply involves an order to transition from the traditional, costly, and protracted judicial process to a more streamlined and effective online sell-off method. Under the old system, collateral values often depreciate significantly, particularly when defaulting borrowers act opportunistically. In contrast, online auctions offer a swift, transparent process with widespread participation, resulting in lower transaction costs and faster recovery of fair market value for creditors in the event of default. This change strengthens creditor rights, increasing the ex-ante value of secured loans. As a result, the adoption of online auctions is likely to drive shifts in both the demand and supply of secured and unsecured loans.

This paper investigates the impact of adopting online court auctions for liquidating defaulting borrowers' collateral. Our identification strategy is to utilize China's staggered city-by-city adoption of the practice. According to public documents, the decision to adopt the change is not directly related to economic conditions, a statement supported by prior empirical work. Our analysis draws on a large, representative sample of loan-level data from a major national bank. Using staggered Difference-in-Differences (DID) regressions, we find a significant increase in secured loans and a substitution of secured for unsecured loans, with the observed changes primarily driven by POEs' borrowing.

We find that, following the adoption of online collateral auctions, unsecured loans experience higher interest rate spreads but lower default rates. This suggests that the remaining unsecured loans adjust to reflect the increased value of secured loans. In contrast, secured loans show no significant changes in interest rate spreads or default rates after the reform. These patterns are primarily driven by private sector firms with greater fixed assets, stronger credit ratings, and higher external finance dependence. In other words, the rising demand for secured loans—driven by their increased ex-ante value—helps explain these shifts. Additionally, branches operating in more competitive markets contribute to these trends. Together, these findings suggest that the simultaneous shifts in credit demand and supply, triggered by the reform, create offsetting effects on the interest rate spreads of secured loans while enabling borrowers to extract greater leverage from their collateral.

Our findings demonstrate that the reform significantly benefits banks, leading to higher loan volumes, larger average loan sizes, and increased interest earnings. These gains are primarily driven by a rise in secured loans to borrowers with stronger credit ratings, all while maintaining stable default risk.

We also find evidence that adopting the reform could raise financial inclusion. Focusing on the change in firms' access to credit, we find that after the reform, all firms experience an increase in the probability of obtaining a bank loan; only firms with low credit ratings experience a decline. Furthermore, the average loan size for secured loans increases, suggesting that borrowers can extract greater leverage from their collateral. Finally, the reform is associated with a notable rise in new firm registrations, indicating a positive impact on entrepreneurial activity and market entry.

In summary, our findings suggest that adopting online collateral auctions leads to significant changes in both the demand and supply of credit, benefiting lending institutions. The reform also supports creditworthy, financially constrained firms with pledgeable assets, thereby promoting financial inclusion. By offering a low-cost legal change, online collateral auctions enhance the value of defaulted loans, which, through backward induction, increases the ex-ante value of collateral-based loans. The reform, combined with competitive banking, drives shifts in credit demand and supply, generating gains for both borrowers and lenders while fostering greater financial inclusion.

It would be useful to examine the reform's impact on firm-level investment, valuation, and overall economic allocation efficiency would be valuable. We leave these investigations for future endeavors due to our current datasets' limited information on firm valuation and investment.

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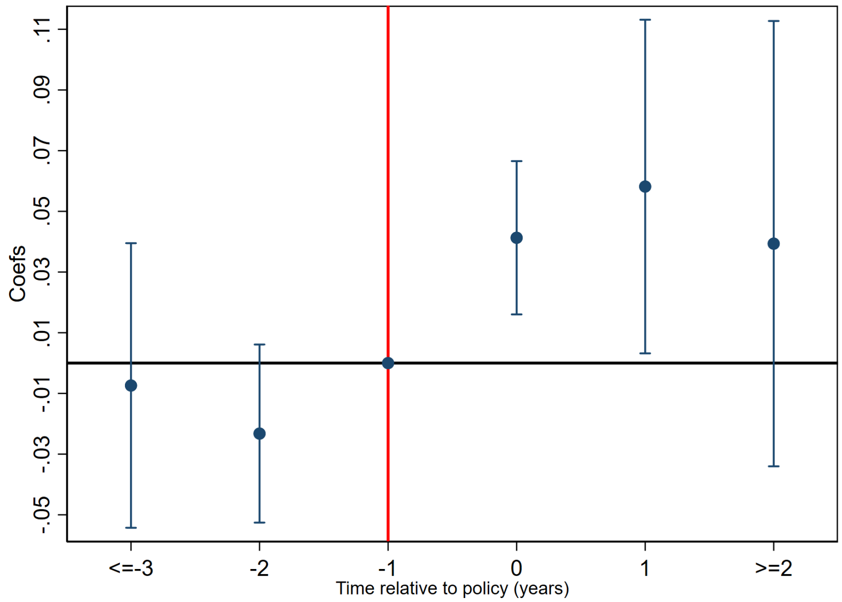
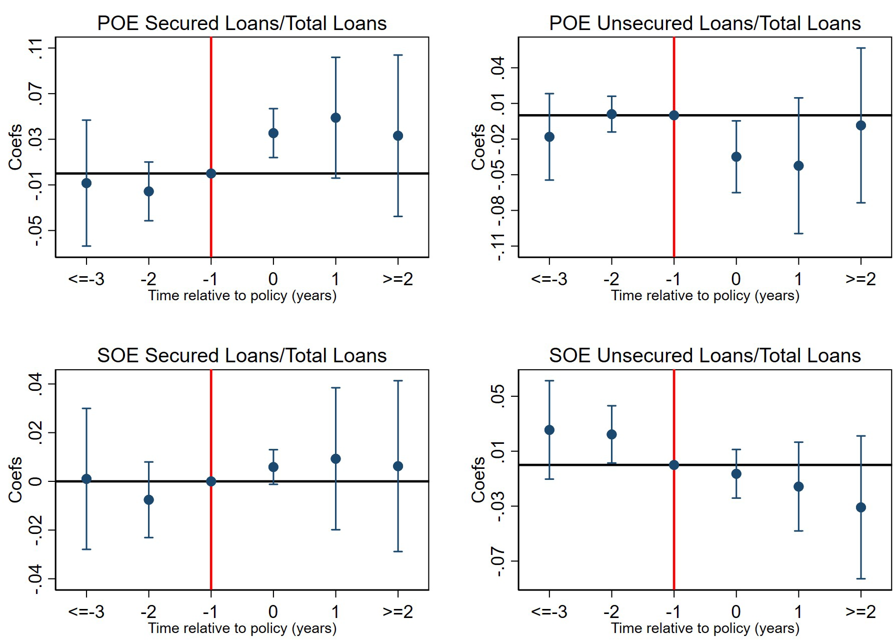


