

Hard Information and Local Lending Markets: Evidence from Invoice Digitalization[§]

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Abstract

Small business lending remains local when opaque firms lack verifiable records that can travel through bank organizations. I study China's staggered Golden Tax Phase III reform, which digitalized invoice recording and authentication and turned routine transaction trails into hard information usable in credit approval. Using confidential loan origination data and provincial rollout timing, I show that the reform improves banks' internal assessment, expands credit lines, lowers rates and spreads, lengthens maturities, and increases lending distance. Credit line responses are strongest where borrowers leave thinner transaction trails, where lenders have less accumulated information, and where local banking markets are more competitive. The gains increase with distance, consistent with invoice digitalization being most valuable where local soft information had been weakest. At the lending frontier, comparable Credit Scores and higher travel time indicate that the remaining rate premium reflects contact and monitoring costs. Public digital infrastructure can expand formal small business credit by improving incumbent banks' ability to assess opaque borrowers.

Keywords: Banking, Small Business Lending, Financial Technology, Information Asymmetry

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Introduction

Small business lending remains local because much of the information banks need about opaque firms is difficult to verify, standardize, and transmit. Branch officers learn through relationships, repeated interaction, local contact, and site visits, but these channels are costly to scale across distance and across bank hierarchies (Petersen and Rajan, 1994; Berger and Udell, 1995; Stein, 2002; Liberti and Petersen, 2019). Distance therefore captures one important local information constraint: it proxies for how difficult it is to collect, update, and use soft information about specific borrowers (Degryse and Ongena, 2005; Agarwal and Hauswald, 2010; Petersen and Rajan, 2002; Beck et al., 2018). This paper studies how public digital infrastructure changes that constraint by turning routine business transactions into information banks can verify and use.

China’s Golden Tax Phase III (GT3) provides the setting. GT3 digitalized invoice creation, authentication, uploading, storage, and verification. Ordinary sales and purchase transactions generated invoice records authenticated by the tax system, which could be attached to loan files, checked by banks, and transmitted through approval layers. The reform changed the information available inside bank underwriting, where hard information is information that banks can verify, standardize, and use within lending organizations (Fama, 1985; Liberti and Petersen, 2019).

I combine a large confidential loan origination dataset with the staggered provincial roll-out of GT3. The main loan data reveal the origination chain from bank assessment to contract terms and lending distance. The auxiliary datasets connect the origination chain to three external margins: the reporting environment, bank balance sheets, and borrowers with abundant formal disclosure. Tax data at the province level validate the reporting channel, bank annual reports describe balance sheet outcomes, and listed firm borrowing announcements provide a comparison group with already rich formal disclosure. Boundary and distance analyses then show how invoice digitalization changes the role of soft information in local lending markets.

First, the reform changes the information banks use at origination. Reported tax collections rise after GT3, consistent with a stronger formal transaction record environment. Inside the bank, $\ln(\text{Income})$, the bank assessed income measure, rises, and Credit Score, the bank’s internal repayment capacity score, improves. Contract terms then adjust: borrowers receive larger credit lines, lower rates and spreads, and longer maturities. The sequence is record creation, internal assessment, and contract design.

Second, gains are larger where invoice digitalization adds more to the prior information set. Credit line responses are larger in consumer facing sectors, where verifiable business transaction trails are thinner than in inter firm trade (Naritomi, 2019; Huang et al., 2020; Chan et al., 2022). Responses are also larger for smaller banks and for banks with lower pre GT3 local industry specialization. These patterns point to higher marginal value where banks had less accumulated organizational or sectoral knowledge before GT3 (Stein, 2002; Liberti and Mian, 2009; Hertzberg et al., 2010; Bolton et al., 2016; Blickle et al., 2026). The reform also broadens banks’ local industry allocation, and credit line responses are stronger in less concentrated local banking markets, where competition allows more of the resulting credit response to reach borrowers (Petersen and Rajan, 1995; Broecker, 1990; Hauswald and Marquez, 2003; Yannelis and Zhang, 2023; He et al., 2024).

Third, the reform expands local lending reach and delivers larger gains at greater distance. Average distance rises after GT3, and borrowers near the expansion boundary have comparable Credit Scores. Within the full local market, more distant borrowers experience larger improvements in internal assessment, credit lines, and borrowing costs. This pattern supports the mechanism that invoice digitalization adds most where local soft information had been weakest. On the pricing margin, the larger gains at distance appear as a compression of the information risk component of the distance premium.

The main text follows the same sequence. Section 1 describes GT3 and the underwriting framework. Section 2 introduces the data and identification. Section 3 traces the reform from reporting records to internal assessment, loan terms, and the distribution of gains.

Section 4 studies local lending reach and market scope. Section 5 studies distance gradients and pointwise effects along the distance distribution, showing that borrowers farther from the lender gain more in assessment, credit quantity, and pricing.

This paper contributes to the literature on small business lending and information production by tracing invoice digitalization through the bank’s internal lending process. Existing work emphasizes that relationship lending emerges when borrower information is difficult to verify and transmit across distance and hierarchy (Petersen and Rajan, 1994; Berger and Udell, 1995; Boot, 2000; Stein, 2002; Liberti and Mian, 2009; Hertzberg et al., 2010; Liberti and Petersen, 2019). I document how public infrastructure enters bank information production: invoice digitalization makes routine transaction records more verifiable, and those records appear first in internal assessment and then in loan contracts. The gains also follow the distribution of prior information: they are larger for borrowers with thinner transaction trails and for banks with less accumulated local industry knowledge. The distance evidence adds the geographic counterpart: borrowers farther from the lender gain more where local soft information had been weakest.

The paper also contributes to research on local lending markets and information based pricing. Local soft information can improve screening, but it can also support distance related pricing premia when some borrowers are harder to evaluate (Degryse and Ongena, 2005; Agarwal and Hauswald, 2010; Blickle et al., 2025). The evidence shows how publicly generated invoice records change both credit quantities and loan prices within local lending markets, consistent with theory in which information technology changes the span, precision, and transmission of information in credit competition (Broecker, 1990; Hauswald and Marquez, 2003; He et al., 2023, 2024; Vives and Ye, 2025). On the pricing margin, the larger gains at distance appear as a compression of the information risk component of the distance premium, while boundary evidence identifies the residual contact and monitoring cost component.

Finally, the paper complements the fintech and information technology literature by showing that screening with richer data can arise inside incumbent banks through public infrastructure, rather than only through new lending platforms or proprietary private data (Berg et al., 2022; Vives, 2019; Di Maggio and Yao, 2021; Fuster et al., 2022; Howell et al., 2024; Kang, 2024; Minnis et al., 2024). The evidence shifts the focus from fintech entry to information production inside incumbent banks.

1 Institutional Setting and Framework

1.1 GT3 and Verifiable Invoice Records

Golden Tax Phase III moved invoice issuance, authentication, submission, storage, and verification into a unified national tax administration system. Firms generated invoice data through tax control systems and tax digital certificates; the data were uploaded to the tax authority and stored in electronic ledgers used for filing, verification, tax source management, and data analysis. The reform changed what ordinary transactions left behind. Afterward, sales and purchase activity generated records authenticated by the tax system, which banks could check, compare, and transmit through underwriting.

In bank credit files, these records appear as invoices, contracts, tax filings, receivables documents, delivery records, and related transaction materials. GT3 raised the verification value of this documentary trail by placing invoice records inside a digital tax infrastructure, where they carried authentication from the tax system and could travel across loan files, branches, and approval layers. I use hard information to refer to records from invoice and transaction trails that banks can verify, standardize, and transmit through underwriting.

Figure 1 summarizes how invoice digitalization enters the bank information set through credit file documents that banks already use in small business underwriting. Borrowers provide invoices, contracts, tax filings, receivables documents, delivery records, and transaction materials when applying for working capital credit, trade finance, or invoice based loans.

Public bank product descriptions confirm that these materials enter credit review and loan approval. Appendix Table A.2 reports representative examples from ICBC, Agricultural Bank of China, and Ping An Bank.

Small business lending remains soft information intensive. Opaque private firms generate limited audited and portable hard information, so banks continue to rely on relationship history, local contact, local verification, repeated interaction, and ongoing monitoring (Berger and Udell, 1995; Boot, 2000; Stein, 2002; Liberti and Mian, 2009; Hertzberg et al., 2010; Beck et al., 2018; Liberti and Petersen, 2019). This soft information has both geographic and sectoral dimensions. Geographic soft information comes from proximity to borrowers and local monitoring. Sectoral soft information comes from repeated lending to familiar local industries. The analysis uses distance and bank specialization as complementary proxies for geographic and sectoral soft information.

1.2 Underwriting Framework

A simple updating framework clarifies why invoice digitalization should matter more when prior information is less precise. Before GT3, banks assessed opaque borrowers using limited hard information and soft information that varied with distance. Distance reduces the precision of local information because local contact, local verification, and monitoring become harder to collect and transmit (Degryse and Ongena, 2005; Agarwal and Hauswald, 2010; Petersen and Rajan, 2002; Beck et al., 2018).

Let r_i denote borrower i 's latent risk and let $\hat{r}_i^{pre}$ denote the bank's pre GT3 internal risk assessment. Let $\tau_p(d_i)$ denote the precision of that assessment, with $\tau_p'(d_i) < 0$ so the bank's prior assessment is less precise at greater distance.

GT3 makes the borrower’s invoice trail usable as an additional signal, denoted h_i , with precision τ_H . The updated assessment can be written as¹

$$\hat{r}_i^{post} = \frac{\tau_p(d_i)\hat{r}_i^{pre} + \tau_H h_i}{\tau_p(d_i) + \tau_H} = \hat{r}_i^{pre} + K_i(h_i - \hat{r}_i^{pre}), \quad K_i = \frac{\tau_H}{\tau_p(d_i) + \tau_H}. \quad (1)$$

In this framework, distance enters through the precision of the bank’s prior assessment. A lower $\tau_p(d_i)$ implies a larger updating weight K_i on information from the invoice trail. The same logic extends to banks’ sectoral knowledge. A bank that repeatedly lends to the same local industries begins with richer comparables, screening routines, and monitoring knowledge. A less specialized bank has less reusable industry knowledge, so information from invoice records matters more. Recent theory likewise emphasizes that information technology can alter both the span and the precision of information banks can use (Hauswald and Marquez, 2003; He et al., 2023, 2024; Vives and Ye, 2025). This logic guides the heterogeneity analysis: borrower information scarcity and bank specialization capture where invoice records should matter more, while local competition captures where more of the gain reaches borrowers.