Panel a) Coefficients for the share of secured loans to total loans



Panel b) Coefficients for single type of loans (POE secured, POE unsecured, SOE secured, and SOE unsecured)

Figure 1. Event study of loan composition at branch level. The figures plot the 90% confident interval for the estimated coefficients in the event study. The first year in which the online auction system was introduced is denoted as T = 0, with the year prior to the reform serving as the benchmark. Panel (a) presents the coefficients for the share of secured loans to total loans. Panel (b) presents the coefficients for single type of loans (POE secured, POE unsecured, SOE secured, and SOE unsecured).

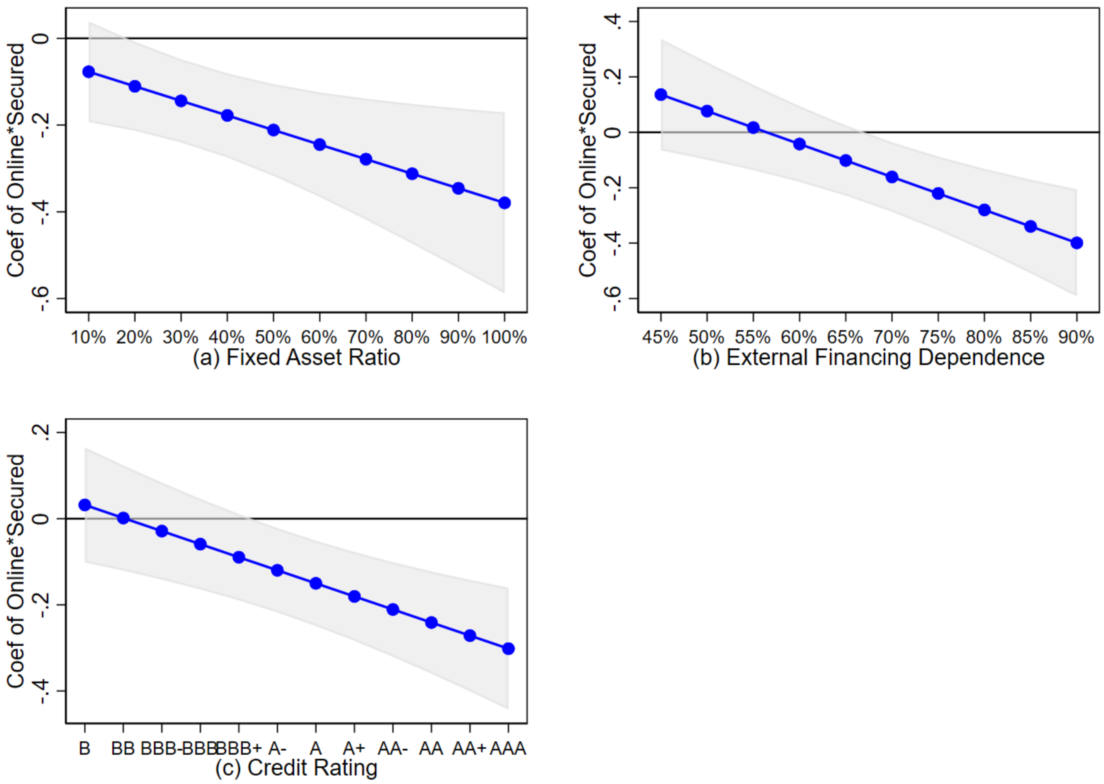


Figure 2. Heterogeneity of fixed asset ratio, external finance dependence, and credit rating. The figure plots the heterogeneity of Fixed Asset Ratio, External Finance Dependence, and Credit Rating. The vertical axis represents the impact of Online Reform on the credit spread of secured loans under different levels of Fixed Asset Ratio, External Finance Dependence, and Credit Rating (i.e., the varying coefficients of Online $\times$ Secured).

Table 1. Variable definition

Variable	Definition
Panel A: Loan–level samples	
Online	A dummy variable equals to 1 if the online auction reform is implemented, and 0 otherwise.
Spread	Loan rate minus benchmark interest rate set by the People's Bank of China (in %).
Log(Amount)	Logarithm of the loan amount (in millions).
Log(Maturity)	Logarithm of the maturity time (in months).
Secured	A dummy variable equals 1 for mortgage and pledge-type loans, and 0 for credit loans.
NPL	A dummy variable equals to one if the loan was classified as "special mention", "substandard", "doubtful" or "loss" at the end of issue year and 0 otherwise.
SOE	A dummy variable equals 1 if the firm is a state-owned enterprise, and 0 otherwise.
Fixed Asset Ratio	Fixed asset / Total asset, calculated as the average between 2007 and 2012 for each firm.
Credit Rating	Credit rating, 1 is the lowest rating for firms classified as B; 2 is for BB; 3 is for BBB-; 4 is for BBB; 5 is for BBB+, 6 is for A-, 7 is for A, 8 is for A+, 9 is for AA-, 10 is for AA, 11 is for AA+, and 12 is for AAA. The value is assigned at the firm level before the launching of the reform, in 2007 to 2012.
External Finance Dependence	External finance dependence is measured as the ratio of capital expenditures minus own funds divided by total capital expenditures based on a four-digit industry aggregate (in %). The measure is constructed using 2012 data from the Statistical Yearbook of the Chinese Investment in Fixed Assets.
Bank Competition	The level of bank competition at the branch's location is measured by the number of commercial bank branches within a 5-kilometer radius, and then normalized.

Table 1. Variable definition (continued)

Panel B: Branch–level samples	
Secured loan amount /Total loan amount	The secured loan amount issued by the branch in a given year / the total loan amount.
POE Secured loan amount /Total loan amount	The secured loan amount issued by the branch to POEs in a given year / the total loan amount.
POE Unsecured loan amount /Total loan amount	The unsecured loan amount issued by the branch to POEs in a given year / the total loan amount.
SOE Secured loan amount /Total loan amount	The secured loan amount issued by the branch to SOEs in a given year / the total loan amount.
SOE Unsecured loan amount /Total loan amount	The unsecured loan amount issued by the branch to SOEs in a given year / the total loan amount.
Log(Total loan amount)	Logarithm of the total loan amount issued by the branch in a given year (in millions).
Log(Secured loan amount)	Logarithm of the secured loan amount issued by the branch in a given year (in millions).
Log(Unsecured loan amount)	Logarithm of the unsecured loan amount issued by the branch in a given year (in millions).
Log(Average loan size)	Logarithm of the average loan amount issued by the branch. (in millions)
Log(Average secured loan size)	Logarithm of the average secured loan amount issued by the branch. (in millions)
Log(Average unsecured loan size)	Logarithm of the average unsecured loan amount issued by the branch. (in millions)
Average Rate	The amount-weighted average loan interest rate.
Average Secured Rate	The amount-weighted average interest rate of secured loans.
Average Unsecured Rate	The amount-weighted average interest rate of unsecured loans.
Log(Interest Income)	Logarithm of the sum of the loan amounts multiplied by their respective interest rates.
Log(Interest Income from Secured Loans)	Logarithm of the sum of the secured loan amounts multiplied by their respective interest rates.
Log(Interest Income from Unsecured Loans)	Logarithm of the sum of the unsecured loan amounts multiplied by their respective interest rates.
Log(Secured loan amount for POE Firms with High Fixed Asset Ratio)	Logarithm of secured loan amounts to high-fixed-asset POEs (top one-third).

Table 1. Variable definition (continued)

Log(Secured loan amount for POE Firms with Low Fixed Asset Ratio)	Logarithm of secured loan amounts to low-fixed-asset POEs (bottom one-third)
Log(Secured loan amount for High-Rated POE Firms)	Logarithm of secured loan amounts to high-rated POE firms (AA- and above).
Log(Secured loan amount for Low-Rated POE Firms)	Logarithm of secured loan amounts to low-rated POE firms (BBB+ and below).
Log(Secured loan amount for POE Firms with High External Finance Dependence)	Logarithm of the secured loan amount provided to POEs in the top third of industries with the highest external finance dependence.
Log(Secured loan amount for POE Firms with Low External Finance Dependence)	Logarithm of the secured loan amount provided to POEs in the bottom third of industries with the lowest external finance dependence.

Table II Summary Statistics

This table provides summary statistics for loan-level and branch-level variables. All variables are defined in Table 1.

Panel A: Loan Level

	Obs.	Mean	SD	P25	Median	P75
Online	173614	0.441	0.497	0.000	0.000	1.000
Spread	173614	0.610	0.670	0.031	0.560	0.915
Log(Amount)	173614	1.171	1.314	0.560	1.281	1.902
Log(Maturity)	173614	2.304	0.346	2.197	2.485	2.485
Secured	173614	0.888	0.315	1.000	1.000	1.000
NPL	173614	0.040	0.196	0.000	0.000	0.000
SOE	173614	0.096	0.294	0.000	0.000	0.000
Credit Rating	133531	6.637	3.000	5.000	8.000	9.000
Fixed Asset Ratio	173614	0.333	0.191	0.191	0.303	0.446
External Finance Dependence	96952	70.451	6.398	66.943	70.178	74.863
Bank Competition	170621	0.108	0.137	0.031	0.067	0.130

Table II (continued)