2 Data and Identification

2.1 Loan Data and Province Assignment

The main empirical setting is a large confidential loan origination panel for small business lending. Each observation is a newly originated loan between 2012 and 2022, recorded at origination together with the internal borrower information used in screening, the contract terms ultimately written, and the city of the originating branch.

A key institutional feature is that a borrower can originate a loan only in the borrower’s registered city. Because cities nest within provinces, each loan maps to a unique province: the borrower’s tax registration province is also the province of the originating branch. The

¹Equation (1) is the scalar Kalman gain form of linear Gaussian Bayesian updating (Kalman, 1960; Kalman and Bucy, 1961; Morris and Shin, 2002).

staggered provincial rollout of GT3 can therefore be assigned loan by loan, and that city to province mapping pins the reform to the local lending market in which the loan is originated. The province rollout calendar is reported in Appendix Table A.1.

2.2 Variables

I group the variables according to the sequence from GT3 exposure to bank assessment and loan outcomes. Appendix Table A.4 reports construction details, units, transformations, and merge levels.

GT3 exposure follows the province rollout date and turns on when the local invoice infrastructure is digitalized. Soft information proxies measure dimensions of underwriting that depend on local, relationship based, or hard to transmit information. The central geographic proxy is distance, a within city borrower to lender measure. Lender side proxies include bank size and pre GT3 bank specialization, which capture differences in organizational information and local industry knowledge.

Bank assessment measures are the bank’s origination stage views of repayment capacity. The main continuous assessment measure is $\ln(\text{Income})$, the income measure recorded by the bank in the underwriting file. Credit Score is the bank’s internal repayment capacity score rather than an external bureau score.

Loan outcomes record the contract and reach margins: $\ln(\text{Credit Line})$, Interest Rate, Interest Spread, Maturity, and $\ln(\text{Distance})$.

2.3 Auxiliary Data

I use three auxiliary datasets and one local boundary exercise. Tax statistics at the province level validate the reporting channel created by GT3. Bank annual reports from public filings describe balance sheet patterns around the expansion of local lending. Listed firm borrowing announcements from CSMAR examine firms whose formal disclosure was already abundant.

The boundary exercise returns to the confidential loan origination data to study contact and monitoring burdens near the GT3 implied expansion boundary.²

2.4 Summary Statistics

Table 1 summarizes the main loan origination sample, which contains roughly 154,000 originations. Average approved credit line is RMB 1.52 million, average Interest Spread is 2.655 percentage points, the mean of $\ln(\text{Income})$ is 14.95, and average distance is 27.2 kilometers among loans with matched borrower and branch city locations.

2.5 Empirical Design

The empirical design follows the province rollout through the same local lending market, from internal assessment to contract terms and lending reach. Let $GT3_{p(i),d(i)}$ equal one if observation i occurs on or after the GT3 rollout date in its assigned province. The baseline difference in differences specification is

$$Y_i = \beta GT3_{p(i),d(i)} + F_i + \varepsilon_i, \quad (2)$$

where F_i denotes the fixed effects and application stage controls used in the relevant specification. Baseline tables absorb the time, bank, city, industry, and underwriting control sets appropriate to each outcome. When the identifying comparison is intended to be local, most importantly in the distance specifications, the design uses $\text{City} \times \text{Year-Month}$ fixed effects to keep the comparison within a common lending environment.

To assess timing, the event study specification is

$$Y_i = \sum_{k \neq -1} \beta_k 1\{\tau_{p(i),t(i)} = k\} + F_i + \varepsilon_i, \quad (3)$$

²Summary statistics for the auxiliary samples appear in Appendix Table A.3.

where event time is measured in quarters relative to the province rollout quarter. The coefficients trace pre GT3 dynamics and post GT3 changes under the same fixed effect logic as the baseline DID. As a robustness check for staggered rollout timing, I also estimate a stacked difference in differences (stacked DID) design for the core assessment, quantity, and pricing outcomes; Appendix E reports the stacked credit line event study and the corresponding column progression estimates.

Many mechanism tests then ask how the reform changes local lending market gradients:

$$Y_i = \beta_1 GT3_{p(i),d(i)} + \beta_2 Z_i + \beta_3 (GT3_{p(i),d(i)} \times Z_i) + F_i + \varepsilon_i, \quad (4)$$

where Z_i is the relevant continuous shifter. In the central application, $Z_i = \ln(Distance_i)$ so that β_3 captures how the reform changes the distance gradient in local lending markets. Supporting applications replace Z_i with market structure or information scarcity measures while preserving the same treatment timing. Auxiliary sample specifications apply the same timing rule at the native frequency of each dataset and are introduced where they first become substantively relevant.

3 Reporting, Assessment, Loan Terms, and the Distribution of Gains

3.1 Tax Reporting

The information channel begins upstream in the formal transaction record environment. Tax collections reported in the CNRDS province level statistics rise after GT3 rollout. The coefficient on GT3 is 0.076, implying an increase of about 7.9% in reported tax collections in Table 2. The result fits a broader literature in which externally verified records and transaction trails become informative inputs into credit assessment and pricing once they

can be reused inside lender workflows (Blackwell et al., 1998; Mester et al., 2007; Chan et al., 2022). The lending analysis starts from this changed record environment.

3.2 Internal Assessment

The reporting improvement appears first inside the bank’s own repayment capacity measures. In the preferred specifications, $\ln(\text{Income})$ rises by 0.193 log points, or about 21.3%, while Credit Score also increases in Table 3. Transaction account activity, checking account behavior, and structured reporting data are known inputs into bank monitoring and assessment (Mester et al., 2007; Norden and Weber, 2010; Minnis and Sutherland, 2017; Liu, 2022). The movement in $\ln(\text{Income})$ and Credit Score shows where invoice digitalization first appears inside underwriting.

3.3 Loan Terms

The downstream contractual margin moves with internal assessment. In the preferred specifications in Table 4, borrowers receive larger credit lines, lower interest spreads and rates, and longer maturities after GT3. The preferred specification implies a 0.179 log point increase in $\ln(\text{Credit Line})$, a 0.442 percentage point decline in Interest Spread, a 0.404 percentage point decline in Interest Rate, and a 49 day increase in maturity. These effects are consistent with evidence that bank information changes both price and non price contract terms (Bharath et al., 2011; Bolton et al., 2016).

The timing is aligned with this sequence. In Figure 2, pre GT3 coefficients remain stable and $\ln(\text{Credit Line})$ shifts after GT3 rollout. In Figure 3, the realized DID estimate lies in the tail of the placebo distribution. After establishing the sequence from records to assessment and contract terms, the analysis turns to the distribution of gains.

3.4 Information Scarcity, Bank Specialization, and Pass Through

Equation (1) implies that verifiable records should matter more when the prior information set is thinner. The heterogeneity tests separate three objects. Borrower record scarcity identifies where invoice digitalization adds most to the borrower’s information set. Bank size and bank specialization identify where lenders had less accumulated local or sectoral knowledge. Local concentration measures how much of the resulting credit response reaches borrowers.

Borrower record scarcity. Consumer facing sectors generate fewer verifiable business transaction trails than inter firm trade. I classify industries by whether final consumers rather than inter firm counterparties dominate transaction demand, following the idea that consumer facing activity provides fewer externally verified records than business to business trade (Naritomi, 2019; Huang et al., 2020). The three definitions broaden the consumer facing sector set from F, H, O, and R to include P and Q, and then L and M. Borrower record scarcity predicts larger credit line gains. Across the three definitions in Table 5, the effect on $\ln(\textit{Credit Line})$ is consistently larger in the consumer facing group (Huang et al., 2020; Chan et al., 2022; Minnis et al., 2024). For transparency, Appendix Table D.1 reports the corresponding one digit industry estimates.

Lender information stock. The same logic applies on the lender side. Smaller banks rely more on branch level judgment and relationship knowledge that are harder to transmit through the lending organization (Stein, 2002; Liberti and Mian, 2009; Hertzberg et al., 2010). The lender side split points in the same direction. The coefficient on GT3 is 0.167 for small banks and 0.072 for large banks in Table 6. The larger response among small banks is consistent with a larger incremental value where organizational information advantages were weaker.

Bank specialization. Sectoral soft information provides a second lender side margin. Following the specialization logic in Blickle et al. (2026), repeated lending to familiar local industries can create screening knowledge, borrower comparables, and monitoring routines. I measure pre GT3 bank specialization as the distance between a bank’s local industry portfolio and the corresponding province quarter industry portfolio; Appendix A.5 reports the exact construction. The reform also changes how banks allocate credit across local industries. Excess specialization, industry HHI, and the top industry share fall, while the number of active industries rises in Table 7. Banks lend across a broader set of local industries as invoice digitalization makes transaction records more portable.

Banks with stronger pre GT3 local industry specialization respond less on the credit line margin. The interaction with GT3 is negative and statistically significant in Table 8. Banks that were already more specialized before GT3 expand credit lines less, while less specialized banks respond more strongly. The specialization result mirrors the borrower and bank size splits: the response is larger where the lender had accumulated less reusable local industry knowledge before GT3.

Market pass through. Local competition governs transmission. It determines how much of the value created by invoice digitalization reaches borrowers. City by year month HHI is constructed from the distribution of bank branches across banks within each city, following the local market branch share approach in Degryse and Ongena (2005) and Agarwal and Hauswald (2010). The negative and statistically significant HHI interaction in Table 9 implies larger credit line responses in less concentrated local banking markets (Petersen and Rajan, 1995; Broecker, 1990; Hauswald and Marquez, 2003; Yannelis and Zhang, 2023; He et al., 2024).

The heterogeneity results separate information value from pass through. Invoice digitalization has larger value where borrower records were thinner or lender knowledge was more

limited. Conditional on that value, more of the credit response reaches borrowers in more competitive local banking markets.

4 Local Lending Reach and Scope

This section characterizes the expansion along three margins. Loan level distance and boundary evidence show where the new local frontier appears. Bank balance sheets show how the expansion appears at the lender level. Listed firm announcements locate the response among borrowers with abundant formal disclosure. At the loan level, $\ln(Distance)$ rises by 0.135 log points, implying about a 14.4% increase in average distance after the reform in Table 10, column (1). Local lending markets expand outward after invoice digitalization enters underwriting.

4.1 Boundary Evidence

The GT3 implied expansion boundary provides a local view of the new lending margin. The boundary exercise follows the loan prospecting and monitoring intuition in Heider and Inderst (2012) and Heitz et al. (2026): the new frontier is where borrower assessment and residual contact costs can be separated. Credit Score can remain comparable, while rates and travel time rise because local information remains more costly to collect and use farther from the branch (Beck et al., 2018; Vives and Ye, 2025).

I define a city specific expansion cutoff by moving inward from the post GT3 maximum distance by the average distance increase estimated in Table 10, column (1). Loans just inside and just outside this cutoff form the boundary comparison. I also estimate a local discontinuity at the same boundary after residualizing outcomes with the same fixed effects; this RD implementation follows Calonico et al. (2014). Appendix A.6 gives the full construction, and Appendix Figure A.1 illustrates the expansion boundary and the inner and outer comparison bands.

Both local designs help distinguish internal borrower assessment from residual contact costs. Credit Score does not change discontinuously at the boundary, indicating that newly reached borrowers are not assigned weaker repayment capacity. Rates and travel time rise outside the boundary: in the outer versus inner comparison, rates are 0.160 percentage points higher and driving time is 14.9 minutes longer outside the boundary; the local RD estimates show the same qualitative pattern. Figure 4 shows the corresponding local jumps.

Appendix Figure A.2 provides road network context for the travel time patterns around the expansion boundary, where dense urban roads give way to surrounding rural areas and contact costs increase.

The boundary evidence characterizes borrowers at the new local lending margin. I next ask how the same expansion appears at broader levels of aggregation: bank balance sheets and borrowers with abundant formal disclosure.

4.2 Bank Balance Sheet Evidence

Bank annual reports show how the local expansion appears on bank balance sheets. In Table 13, net interest income rises through higher asset side returns, while funding costs remain stable. Loan growth, loan to asset ratios, and total loans show little movement. Nonperforming loans do not rise, and reserve coverage does not fall. At the bank level, the expansion appears through higher returns rather than broad loan quantity growth.

4.3 Listed Firm Evidence

The listed firm comparison examines borrowers whose formal information was already abundant. Listed firms provide this benchmark because audited and standardized disclosure already supplies lenders with substantial hard information (Blackwell et al., 1998; Minnis and Sutherland, 2017).

In that sample, announced credit lines show little response across specifications with firm, bank, year month, and contract controls in Table 14. The listed firm contrast points back to the opaque segment of local small business lending.

The new local margin is concentrated in opaque local small business lending, where formal information was scarce and locally gathered soft information mattered more. The boundary evidence identifies the residual cost component at the new lending frontier. The next section turns from that frontier comparison to the full distance distribution, where invoice digitalization generates larger gains for borrowers farther from the lender.

5 Distance and Soft Information

This section closes the mechanism by asking whether the benefits of invoice digitalization increase with distance, the paper’s main geographic proxy for dependence on local soft information. The borrower scarcity and bank specialization results show that the gains are larger where prior information was thinner. Distance provides the continuous geographic counterpart: borrowers farther from the lender had weaker local soft information before GT3, so invoice records should add more to the bank’s information set for them. The section first shows that distance schedules flatten after GT3, and then shows that the implied gains increase systematically along the distance distribution.

5.1 Distance Gradients

Before GT3, distance segments both credit quantities and loan prices: credit lines decline with distance, while rates and spreads rise. After GT3, both gradients flatten. In Table 15 and Figure 5, the slope of $\ln(\textit{Credit Line})$ shifts from -0.123 to -0.070 , the distance gradient in Interest Rate from 0.187 to 0.084 , and the corresponding distance gradient in Interest Spread from 0.186 to 0.081 . Distance plays a weaker role in segmenting local credit allocation and pricing.

Table 16 estimates the continuous distance interaction that underlies the pointwise effects in Section 5.2. The signs of the interaction terms line up with the schedule evidence: the interaction is positive for assessment and credit quantity, and negative for pricing outcomes. The same pattern holds when straight-line distance is replaced by routed driving distance; Appendix Table C.1 reports this robustness check.

5.2 Larger Gains at Greater Distance

The interaction specification in Equation (4) tests whether the gains from invoice digitalization increase with distance. I set $Z_i = \ln(\text{Distance}_i)$, so the coefficient on $GT3 \times \ln(\text{Distance})$ measures how the GT3 effect varies with distance within the same local lending market. Table 16 shows a consistent pattern across assessment, quantity, and pricing. The interaction term is positive for $\ln(\text{Income})$ and $\ln(\text{Credit Line})$, and negative for Interest Spread and Interest Rate. Borrowers farther from the lender therefore experience larger improvements in internal assessment, larger credit line gains, and increasingly favorable pricing effects.

This pattern is the central implication of the distance mechanism. In branch based small business lending, greater distance makes borrower specific soft information harder to collect, update, and transmit. Invoice digitalization makes transaction records easier for banks to verify and use, so the informational gain is larger for distant borrowers, where local soft information had been weakest before GT3.

To give the interaction coefficient economic content, I evaluate the implied GT3 effect along the observed distance support. For each support point x , the implied effect is

$$\hat{\tau}(x) = \hat{\beta}_{GT3} + x\hat{\beta}_{GT3 \times \ln(\text{Distance})}.$$

Appendix Table C.2 reports these pointwise effects at the 10th, 25th, 50th, 75th, and 90th percentiles of the pre GT3 $\ln(\text{Distance})$ distribution, at the pre GT3 maximum, and at the

post GT3 maximum. Figure 6 plots the same profile. The percentile profile shows that the implied gains rise systematically over the actual distance distribution.

The assessment margin moves first. In the $\ln(\text{Income})$ plot in Figure 6, the implied effect rises from 0.426 at the 10th percentile of the pre GT3 distance distribution to 1.086 at the post GT3 maximum. The bank’s internal assessment therefore improves most for borrowers farther from the lender, where distance had previously limited the information available for underwriting.

The same distance pattern appears on the quantity margin. In the $\ln(\text{Credit Line})$ plot, the implied effect rises from 0.153 at the 10th percentile to 0.389 at the post GT3 maximum. More distant borrowers therefore receive larger credit line gains. This result links the distance evidence back to the information scarcity results in Section 3.4: invoice digitalization has larger value where the prior information set was thinner.

Pricing moves in the same direction. The Interest Rate and Interest Spread plots show that the effects become increasingly favorable as distance rises, reaching about -0.297 percentage points at the post GT3 maximum. This pricing pattern is the price side counterpart of the same mechanism. More distant borrowers had previously faced a larger information risk component in the distance premium, and invoice digitalization compresses that component by making borrower information easier to verify and transmit.

The distance results show that the benefits of invoice digitalization increase with distance. Farther borrowers gain more in internal assessment, credit quantity, and pricing because distance had proxied for weaker local soft information before GT3. The boundary evidence in Section 4.1 complements this result by identifying the residual cost component at the lending frontier: the information risk component shrinks with verifiable records, while the remaining frontier premium aligns with contact and monitoring costs.

6 Conclusion

This paper shows how public digital infrastructure enters bank information production. By digitalizing invoice recording and authentication, GT3 turns ordinary transactions into records that banks can verify and transmit through underwriting. These records appear throughout the lending process, from formal reporting to internal assessment, contract terms, and lending reach.

The gains are largest where invoice digitalization adds most to what banks knew before the reform: among borrowers with thinner transaction trails and banks with less accumulated local or sectoral knowledge. More competitive local markets transmit more of the gain to borrowers. The distance evidence shows that borrowers farther from the lender gain more in assessment, credit quantity, and pricing. This pattern is consistent with invoice digitalization adding most where local soft information had been weakest. The boundary evidence then identifies the residual cost component at the new lending frontier: higher rates coincide with longer driving time but comparable Credit Scores.

The broader implication is that publicly produced verifiable records can reduce information based credit frictions for opaque firms inside incumbent banking systems. Public digital infrastructure can therefore expand formal credit access by lowering the risk premium attached to missing hard information, not only by digitizing administrative records.

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Tables

General table notes: Unless stated otherwise, parentheses report t -statistics; significance is denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. Variable construction is reported in Appendix Table A.4, and loan level fixed effects and control blocks are described in Appendix B.

Reporting, Assessment, and Contract Terms

Table 1: Summary Statistics

	N	Mean	Std. Dev.	P25	Median	P75
Credit Line (RMB)	154,233	1,521,540	2,050,424	330,000	800,000	1,890,000
Interest Rate	154,233	7.290	2.133	5.655	6.960	8.528
Interest Spread	154,233	2.655	2.015	1.250	2.213	3.700
Maturity	154,233	506.9	598.722	356	364	366
Credit Score	101,242	45.997	28.680	21.000	49.130	64.385
$\ln(Income)$	126,282	14.95	2.018	13.592	15.294	16.300
Distance	96,883	27.2	25.035	8.073	22.351	38.772

Notes: Row-wise summary statistics are shown for the main loan level sample. Statistics are computed on non-missing observations for each variable.

Table 2: GT3 and the Reporting Environment

	$\ln(\text{Tax Amount})$
GT3	0.076** (2.29)
Lagged $\ln(\text{GDP per capita})$	1.142*** (7.08)
Lagged $\ln(\text{Population})$	1.328*** (3.92)
Lagged $\ln(\text{Road infrastructure})$	-0.196** (-2.60)
Lagged secondary sector share	0.532 (0.50)
Lagged tertiary sector share	0.212 (0.15)
Lagged $\ln(\text{Trade})$	-0.100 (-1.69)
Constant	-10.081*** (-2.78)
Province FE	Yes
Tax Category $\times$ Year FE	Yes
Taxpayer Category $\times$ Year FE	Yes
Observations	44,239
R^2	0.759

Notes: Annual regressions use CNRDS tax statistics at the province level. Macro controls are lagged one year. The estimation sample is the non-missing intersection of the outcome and lagged controls; Appendix Table A.3, Panel B reports row-wise summary statistics.

Table 3: GT3 and Bank Assessment

	$\ln(\text{Income})$		Credit Score	
	(1)	(2)	(3)	(4)
GT3	0.132*** (2.84)	0.193*** (3.31)	2.987*** (2.75)	6.642*** (4.99)
Constant	14.869*** (381.84)	14.831*** (428.88)	43.459*** (42.45)	40.354*** (35.74)
Year-Month FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
City FE	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes
Control FE	No	Yes	No	Yes
Observations	126,282	126,268	101,240	101,228
R^2	0.337	0.480	0.090	0.151

Notes: Columns (2) and (4) are the preferred specifications; columns (1) and (3) include only Year-Month FE and Bank FE. Outcome-specific omissions follow Appendix B.