Panel B: Branch Level	Obs.	Mean	SD	P25	Median	P75
Secured loan amount/Total loan amount	2027	0.707	0.323	0.506	0.832	1.000
POE Secured loan amount/Total loan amount	2027	0.629	0.325	0.388	0.701	0.927
POE Unsecured loan amount/Total loan amount	2027	0.192	0.259	0.000	0.078	0.295
SOE Secured loan amount/Total loan amount	2027	0.078	0.153	0.000	0.008	0.085
SOE Unsecured loan amount/Total loan amount	2027	0.101	0.234	0.000	0.000	0.045
Log(Total loan amount)	2027	5.610	1.493	4.762	5.740	6.633
Log(Secured loanamount)	2027	4.978	1.649	4.108	5.181	6.077
Log(Unsecured loanamount)	2027	3.435	2.552	0.000	3.932	5.535
Log(Average loan size)	2027	2.229	0.915	1.612	2.090	2.741
Log(Average secured loan size)	1984	1.880	0.768	1.406	1.811	2.261
Log(Average unsecured loan size)	1459	2.878	1.176	2.069	2.896	3.754
Average Rate	2027	5.911	1.056	4.829	6.168	6.735
Average Secured Rate	1984	6.061	1.083	4.988	6.354	6.885
Average Unsecured Rate	1459	5.664	1.008	4.558	5.883	6.405
Log(Interest Income)	2027	2.912	1.274	2.053	2.925	3.809
Log(Interest Income from Secured Loans)	2027	2.424	1.276	1.517	2.445	3.278
Log(Interest Income from Unsecured Loans)	2027	1.571	1.441	0.000	1.386	2.699
Log(Secured loan amount for POE Firms with High Fixed Asset Ratio)	2027	3.542	1.925	2.468	3.932	4.991
Log(Secured loan amount for POE Firms with Low Fixed Asset Ratio)	2027	2.970	2.150	0.000	3.325	4.595
Log(Secured loan amount for High-Rated POE Firms)	2027	3.786	1.953	2.684	4.114	5.179
Log(Secured loan amount for Low-Rated POE Firms)	2027	2.819	2.147	0.000	3.178	4.548
Log(Secured loan amount for POE Firms with High External Finance Dependence)	2027	2.678	2.020	0.000	2.990	4.331
Log(Secured loan amount for POE Firms with Low External Finance Dependence)	2027	2.431	2.044	0.000	2.747	4.029

Table III

The Impact of Online Auction Reforms on Loan Type

This table examines the impact of online auction reforms on loan type. All columns control for the branch's loan volume in a given year, branch-, and year- fixed effects. All variables are defined in Table 1. Standard errors are two-way clustered at the city and year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	*Secured loan amount /Total loan amount*	*POE Secured loan amount /Total loan amount*	*POE Unsecured loan amount /Total loan amount*	*SOE Secured loan amount /Total loan amount*	*SOE Unsecured loan amount /Total loan amount*
Online	0.056**	0.045**	-0.042**	0.011	-0.014
	(0.016)	(0.016)	(0.017)	(0.006)	(0.014)
Controls (Branch Size)	Yes	Yes	Yes	Yes	Yes
Observations	2,022	2,022	2,022	2,022	2,022
Adjusted R-squared	0.623	0.642	0.554	0.485	0.650
Branch FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table IV

The Impact of Online Auction Reforms on Loan Spread

This table examines the impact of online auction reforms on loan interest rates. The dependent variable is loan spread, defined as loan rate minus benchmark interest rate (in %). Column 1 controls for secured dummy, city and year fixed effects. Column (2) additionally controls for Log(Amount) and Log(Maturity), while column (3) further includes firm and branch fixed effects. Column (4) replace year fixed effcts by the interaction between firm-level initial variables and year fixed effects, including firm size, leverage and the ratio of fixed assets to total assets. Column (5) and (6) repeat the specification in column (4), but for SOE and POE samples, respectively. The last row shows the p-value for test of the sum of "online" and "online * secured" is equal to zero. All variables are defined in Table 1. Standard errors are two-way clustered at the city and year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Full Sample				SOE	POE
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Spread	Spread	Spread	Spread	Spread	Spread
Online	0.198**	0.206**	0.191**	0.172**	0.180**	0.144**
	(0.080)	(0.078)	(0.058)	(0.054)	(0.062)	(0.055)
Online * Secured	-0.210**	-0.221**	-0.170**	-0.193**	-0.269***	-0.155**
	(0.080)	(0.078)	(0.052)	(0.059)	(0.067)	(0.056)
Log(Amount)		-0.130***	-0.015*	-0.015*	0.003	-0.017*
		(0.019)	(0.007)	(0.007)	(0.008)	(0.008)
Log(Maturity)		0.094*	0.014	0.006	0.004	0.008
		(0.039)	(0.025)	(0.025)	(0.036)	(0.026)
Observations	177,700	177,135	173,689	173,614	16,594	156,997
Adjusted R-squared	0.295	0.344	0.582	0.577	0.559	0.574
Secured FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	—	—	—	—
Year FE	Yes	Yes	Yes	—	—	—
Firm FE	No	No	Yes	Yes	Yes	Yes
Sub-branch FE	No	No	Yes	Yes	Yes	Yes
Initial*Year FE	No	No	No	Yes	Yes	Yes
Test of Row1 + Row2	0.809	0.772	0.641	0.692	0.300	0.825

Table V

Heterogeneity of Fixed Asset Ratio (POEs)