Table 4: GT3 and Contract Terms

Panel A. ln(Credit Line) and Interest Rate

	ln(Credit Line)		Interest Rate	
	(1)	(2)	(3)	(4)
GT3	0.360*** (8.96)	0.179*** (4.21)	-0.315*** (-3.22)	-0.404*** (-3.77)
Constant	6.464*** (241.48)	6.575*** (268.03)	7.482*** (119.35)	7.537*** (116.28)
Year-Month FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
City FE	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes
Control FE	No	Yes	No	Yes
Observations	154,182	154,170	154,233	154,221
R^2	0.384	0.543	0.579	0.670

Panel B. Interest Spread and Maturity

	Interest Spread		Maturity	
	(5)	(6)	(7)	(8)
GT3	-0.338*** (-3.34)	-0.442*** (-3.95)	110.939*** (5.40)	49.014** (2.22)
Constant	2.862*** (44.33)	2.926*** (43.13)	438.933*** (29.61)	476.854*** (32.96)
Year-Month FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
City FE	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes
Control FE	No	Yes	No	Yes
Observations	154,233	154,221	154,182	154,170
R^2	0.523	0.628	0.419	0.610

Notes: Columns (2), (4), (6), and (8) are the preferred specifications; columns (1), (3), (5), and (7) include only Year-Month FE and Bank FE. Outcome-specific omissions follow Appendix B.

Information Scarcity and Pass Through

Table 5: Borrower Information Scarcity and Credit Line Effects

Dep. Var.:	$\ln(\text{Credit Line})$					
	Version 1		Version 2		Version 3	
	B2B	B2C	B2B	B2C	B2B	B2C
GT3	0.135*** (3.69)	0.213*** (3.59)	0.141*** (3.82)	0.209*** (3.54)	0.128*** (3.66)	0.206*** (3.51)
Constant	6.666*** (301.98)	6.552*** (188.96)	6.660*** (299.21)	6.558*** (190.84)	6.649*** (310.24)	6.578*** (192.60)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Control FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68,767	73,146	67,658	74,254	61,934	79,983
R^2	0.603	0.522	0.605	0.521	0.612	0.523

Notes: The outcome is $\ln(\text{Credit Line})$ in each grouped DID specification. B2C versions use progressively broader consumer facing sector definitions described in the text. The definitions expand the consumer facing sector set across versions. The comparison group contains remaining B2B industries; observations with unclassified or missing one digit industry codes are omitted. Industry letters follow the one digit GB/T 4754 classification, with names listed in Appendix Table D.1.

Table 6: Bank Size and Credit Line Effects

Dep. Var.:	$\ln(\text{Credit Line})$	
	Small banks	Large banks
GT3	0.167*** (3.19)	0.072** (2.20)
Constant	6.497*** (212.05)	7.422*** (508.08)
City FE	Yes	Yes
Year-Month FE	Yes	Yes
Bank FE	Yes	Yes
Industry FE	Yes	Yes
Control FE	Yes	Yes
Observations	139,260	14,870
R^2	0.518	0.660

Notes: The estimates split the preferred loan level credit line specification between nationally listed large banks and more locally oriented small banks.

Table 7: GT3 and Banks' Local Industry Allocation

Dep. Var.:	Local Excess Specialization (1)	Industry HHI (2)	Top-Industry Share (3)	Active Industries (4)
GT3	−0.138** (−2.28)	−0.211*** (−3.39)	−0.167*** (−3.17)	1.372** (2.46)
Constant	0.289*** (11.96)	0.730*** (30.28)	0.798*** (38.96)	3.101*** (14.49)
Bank FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	1,020	1,020	1,020	1,020
R^2	0.393	0.470	0.428	0.493

Notes: The unit of observation is bank $\times$ province $\times$ year-quarter.

Table 8: Pre GT3 Bank Specialization and Credit Line Effects

Dep. Var.:	$\ln(\text{Credit Line})$ (1)
GT3	0.073** (2.08)
Bank Specialization	0.050 (1.53)
GT3 $\times$ Bank Specialization	−0.125** (−2.11)
Constant	6.781*** (187.15)
City FE	Yes
Year-Month FE	Yes
Bank FE	Yes
Industry FE	Yes
Control FE	Yes
Observations	117,945
R^2	0.525

Notes: Pre GT3 bank specialization is defined in Appendix A.5.

Table 9: Local Market Concentration and Credit Line Effects

Dep. Var.:	$\ln(\textit{Credit Line})$
	(1)
GT3	0.341*** (3.81)
HHI	-0.496 (-1.31)
GT3 $\times$ HHI	-1.327*** (-3.37)
Constant	6.542*** (129.27)
City FE	Yes
Year-Month FE	Yes
Bank FE	Yes
Industry FE	Yes
Control FE	Yes
Observations	140,253
R^2	0.517

Notes: The specification estimates Equation (4) using city by year month HHI and $\ln(\textit{Credit Line})$ as the outcome. Lower HHI indicates a more competitive local banking market.

Local Lending Reach and Scope

Table 10: Average Distance Expansion

Dep. Var.:	$\ln(Distance)$
	(1)
GT3	0.135** (2.10)
Constant	2.855*** (91.95)
City $\times$ Year-Month FE	Yes
Bank FE	Yes
Industry FE	Yes
Control FE	Yes
Observations	93,993
R^2	0.395

Notes: The specification follows the baseline distance equation in Equation (2). City $\times$ Year-Month FE keep the comparison within the same city and month.

Table 11: Boundary Band Comparison

Dep. Var.:	Interest Rate (1)	Credit Score (2)	Driving Time (3)
Outer band	0.160** (2.00)	0.744 (0.46)	14.922*** (10.03)
City $\times$ Year-Month FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Control FE	Yes	Yes	Yes
Observations	14,303	10,107	14,303
R^2	0.767	0.309	0.986

Notes: Reported coefficients compare loans in the outer band with loans in the inner band around the expansion boundary. Band construction follows Appendix A.6. Controls follow Appendix B; Credit-score FE are omitted when Credit Score is the dependent variable.

Table 12: Local RD at the Expansion Boundary

Dep. Var.:	Baseline h			Robustness $2h$		
	Interest Rate (1)	Credit Score (2)	Driving Time (3)	Interest Rate (4)	Credit Score (5)	Driving Time (6)
RD estimate	0.430*** (2.91)	-3.358 (-1.03)	10.225*** (2.62)	0.313*** (3.15)	-2.791 (-1.01)	10.327*** (4.53)
City $\times$						
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Control FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,303	10,107	14,303	14,303	10,107	14,303

Notes: Each outcome is first residualized using the fixed effects and controls described in Appendix B; the residualized outcome is then used in the local polynomial RD. Running variable and cutoff construction follow Appendix A.6. RD inference uses local linear fits, a triangular kernel, and a mass point adjustment. Credit-score FE are omitted when Credit Score is the dependent variable.

Table 13: Bank Balance Sheet Evidence

Panel A. Interest Income and Returns

Dep. Var.:	(1) Net Interest Income / Assets	(2) Log(Net Interest Income / Assets)	(3) Interest Income / Assets	(4) Interest Expense / Assets
GT3	0.0022*** (3.39)	0.096** (2.18)	0.0031*** (3.27)	0.0009 (1.22)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Lagged Controls	Yes	Yes	Yes	Yes
Observations	1,500	1,497	1,500	1,492

Panel B. Loan Quantity

Dep. Var.:	(5) Loan Growth	(6) Loan-to- Asset Ratio	(7) Log Total Loans
GT3	0.017 (0.28)	-0.007 (-0.53)	0.003 (0.17)
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Lagged Controls	Yes	Yes	Yes
Observations	1,494	1,494	1,494

Panel C. Asset Quality

Dep. Var.:	(8) NPL Ratio	(9) Reserve Coverage Ratio
GT3	0.209 (1.49)	32.893 (0.96)
Bank FE	Yes	Yes
Year FE	Yes	Yes
Lagged Controls	Yes	Yes
Observations	1,477	1,328

Notes: The bank year sample is restricted to banks whose domestic branch networks are confined to a single province. Specifications include bank fixed effects, year fixed effects, and lagged balance sheet controls described in Appendix Table A.4.

Table 14: Listed-Firm Credit Lines

Dep. Var.:	$\ln(\textit{Credit Line})$		
	(1)	(2)	(3)
GT3	−0.006 (−0.25)	0.011 (0.52)	0.010 (0.50)
Constant	9.235*** (493.76)	9.221*** (512.34)	9.221*** (519.93)
Firm FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Loan Type FE	No	Yes	Yes
Loan Purpose FE	No	Yes	Yes
Currency FE	No	Yes	Yes
Collateral FE	No	No	Yes
Syndicate FE	No	No	Yes
Observations	151,074	151,066	151,065
R^2	0.613	0.656	0.657

Notes: The listed firm comparison uses firm, year month, and bank fixed effects. Columns (2) and (3) add contract attribute fixed effects.

Distance Gradients

Table 15: Pre and Post GT3 Distance Gradients

Dep. Var.:	$\ln(\text{Credit Line})$		Interest Rate		Interest Spread	
	(1) Pre	(2) Post	(3) Pre	(4) Post	(5) Pre	(6) Post
$\ln(\text{Distance})$	-0.123*** (-22.90)	-0.070*** (-8.33)	0.187*** (10.77)	0.084*** (3.80)	0.186*** (10.71)	0.081*** (3.45)
Constant	6.582*** (404.18)	6.930*** (293.72)	8.248*** (157.08)	6.578*** (105.85)	2.919*** (55.54)	2.302*** (35.23)
City $\times$ Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Control FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,609	45,354	48,609	45,354	48,609	45,354
R^2	0.458	0.544	0.465	0.758	0.583	0.755

Notes: The table describes how distance slopes change before and after GT3. Specifications use the fixed effects and controls indicated in the table.

Table 16: Distance Heterogeneity in GT3 Effects on Assessment and Loan Terms

Dep. Var.:	$\ln(\text{Credit Line})$	Interest Rate	Interest Spread	$\ln(\text{Income})$
	(1)	(2)	(3)	(4)
GT3	0.083 (0.62)	0.309** (2.30)	0.332** (2.44)	0.172 (0.57)
$\ln(\text{Distance})$	-0.124*** (-21.06)	0.190*** (10.09)	0.190*** (10.03)	-0.212*** (-12.15)
GT3 $\times$ $\ln(\text{Distance})$	0.052*** (4.78)	-0.103*** (-3.39)	-0.107*** (-3.40)	0.155*** (7.65)
Constant	6.715*** (101.98)	7.284*** (94.02)	2.451*** (31.80)	15.273*** (96.83)
City $\times$ Year-Month FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Control FE	Yes	Yes	Yes	Yes
Observations	93,993	93,993	93,993	86,026
R^2	0.533	0.683	0.668	0.430

Notes: Specifications estimate Equation (4) with $Z_i = \ln(\text{Distance}_i)$. The interaction term and the implied post GT3 slope are the economically central objects. The GT3 main effect is evaluated at $\ln(\text{Distance}) = 0$, below the observed support, so the interpretation focuses on the interaction term and implied slopes. Income-group FE are omitted in column (4).

Figures

Information Channel and Timing

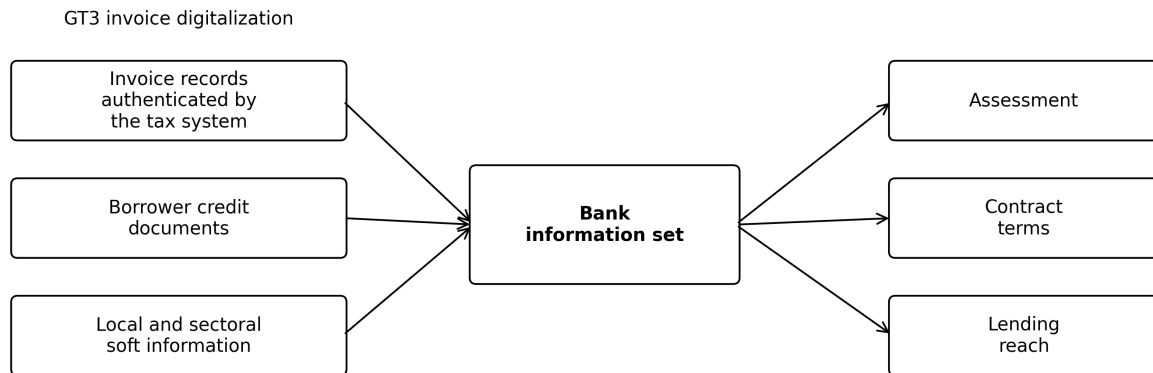


Figure 1: Invoice Digitalization and the Bank Information Set

Notes: Invoice digitalization enters credit files through borrower documents and expands the bank information set. Local and sectoral soft information enter through relationships, monitoring, branch knowledge, and industry familiarity.

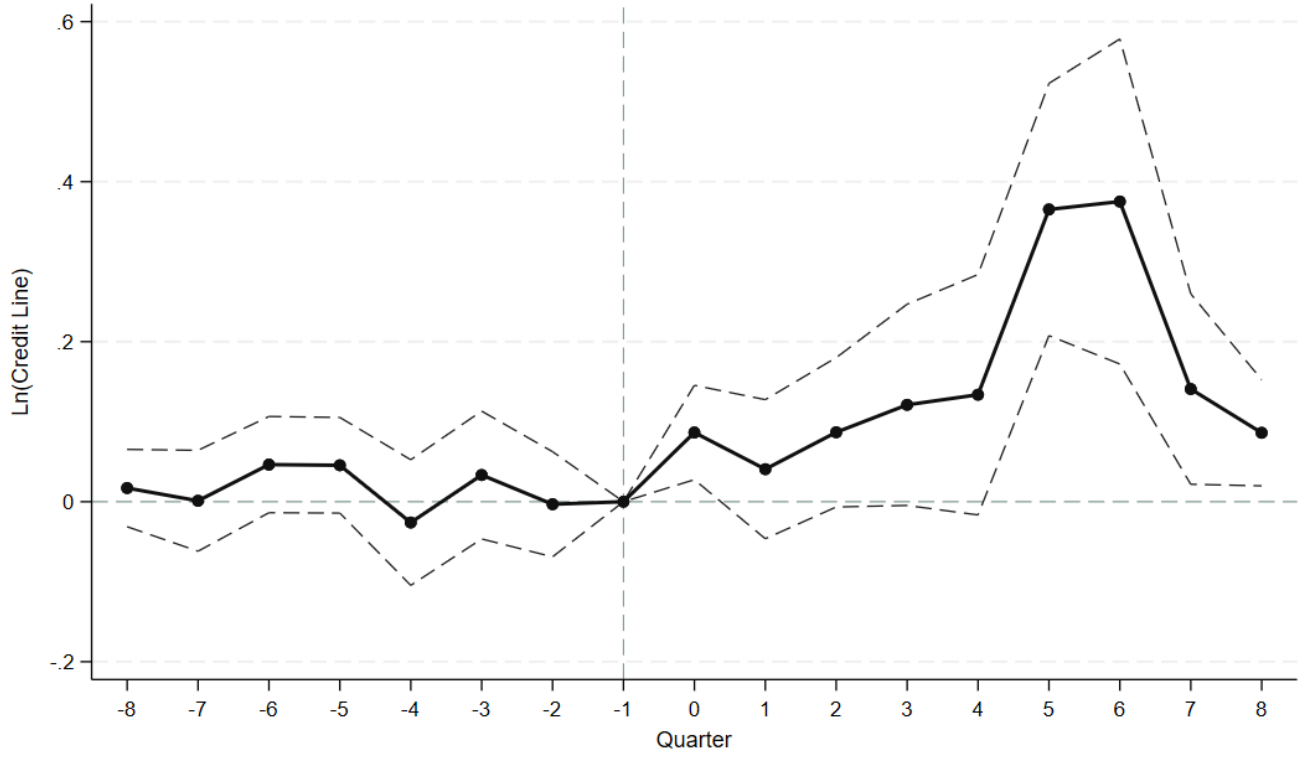


Figure 2: Event Study for $\ln(\text{Credit Line})$

Notes: Event time coefficients come from the preferred event study specification for $\ln(\text{Credit Line})$, with the quarter immediately before GT3 rollout omitted.

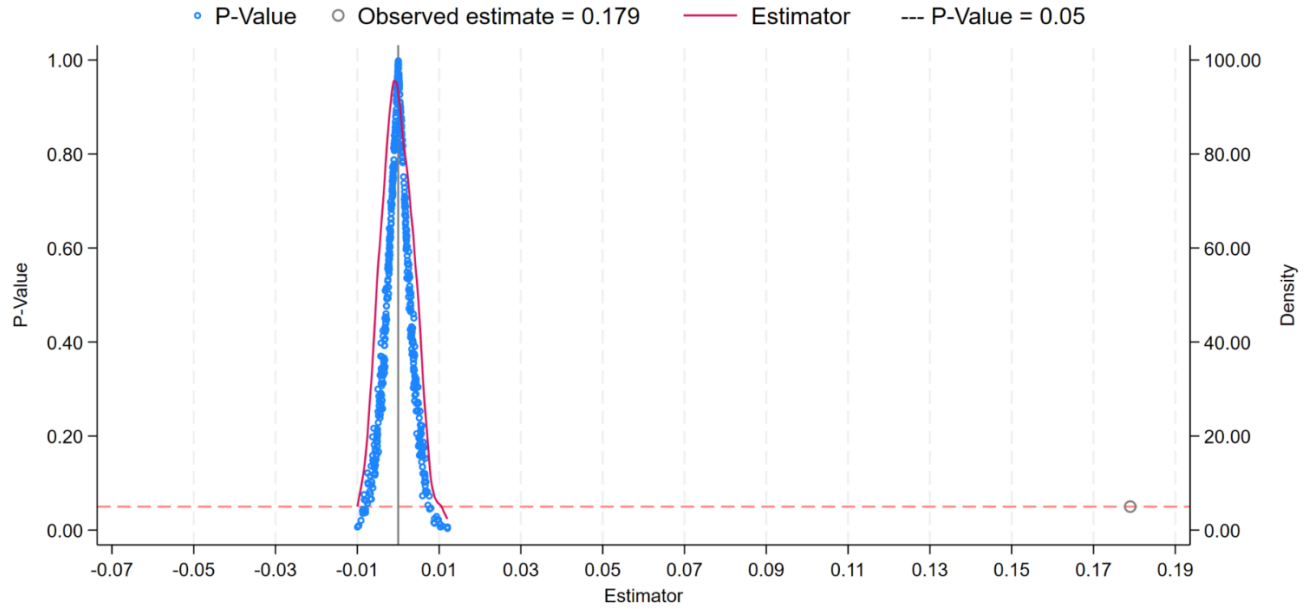


Figure 3: Placebo Distribution for $\ln(\text{Credit Line})$

Notes: The figure shows the placebo distribution of DID estimates for $\ln(\text{Credit Line})$. The observed estimate is marked in the figure.

Lending Frontier

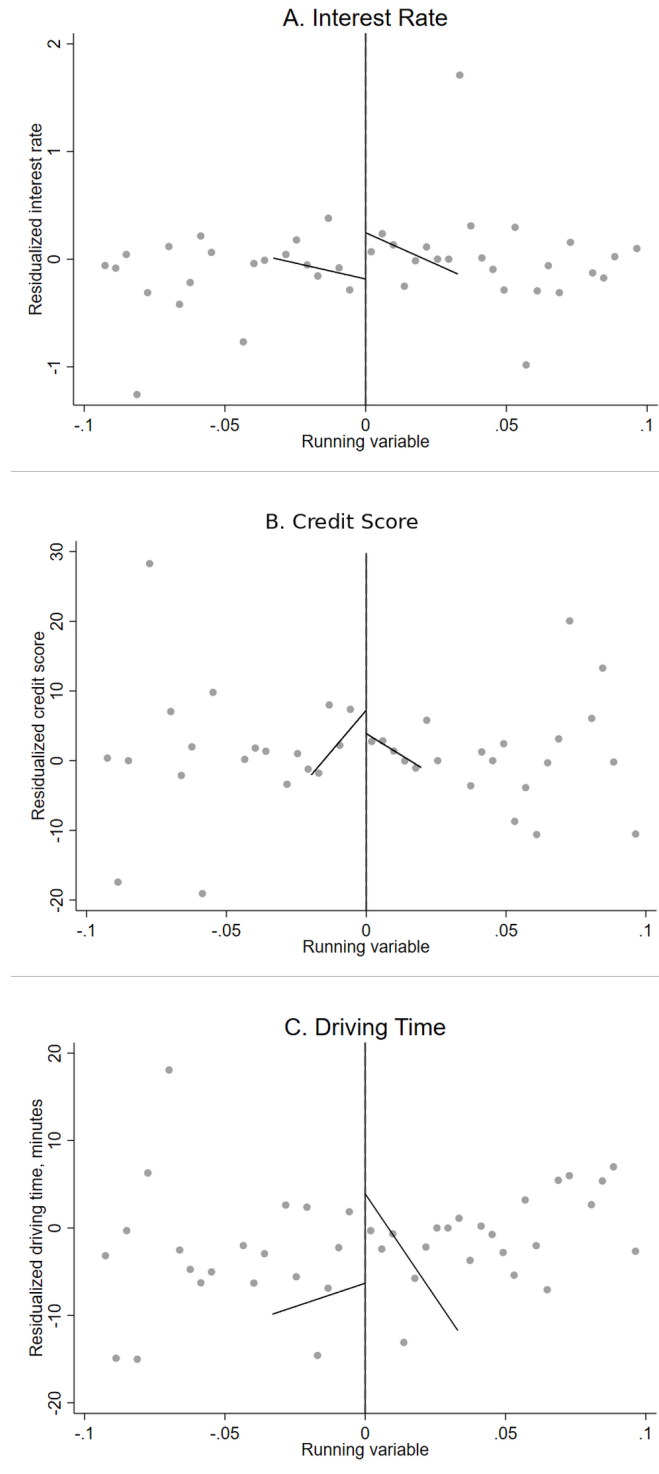


Figure 4: Local RD Plots at the GT3 Implied Expansion Boundary
Notes: Binned means of the residualized outcome are plotted against the boundary running variable. Panel A reports Interest Rate, Panel B reports Credit Score, and Panel C reports Driving Time.