This table estimates the heterogeneity in the impact of the online auction reform on loan interest rates across different fixed asset ratios. The dependent variable is loan spread, defined as loan rate minus benchmark interest rate (in %). All columns control for Log(Amount), Log(Maturity), secured dummy, firm, branch, and the interaction between firm-level initial variables and year fixed effects, including firm size, leverage and the ratio of fixed assets to total assets. This table uses a sample of privately owned firms (POEs), excluding state-owned firms (SOEs). Column (1) uses the sample of POEs with the highest third of fixed asset ratios, while Column (2) uses the sample of POEs with the lowest third of fixed asset ratios. The last row shows the p-value for test of the sum of "online" and "online * secured" is equal to zero. To test the coefficient difference between groups, we perform the T-tests and Fisher's Permutation test. The p-values, corresponding to t-statistics constructed following Acquaah (2012), and the empirical p-values from Fisher's Permutation test, based on 500 bootstrap samples, are reported. All variables are defined in Table 1. Standard errors are two-way clustered at the city and year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	Diff-test	
	High Fixed Asset Ratio	Low Fixed Asset Ratio	T-test	Fisher's Permutation test
VARIABLES	Spread	Spread	p-value of t-statistic	empirical p-value
Online * Secured	-0.223**	-0.123*	0.000	0.000
	(0.068)	(0.058)		
Online	0.185**	0.125*	0.000	0.010
	(0.064)	(0.056)		
Log(Amount)	-0.013	-0.018**		
	(0.009)	(0.007)		
Log(Maturity)	-0.016	0.007		
	(0.030)	(0.031)		
Observations	47,599	49,998		
Adjusted R-squared	0.591	0.568		
Secured FE	Yes	Yes		
Firm FE	Yes	Yes		
Sub-branch FE	Yes	Yes		
Initial*Year FE	Yes	Yes		
Test of Row1 + Row2	0.393	0.967		

Table VI

Heterogeneity of External Finance Dependence (POEs)

This table estimates the heterogeneity in the impact of the online auction reform on loan interest rates across different levels of external finance dependence. The dependent variable is loan spread, defined as loan rate minus benchmark interest rate (in %). The four digit industry-level index of external finance dependence is measured as capital expenditures minus own funds and divided by capital expenditures (%). All columns control for Log(Amount), Log(Maturity), secured dummy, firm, branch and the interaction between firm-level initial variables and year fixed effects, including firm size, leverage and the ratio of fixed assets to total assets. This table uses a sample of privately owned firms (POEs), excluding state-owned firms (SOEs). Column (1) uses the sample from industries with the highest third of external finance dependence, while Column (2) uses the sample from industries with the lowest third of external finance dependence. The last row shows the p-value for test of the sum of "online" and "online * secured" is equal to zero. To test the coefficient difference between groups, we perform the T-tests and Fisher's Permutation test. The p-values, corresponding to t-statistics constructed following Acquaah (2012), and the empirical p-values from Fisher's Permutation test, based on 500 bootstrap samples, are reported. All variables are defined in Table 1. Standard errors are two-way clustered at the city and year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	Diff-test	
	High External Finance Dependence	Low External Finance Dependence	T-test	Fisher's Permutation test
VARIABLES	Spread	Spread	p-value of t-statistic	empirical p-value
Online * Secured	0.206**	0.127*	0.000	0.000
	(0.068)	(0.058)		
Online	-0.221**	-0.087	0.000	0.008
	(0.073)	(0.076)		
Log(Amount)	-0.015	-0.012		
	(0.009)	(0.008)		
Log(Maturity)	0.009	0.001		
	(0.036)	(0.040)		
Observations	24,927	29,709		
Adjusted R-squared	0.579	0.571		
Secured FE	Yes	Yes		
Firm FE	Yes	Yes		
Sub-branch FE	Yes	Yes		
Initial*Year FE	Yes	Yes		
Test of Row1 + Row2	0.797	0.452		

Table VII

Heterogeneity of Credit Rating (POEs)

This table estimates the heterogeneity in the impact of the online auction reform on loan interest rates across different credit ratings. The dependent variable is loan spread, defined as loan rate minus benchmark interest rate (in %). All columns control for Log(Amount), Log(Maturity), secured dummy, city, firm, branch and the interaction between firm-level initial variables and year fixed effects, including firm size, leverage and the ratio of fixed assets to total assets. This table uses a sample of privately owned firms (POEs), excluding state-owned firms (SOEs). Column (1) uses the loan sample for POE firms with a credit rating of AA- and above, while Column (2) uses the loan sample for POE firms with a credit rating of BBB+ and below. The last row shows the p-value for test of the sum of "online" and "online * secured" is equal to zero. To test the coefficient difference between groups, we perform the T-tests and Fisher's Permutation test. The p-values, corresponding to t-statistics constructed following Acquaah (2012), and the empirical p-values from Fisher's Permutation test, based on 500 bootstrap samples, are reported. All variables are defined in Table 1. Standard errors are two-way clustered at the city and year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	Diff-test	
	High Credit Rating	Low Credit Rating	T-test	Fisher's Permutation test
VARIABLES	Spread	Spread	p-value of t-statistic	empirical p-value
Online * Secured	-0.228***	0.018	0.000	0.000
	(0.058)	(0.070)		
Online	0.184***	0.004	0.000	0.000
	(0.049)	(0.079)		
Log(Amount)	-0.022*	-0.005		
	(0.010)	(0.012)		
Log(Maturity)	-0.002	0.027		
	(0.026)	(0.040)		
Observations	37,505	35,385		
Adjusted R-squared	0.533	0.503		
Secured FE	Yes	Yes		
Firm FE	Yes	Yes		
Sub-branch FE	Yes	Yes		
Initial*Year FE	Yes	Yes		
Test of Row1 + Row2	0.460	0.719		

Table VIII

Heterogeneity of Bank Competition (POEs)

This table estimates the heterogeneity in the impact of the online auction reform on loan interest rates across different bank competitions. The dependent variable is loan spread, defined as loan rate minus benchmark interest rate (in %). The level of bank competition at the branch's location is measured by the number of commercial bank branches within a 5-kilometer radius, and then normalized. All columns control for Log(Amount), Log(Maturity), secured dummy, firm, branch and the interaction between firm-level initial variables and year fixed effects, including firm size, leverage and the ratio of fixed assets to total assets. This table uses a sample of privately owned firms (POEs), excluding state-owned firms (SOEs). Column (1) uses the sample of sub-branches facing the highest third of bank competition, while Column (2) uses the sample of sub-branches with the lowest third of bank competition. The last row shows the p-value for test of the sum of "online" and "online * secured" is equal to zero. To test the coefficient difference between groups, we perform the T-tests and Fisher's Permutation test. The p-values, corresponding to t-statistics constructed following Acquaah (2012), and the empirical p-values from Fisher's Permutation test, based on 500 bootstrap samples, are reported. All variables are defined in Table 1. Standard errors are two-way clustered at the city and year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	Diff-test	
	High Bank Competition	Low Bank Competition	T-test	Fisher's Permutation test
VARIABLES	Spread	Spread	p-value of t-statistic	empirical p-value
Online * Secured	0.194***	0.135	0.000	0.242
	(0.049)	(0.072)		
Online	-0.192**	-0.177*	0.000	0.010
	(0.055)	(0.073)		
Log(Amount)	-0.024*	-0.019*		
	(0.011)	(0.008)		
Log(Maturity)	-0.016	0.009		
	(0.034)	(0.038)		
Observations	36,870	48,817		
Adjusted R-squared	0.597	0.557		
Secured FE	Yes	Yes		
Firm FE	Yes	Yes		
Sub-branch FE	Yes	Yes		
Initial*Year FE	Yes	Yes		
Test of Row1 + Row2	0.971	0.461		

Table IX

The Impact of Online Auction Reforms on Default (POEs)

This table examines the impact of online auction reforms on loan default. The dependent variable is a dummy variable equal one if the loan was classified as "special mention", "substandard", "doubtful" or "loss" at the end of the issue year and zero otherwise. All columns control for Log(Amount), Log(Maturity), Spread, secured dummy, firm, branch, and the interaction between firm-level initial variables and year fixed effects, including firm size, leverage, and the ratio of fixed assets to total assets. This table uses a sample of privately owned firms (POEs), excluding state-owned firms (SOEs). Column (1) shows the full sample, Column (2) uses the sample of sub-branches facing the highest third of bank competition, and Column (3) uses the sample of sub-branches with the lowest third of bank competition. The last row shows the p-value for test of the sum of "online" and "online * secured" is equal to zero. To test the coefficient difference between groups, we perform the T-tests and Fisher's Permutation test. The p-values, corresponding to t-statistics constructed following Acquaah (2012), and the empirical p-values from Fisher's Permutation test, based on 500 bootstrap samples, are reported. All variables are defined in Table 1. Standard errors are two-way clustered at the city and year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	Diff-test	
	Full Samples	High Bank Competition	Low Bank Competition	T-test	Fisher's Permutation test
VARIABLES	NPL	NPL	NPL	p-value of t-statistic	empirical p-value
Online	-0.034**	-0.042*	-0.008	0.000	0.002
	(0.011)	(0.018)	(0.020)		
Online * Secured	0.040**	0.046*	0.021	0.000	0.012
	(0.013)	(0.020)	(0.023)		
Log(Amount)	0.001	0.003	0.005		
	(0.002)	(0.002)	(0.003)		
Log(Maturity)	-0.025***	-0.017*	-0.028**		
	(0.006)	(0.008)	(0.010)		
Spread	0.005*	-0.001	0.007		
	(0.002)	(0.006)	(0.005)		
Observations	156,997	36,870	48,817		
Adjusted R-squared	0.413	0.415	0.392		
Secured FE	Yes	Yes	Yes		
Firm FE	Yes	Yes	Yes		
Sub-branch FE	Yes	Yes	Yes		
Initial*Year FE	Yes	Yes	Yes		
Test of Row1 + Row2	0.305	0.593	0.224		

Table X

The Impact of Online Auction Reforms on Branch Performance

This table examines the impact of online auction reforms on branch performance. All variables are defined in Table 1. Standard errors are two-way clustered at the city and year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Panel A: The total loan amount issued by the branch			
VARIABLES	*Log(Total loan amount)*	*Log(Secured loan amount)*	*Log(Unsecured loan amount)*
Online	0.169**	0.242**	-0.106
	(0.061)	(0.075)	(0.108)
Observations	2,022	2,022	2,022
Adjusted R-squared	0.825	0.790	0.665
Panel B: The average loan amount per loan			
VARIABLES	*Log(Average loan size)*	*Log(Average secured loan amount)*	*Log(Average unsecured loan amount)*
Online	0.116*	0.121**	-0.035
	(0.050)	(0.047)	(0.069)
Observations	2,022	1,981	1,439
Adjusted R-squared	0.679	0.542	0.618
Panel C: The interest income of the branch			
VARIABLES	*Log(Interest Income)*	*Log(Interest Income from Secured Loans)*	*Log(Interest Income from Unsecured Loans)*
Online	0.134**	0.140**	-0.005
	(0.043)	(0.041)	(0.054)
Observations	2,022	2,022	2,022
Adjusted R-squared	0.850	0.852	0.731
Cluster at City and Year	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table XI