Distance Gradients

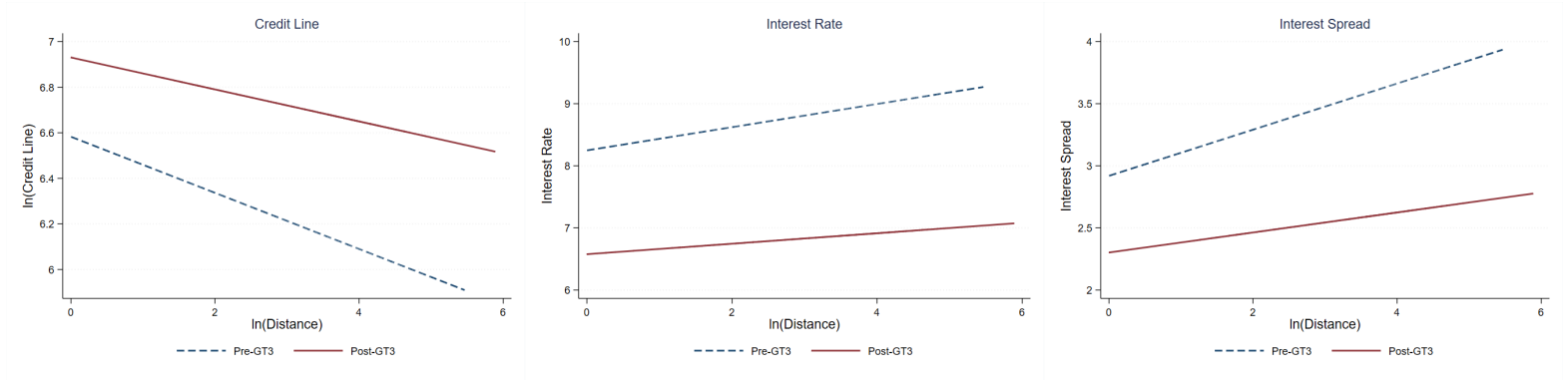


Figure 5: Pre- and Post-GT3 Distance Schedules

Notes: The three plots show fitted pre- and post-GT3 distance schedules for $\ln(\text{Credit Line})$, Interest Rate, and Interest Spread.

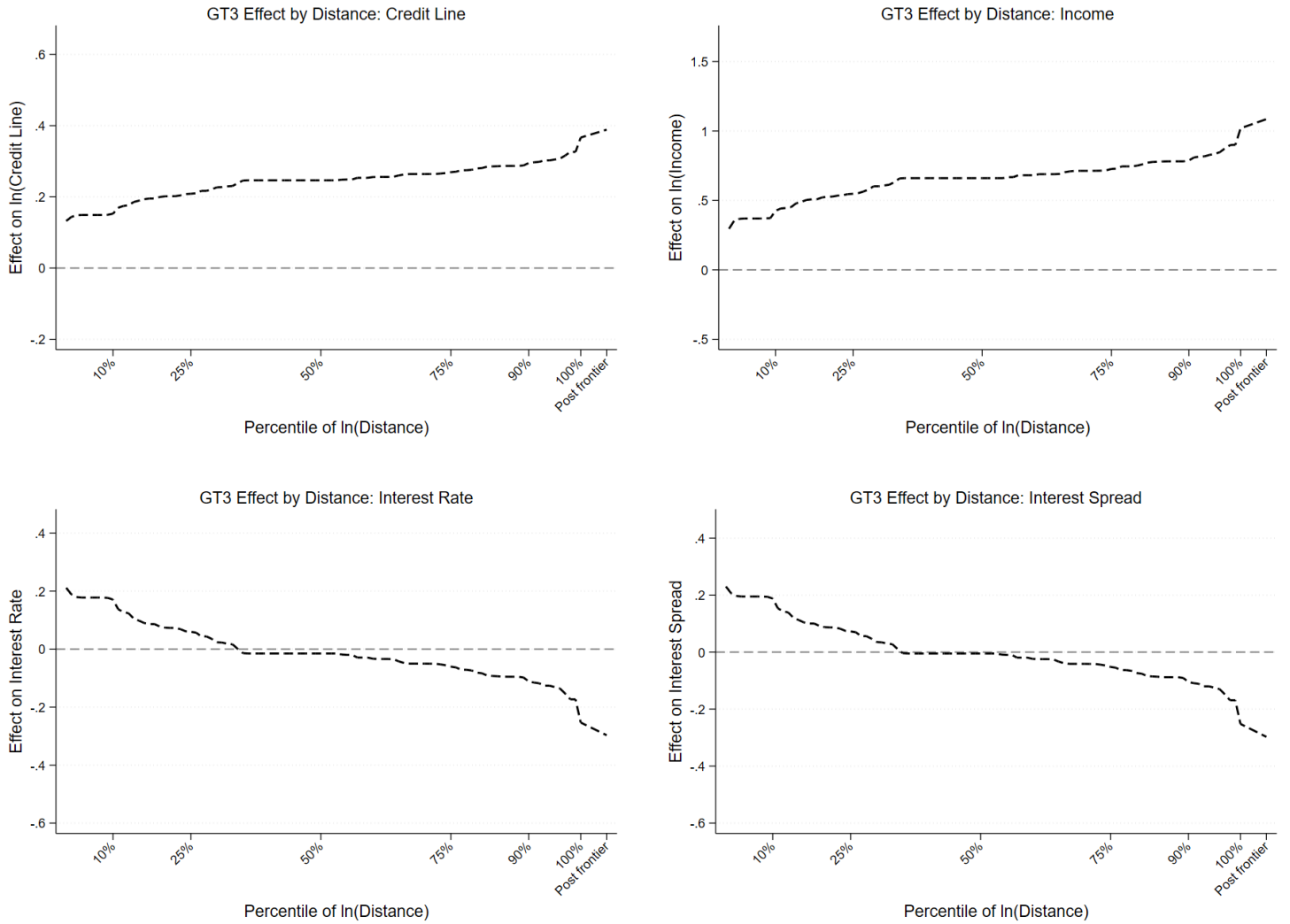


Figure 6: GT3 Effects Along the Distance Distribution

Notes: Each plot shows implied point estimates evaluated at support points of the relevant distance distribution. The four plots report $\ln(\text{Credit Line})$, $\ln(\text{Income})$, Interest Rate, and Interest Spread. The support points are the pre GT3 percentiles, the pre GT3 maximum, and the post GT3 frontier. The implied effect equals $\hat{\beta}_{GT3} + x\hat{\beta}_{GT3 \times \ln(\text{Distance})}$. The income plot uses the income sample, while the remaining plots use the common loan sample. Appendix Table C.2 reports the underlying pointwise estimates.

A Rollout, Samples, and Variables

Appendix A has six parts: rollout timing, public bank product evidence, auxiliary sample summaries, variable construction, the bank specialization measure, and the expansion boundary construction.

A.1 Rollout Calendar

Table A.1: GT3 Rollout by Province

Province or Municipality	Implementation Date	Province or Municipality	Implementation Date
Chongqing Municipality	2013.02.22	Shanxi Province	2013.10.08
Shandong Province	2013.10.08	Guangdong Province	2015.01.08
Henan Province	2015.01.08	Inner Mongolia Autonomous Region	2015.01.08
Ningxia Hui Autonomous Region	2015.07.01	Tibet Autonomous Region	2015.09.01
Hebei Province	2015.09.08	Guizhou Province	2015.09.08
Yunnan Province	2015.09.08	Guangxi Zhuang Autonomous Region	2015.09.08
Hunan Province	2015.10.08	Qinghai Province	2015.10.08
Hainan Province	2015.10.08	Gansu Province	2015.10.08
Anhui Province	2016.01.08	Xinjiang Uygur Autonomous Region	2016.01.08
Sichuan Province	2016.01.08	Jilin Province	2016.01.08
Shanghai Municipality	2016.07.08	Fujian Province	2016.07.08
Jiangxi Province	2016.07.08	Liaoning Province	2016.07.08
Beijing Municipality	2016.08.08	Tianjin Municipality	2016.08.08
Heilongjiang Province	2016.08.08	Hubei Province	2016.08.08
Shaanxi Province	2016.08.08	Jiangsu Province	2016.10.08
Zhejiang Province	2016.10.08		

Notes: GT3 rollout dates are listed for each province unit. Dates use the YYYY.MM.DD format.

A.2 Public Bank Product Evidence

Public bank product descriptions show how invoices and related transaction documents enter small business credit review. GT3 digitalized the infrastructure that creates and verifies the class of transaction records used in small business lending.