The Impact of Reforms on Total Loans by Firm Types

This table estimates changes in the total lending to different firm types under the impact of online auction reforms. In Panel A, Column (1) uses the logarithm of secured loan amounts to high-fixed-asset POEs (top one-third) as the dependent variable. Column (2) uses the logarithm of secured loan amounts to low-fixed-asset POEs (bottom one-third). In Panel B, the dependent variable in Column (1) is the logarithm of the secured loan amount provided to POEs in the top third of industries with the highest external finance dependence. The dependent variable in Column (2) is the logarithm of the secured loan amount provided to POEs in the bottom third of industries with the lowest external finance dependence. In Panel C, the dependent variable is the logarithm of secured loan amounts to high-rated POE firms (AA- and above) in Column (1), and the logarithm of secured loan amounts to low-rated POE firms (BBB+ and below) in Column (2). Standard errors are two-way clustered at the city and year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Heterogeneity of Fixed Asset Ratio		
	(1)	(2)
VARIABLES	*Log(Secured loan amount for POE Firms with **High Fixed Asset Ratio**)*	*Log(Secured loan amount for POE Firms with **Low Fixed Asset Ratio**)*
Online	0.225**	0.199
	(0.091)	(0.115)
Observations	2,022	2,022
Adjusted R-squared	0.729	0.783
Panel B: Heterogeneity of External Finance Dependence		
VARIABLES	*Log(Secured loan amount for POE Firms with **High External Finance Dependence**)*	*Log(Secured loan amount for POE Firms with **Low External Finance Dependence**)*
Online	0.080	0.013
	(0.084)	(0.091)
Observations	2,022	2,022
Adjusted R-squared	0.732	0.744
Panel C: Heterogeneity of Credit Rating		
VARIABLES	*Log(Secured loan amount for **High-Rated** POE Firms)*	*Log(Secured loan amount for **Low-Rated** POE Firms)*
Online	0.292**	0.032
	(0.100)	(0.101)
Observations	2,022	2,022
Adjusted R-squared	0.746	0.774
Cluster at City and Year	Yes	Yes
Branch FE	Yes	Yes
Year FE	Yes	Yes

Table XII
The Impact of Online Auction Reforms on Firms' Access to Loan

The table examines the impact of online auction reforms on the probability of POE firms to get loans from the bank. The sample in this table consists of an annual panel of POE firms. *LoanDummy* equals 1 if a firm received a loan in a given year. *LowFA* equals 1 if the firm's fixed asset ratio is in the lowest third. *LowRating* equals 1 if a POE firm's credit rating is BBB+ or below. *HighEFD* equals 1 if the firm's industry is in the highest third for External-Finance Dependence. All columns use a Logit regression, controlling for firm and year-fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	LoanDummy	LoanDummy	LoanDummy	LoanDummy	LoanDummy	LoanDummy
Online	0.109***	0.221***	0.229***	0.118***	0.227***	0.228***
	(0.0311)	(0.0296)	(0.0325)	(0.0329)	(0.0310)	(0.0344)
Online × LowFA	-0.0301		-0.0208	-0.00897		-0.00346
	(0.0382)		(0.0383)	(0.0415)		(0.0416)
Online × LowRating		-0.570***	-0.570***		-0.527***	-0.527***
		(0.0453)	(0.0453)		(0.0499)	(0.0499)
Online × HighEFD				-0.0474	-0.0319	0.00392
				(0.0581)	(0.0548)	(0.0628)
Online × LowFA × HighEFD				-0.165		-0.131
				(0.106)		(0.107)
Online × LowRating × HighEFD					-0.238**	-0.229*
					(0.120)	(0.120)
Observations	77,483	77,483	77,483	77,483	77,483	77,483
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.0527	0.0552	0.0552	0.0528	0.0553	0.0553
Test of Row1 + Row2	0.034		0.000			
Test of Row1 + Row3		0.000	0.000			
Test of Row1 + Row2 + Row4 + Row5				0.225		0.277
Test of Row1 + Row3 + Row4 + Row6					0.000	0.000

Table XIII

The Impact of Online Auction Reforms on Firm Registration

This table examines the impact of online auction reforms on the number of firm registrations. The dependent variable is the city-level number of SOE (or POE) firm registrations. Online reform takes value of 1 if the city adopted the online auction. Online reform (2 year earlier) moves the adoption year two years ahead. Standard errors clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

DV: Firm Registration	(1)	(2)	(3)	(4)
	SOE firms		POE firms	
Online reform	0.00545		3.094**	
	(1.16)		(2.38)	
Online reform (2 year earlier)		-0.00256		0.55
		(0.44)		(1.02)
Observations	6754	6754	6754	6754
R-squared	0.419	0.419	0.669	0.668
Cluster at province level	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