Table A.2: Public Bank Product Evidence on Invoice and Transaction Records in Small Business Lending

Bank or product	Records used	Role in credit review
ICBC small business domestic invoice financing	Domestic transaction invoices, transaction contracts, receivables	Invoice backed receivables support short term financing, with receivables identified as the first repayment source.
Agricultural Bank of China domestic invoice financing	Purchase and sale contracts, invoices, transport documents	Borrower documents enter the investigation, review, approval, and disbursement workflow.
Agricultural Bank of China “Zhang Ying Tong”	Receivables, purchase and sale contracts, invoices, delivery or transfer documents	Receivables based financing uses invoices and related transaction documents to support small business credit approval.
Ping An Bank supermarket supplier invoice loan	Supplier invoice data	Supplier invoice records are transmitted electronically and used in rapid credit review for upstream suppliers.
Ping An Bank Speed Invoice Loan	Invoicing behavior and invoicing history	Enterprise invoicing behavior and at least 18 months of invoicing records enter internet credit approval for small business owners.

Notes: Public bank product descriptions show how invoices and related transaction records enter small business credit review.

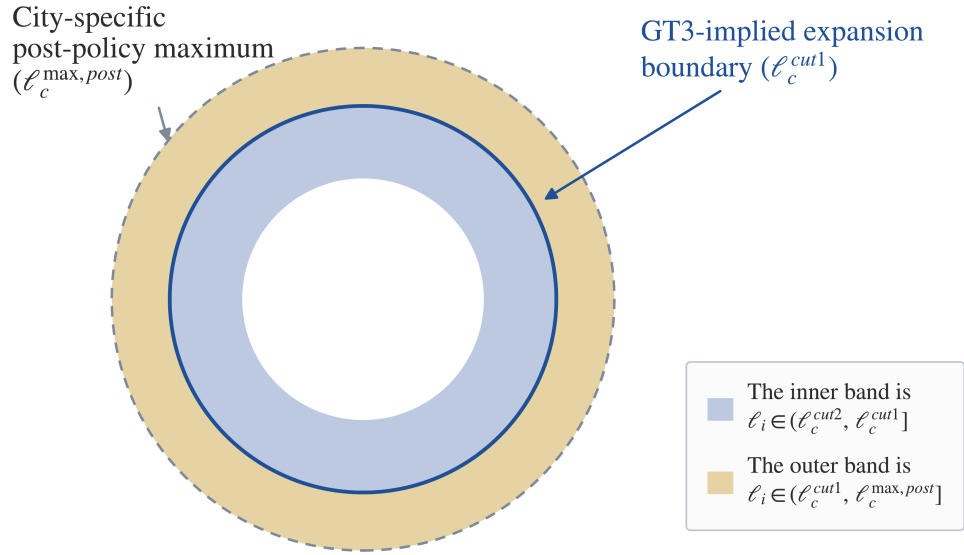


Figure A.1: GT3 Implied Expansion Boundary

Notes: The figure illustrates the city specific expansion boundary and the inner and outer bands used in the post GT3 boundary comparisons.

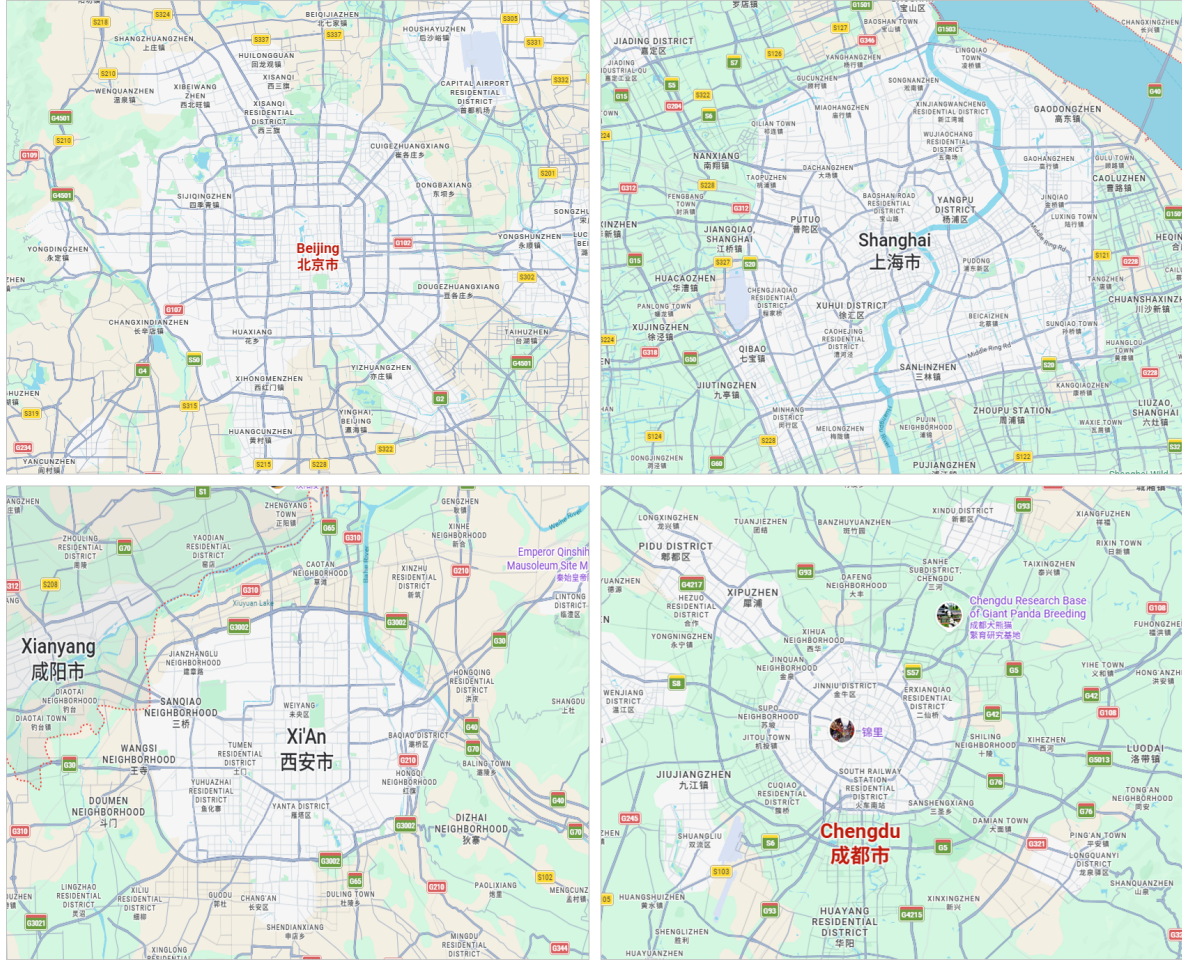


Figure A.2: Illustrative Urban Road Networks and the Expansion Boundary

Notes: Road network context is shown for Beijing, Shanghai, Xi'an, and Chengdu. Travel conditions can change sharply near the outer edge of city based lending markets, where local monitoring becomes more burdensome.

A.3 Auxiliary Sample Summaries

Table A.3: Auxiliary Sample Summaries

<i>Panel A. Listed-firm borrowing-announcement sample</i>						
	N	Mean	Std. Dev.	P25	Median	P75
Announced Credit Line (million RMB)	151,074	342.522	13,544.210	50	100	250
<i>Panel B. Provincial tax panel</i>						
	N	Mean	Std. Dev.	P25	Median	P75
Accounting year	52,173	2010.124	5.612039	2005	2010	2015
GT3 rollout year	52,140	2015.29	.8871095	2015	2015	2016
GT3 exposure indicator	52,173	.2521611	.4342574	0	0	1
Tax Amount	44,257	445212.4	1631849	2272	28450	213823
ln(<i>Tax Amount</i>)	44,239	9.817983	3.32395	7.730614	10.25696	12.27417
Lagged ln(<i>GDP per capita</i>)	52,173	10.0312	.8303778	9.381264	10.15518	10.65495
Lagged ln(<i>Population</i>)	52,173	8.082321	.8617372	7.784473	8.243808	8.711443
Lagged ln(<i>Road infrastructure</i>)	52,173	5.082042	.9350047	4.691348	5.267858	5.700444
Lagged secondary sector share	52,173	.4265007	.0829062	.3821188	.4356856	.4825657
Lagged tertiary sector share	52,173	.4507732	.0883211	.3977692	.4326409	.487055
Lagged ln(<i>Trade</i>)	52,173	16.72243	1.902105	15.37783	16.73073	17.98333
<i>Panel C. Bank annual report panel</i>						
	N	Mean	Std. Dev.	P25	Median	P75
Net Interest Income / Assets	1,500	0.0229	0.0099	0.0165	0.0215	0.0281
Log(Net Interest Income / Assets)	1,497	-3.8753	0.4881	-4.1012	-3.8371	-3.5708
Interest Income / Assets	1,500	0.0436	0.0118	0.0366	0.0420	0.0490
Interest Expense / Assets	1,493	0.0208	0.0085	0.0171	0.0200	0.0233
Loan Growth	1,494	0.2493	2.0537	0.1141	0.1626	0.2227
Loan to Asset Ratio	1,494	0.5024	0.1606	0.4363	0.5092	0.5712
Log(Total Loans)	1,494	24.3890	1.1443	23.5962	24.3206	25.2078
NPL Ratio	1,479	1.7295	1.3987	0.9900	1.5000	1.9800
Reserve Coverage Ratio	1,331	296.9807	333.2781	174.8200	223.8500	324.4100
Log(Total Assets)	1,500	25.1083	1.1744	24.2798	25.0917	25.9433
Equity / Assets	1,500	0.0783	0.0203	0.0653	0.0771	0.0880
Liquid Assets / Assets	1,245	0.2374	0.1086	0.1549	0.2155	0.3026
Operating Expenses / Assets	1,488	0.0095	0.0038	0.0071	0.0090	0.0113
Deposits / Assets	1,493	0.7541	0.2589	0.6676	0.7570	0.8333

Notes: Panel A reports listed firm borrowing-announcement statistics; Panel B reports the province-by-tax-category-by-taxpayer-category-by-year tax panel; Panel C reports the bank fiscal-year panel. Statistics are row-wise, so observation counts differ across variables. Table-specific estimation samples are the corresponding non-missing intersections of outcomes and controls.