X. Appendix

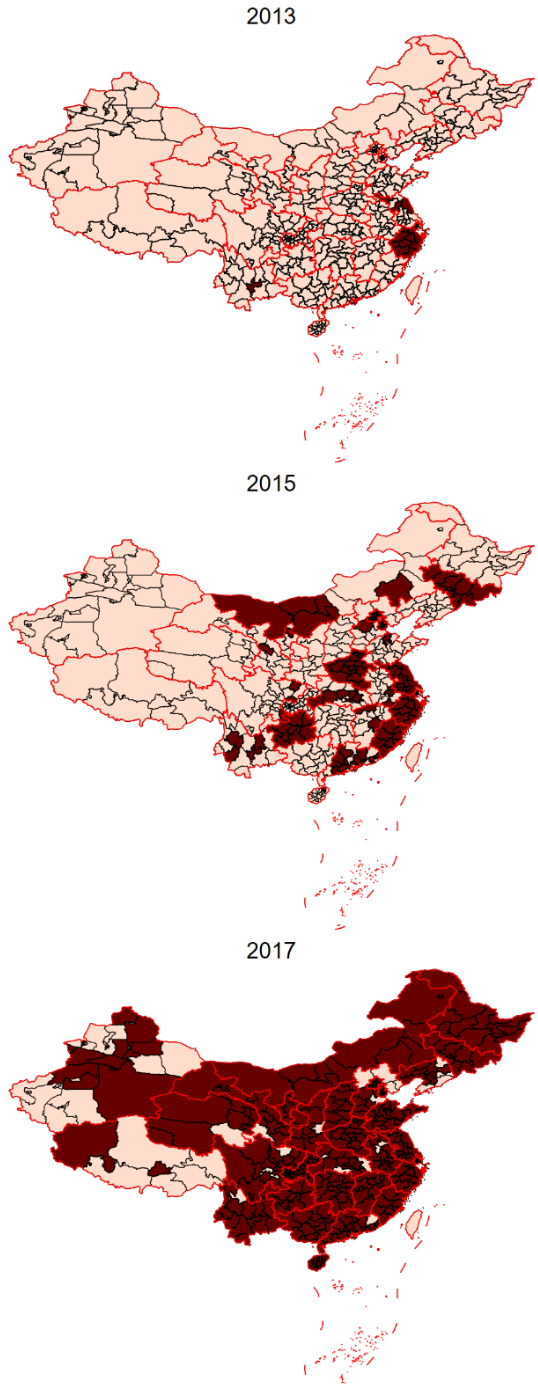


Figure A1. The adoption of online court auction. The figure shows the adoption of online court auction over time. Data is manually collected based on the first auction date from Taobao platform.

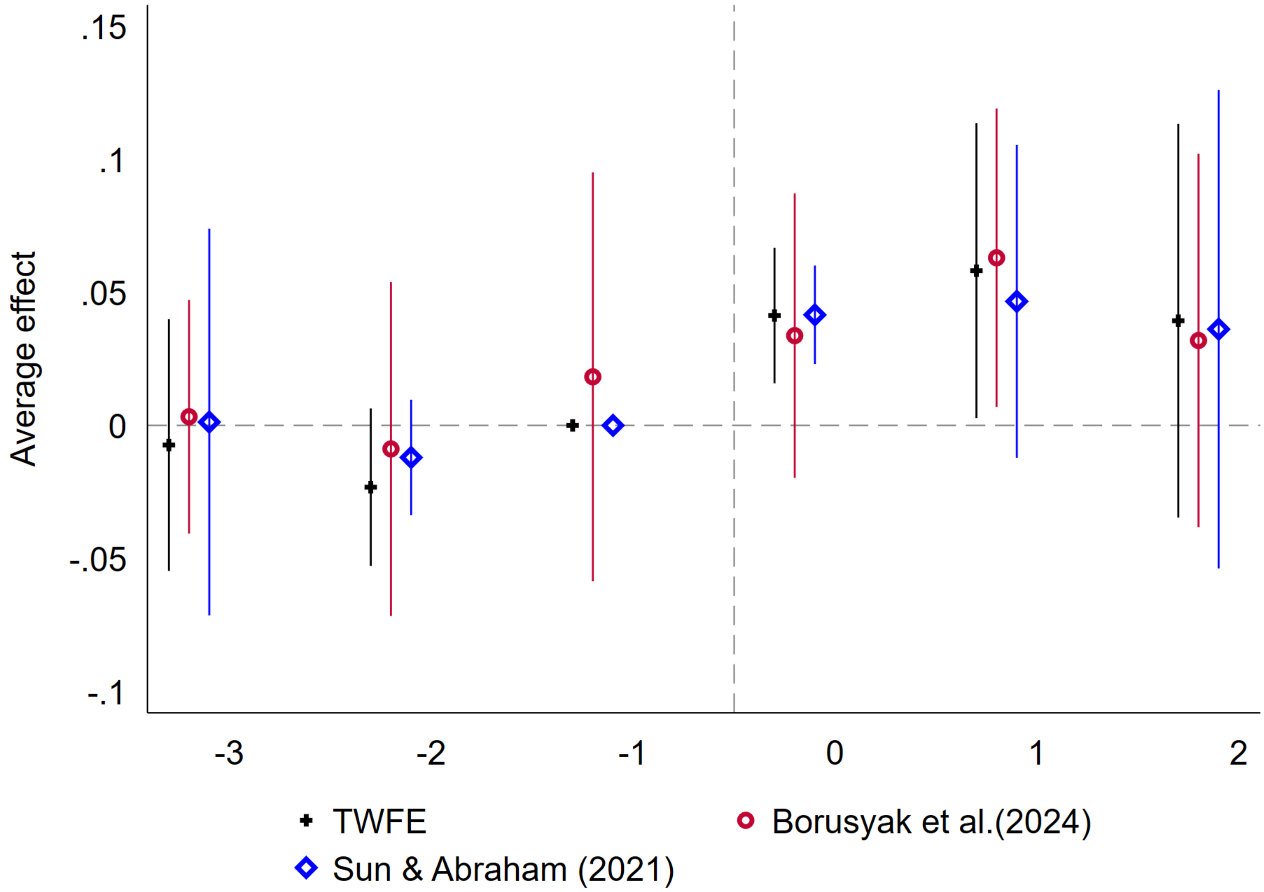


Figure A2. Robustness: alternative estimation methods The figure conducts a robustness test on the dynamics of loan composition over time using different estimation methods in event study. The first year in which the online auction system was introduced is denoted as T = 0, with the year prior to the reform serving as the benchmark.