A.4 Variables and Transformations

Table A.4: Variable Construction and Transformations

Variable	Construction	Unit or merge level
<i>Panel A. Treatment and geography</i>		
GT3	Indicator equal to one if the observation falls on or after the GT3 rollout date in the mapped province. In the main loan origination sample, the mapped province is the unique province implied by the borrower's registered city and the originating branch city. In annual panels, exposure begins in the rollout year; in the listed firm sample, exposure uses the lending-branch province and announcement date.	Province date or year
$Distance_i$	Distance in kilometers between the centroid of the borrower's registered district or county and the centroid of the originating branch city, computed from WGS84 coordinates. Because borrowers can originate only within their own city and the loan data identify the originating city rather than the exact branch address, this is a within-city distance measure.	Loan level
$\ln(Distance)$	Log of $Distance_i$.	Loan level
$DrivingDistance_i$	Routed road distance between the same borrower and originating city endpoints used for $Distance_i$.	Loan level
$DrivingTime_i$	Estimated travel time between the same borrower and originating city endpoints. The paper uses it as a proxy for contact and monitoring burden, especially in the expansion boundary analysis.	Minutes
<i>Panel B. Loan outcomes</i>		
Credit Line	Approved credit limit recorded at loan origination. In the listed firm comparison sample, Credit Line is the disclosed upper bound of the announced credit line.	RMB
$\ln(Credit\ Line)$	Log of Credit Line after dividing the RMB amount by 1,000. The same transformation is applied to the listed firm announced upper bound.	Loan/announcement
Interest Rate	Contractual nominal annual interest rate.	Percentage points
Interest Spread	Interest Rate minus the contemporaneous Loan Prime Rate.	Percentage points
Maturity	Contractual loan maturity.	Days
<i>Panel C. Bank assessment measures</i>		

Table A.4 continued

Variable	Construction	Unit or merge level
$\ln(\text{Income})$	Log of the bank assessed annual borrower income recorded in the underwriting file.	Loan level
Credit Score	Bank specific internal repayment-capacity assessment mapped into within bank percentile ranks from 1 to 100, with 100 denoting the strongest credit quality within bank. Regressions that condition on credit score use the underlying score category fixed effects rather than the displayed percentile.	Loan level
<i>Panel D. Market structure and bank specialization</i>		
HHI_{ct}	Herfindahl-Hirschman index of local banking concentration, constructed from branch shares at the city-by-year month level. Larger values indicate more concentrated local banking markets.	City by year month
Pre GT3 Bank Specialization	Leave one out, pre GT3 measure of how far a bank's local industry credit line shares deviate from the province quarter industry portfolio. The formula is reported in Appendix A.5.	Loan level
Local Excess Specialization	One half of the sum of absolute deviations between a bank's industry credit shares within a bank province quarter and the corresponding province quarter industry credit shares.	Bank province quarter
Industry HHI	Herfindahl-Hirschman index of amount weighted industry credit line shares.	Bank province quarter
Top Industry Share	Largest amount weighted industry credit line share.	Bank province quarter
Active Industries	Number of one digit industries receiving positive credit.	Bank province quarter
<i>Panel E. Tax and bank panel variables</i>		
Tax Amount	Reported tax collections from CNRDS provincial tax statistics.	Province $\times$ tax category $\times$ taxpayer category $\times$ year
$\ln(\text{Tax Amount})$	Log transformed Tax Amount used as the reporting environment outcome.	Annual tax panel
Net Interest Income / Assets	Net interest income divided by total assets.	Bank fiscal year
Interest Income / Assets	Interest income divided by total assets.	Bank fiscal year

Table A.4 continued

Variable	Construction	Unit or merge level
Interest Expense / Assets	Interest expense divided by total assets.	Bank fiscal year
Log(Net Interest Income / Assets)	Log of Net Interest Income / Assets, defined on positive observations.	Bank fiscal year
Loan Growth	Annual growth in total loans.	Bank fiscal year
Loan to Asset Ratio	Total loans divided by total assets.	Bank fiscal year
Log Total Loans	Log of total loans reported in bank annual statements.	Bank fiscal year
NPL Ratio	Nonperforming loans divided by total loans.	Bank fiscal year
Reserve Coverage Ratio	Loan loss reserves divided by nonperforming loans, reported from annual statements.	Bank fiscal year

A.5 Bank Specialization Measure

Following the specialization logic in Blickle et al. (2026), the bank specialization measure is the distance between a bank's local industry portfolio and the province quarter industry portfolio. Let ω_{bpqj} denote bank b 's credit line share in industry j within province p and quarter q , and let ω_{pqj} denote the corresponding province quarter industry share:

$$\omega_{bpqj} = \frac{\sum_{\ell \in \mathcal{L}_{bpqj}} CL_{\ell}}{\sum_{\ell \in \mathcal{L}_{bpq}} CL_{\ell}}, \quad \omega_{pqj} = \frac{\sum_{\ell \in \mathcal{L}_{pqj}} CL_{\ell}}{\sum_{\ell \in \mathcal{L}_{pq}} CL_{\ell}}.$$

The bank province quarter specialization measure is

$$Spec_{bpq} = \frac{1}{2} \sum_j |\omega_{bpqj} - \omega_{pqj}|.$$

Here, CL_{ℓ} is the approved credit line for loan ℓ , $\mathcal{L}_{bpqj}$ is the set of loans by bank b in province p , quarter q , and industry j , and $\mathcal{L}_{bpq}$ is the corresponding bank province quarter loan set. The terms $\mathcal{L}_{pqj}$ and $\mathcal{L}_{pq}$ denote the corresponding province quarter industry and province quarter loan sets. The pre GT3 specialization measure used in Table 8 is constructed using only pre GT3 observations and standardized as described in the table note.

A.6 Expansion Boundary and Local RD Construction

This appendix records the construction of the expansion boundary and the local RD used in Section 4.1. The economic idea follows the loan prospecting and monitoring logic in Heider and Inderst (2012) and Heitz et al. (2026): at the outer edge of branch based lending, borrower assessment and residual contact costs can move separately. The local RD implementation follows Calonico et al. (2014).

Let $\ell_i = \ln(\text{Distance}_i)$ denote the log distance for loan i , and let $\ell_c^{\max, \text{post}}$ denote the city specific post GT3 maximum of ℓ_i in city c . The local window is anchored to the average GT3 induced increase in $\ln(\text{Distance})$ from Table 10, column (1), which is 0.135. The first cutoff is

$$\ell_c^{\text{cut1}} = \ell_c^{\max, \text{post}} - 0.135,$$

and the second cutoff is

$$\ell_c^{\text{cut2}} = \ell_c^{\max, \text{post}} - 2 \times 0.135.$$

The inner band is $\ell_i \in (\ell_c^{\text{cut2}}, \ell_c^{\text{cut1}}]$, and the outer band is $\ell_i \in (\ell_c^{\text{cut1}}, \ell_c^{\max, \text{post}}]$. The post GT3 band comparison estimates

$$Y_i = \delta \mathbf{1}\{x_i^{\text{band}} \geq 0\} + \alpha_{FE(i)} + \varepsilon_i,$$

where $x_i^{\text{band}} = \ell_i - \ell_{c(i)}^{\text{cut1}}$.

The local RD uses the same cutoff. Each outcome is first residualized using the fixed effects and controls indicated in the boundary tables. The RD estimand is

$$\tau_Y = \lim_{x \downarrow 0} E[\tilde{Y}_i \mid x_i^{\text{band}} = x] - \lim_{x \uparrow 0} E[\tilde{Y}_i \mid x_i^{\text{band}} = x].$$

The implementation uses local linear fits, a triangular kernel, robust bias corrected inference, and an adjustment for mass points in the running variable.

B Estimation Details

This appendix records the fixed effects, coarsened control indicators, and column progressions behind the main loan level specifications.

B.1 Loan-Level Fixed Effects

The baseline loan level specifications use four core fixed effects.

- **Year-Month FE:** absorb aggregate shocks common to all loans originated in calendar month t .
- **City FE:** absorb time-invariant differences across originating-branch cities.
- **Bank FE:** absorb time-invariant differences across banks, including business model, risk appetite, and underwriting policies.
- **Industry FE:** defined at the one digit level of GB/T 4754 (2017), absorbing time-invariant sectoral heterogeneity.

Some mechanism designs replace Year-Month FE and City FE with $\text{City} \times \text{Year-Month}$ FE, so that identification comes from within-city-month variation. For the distance specifications, this keeps the comparison within the same city and month. Each table header lists the exact fixed effects included in that specification.

B.2 Control Fixed Effects

To maximize sample size, borrower and contract covariates are discretized into coarse groups and included as sets of indicator variables. Each set includes an explicit missing group so observations are not dropped when a covariate is unavailable.

The full set of control fixed effects used in the main loan level tables is:

- **Payment Method FE:** absorb systematic differences across repayment schedules.

- **Borrower Type FE:** indicate whether the loan is booked under a personal name or a corporate name.
- **Age Group FE:** apply only to personal-name loans and are formed from five age groups.
- **Income-group FE:** formed from within-sample quintiles of bank-assessed annual borrower income.
- **Leverage Quintile FE:** apply only to corporate-name loans and are formed from the asset-to-liability ratio distribution.
- **Credit-score FE:** absorb bank-specific rating categories. For banks reporting letter grades, the bank identifier is interacted with the grade; for banks reporting numeric scores, the bank identifier is interacted with score bins.
- **Loan Term FE:** capture non-linear level differences tied to maturity using four maturity buckets: less than 1 year, 1 to 3 years, 3 to 5 years, and above 5 years.

B.3 Column Progressions

The baseline tables with columns (1) to (4) build fixed effects cumulatively:

Column (1) Year-Month FE and Bank FE.

Column (2) Column (1) plus City FE.

Column (3) Column (2) plus Industry FE.

Column (4) Column (3) plus the full set of control fixed effects above.

Outcome-specific omissions. To avoid mechanically partialling out the dependent variable, the paper omits Income-group FE in income regressions, Loan Term FE in maturity regressions, and Credit-score FE when the dependent variable is the within-bank percentile version of the Credit Score. All other fixed effects and control blocks are retained.

Table B.1: Column Progression: Repayment-Capacity Assessment

Panel A. Bank-Assessed Annual Borrower Income

	(1)	(2)	(3)	(4)
GT3	0.132*** (2.84)	0.210*** (3.73)	0.211*** (3.68)	0.193*** (3.31)
Year-Month FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
City FE	No	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
Control FE	No	No	No	Yes
Observations	126,282	126,268	126,268	126,268
R^2	0.337	0.376	0.385	0.480

Panel B. Credit Score

	(1)	(2)	(3)	(4)
GT3	2.987*** (2.75)	1.880 (1.56)	3.233*** (2.61)	6.642*** (4.99)
Year-Month FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
City FE	No	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
Control FE	No	No	No	Yes
Observations	101,240	101,229	101,228	101,228
R^2	0.090	0.118	0.120	0.151

Notes: Income-group FE are omitted in Panel A; Credit-score FE are omitted in Panel B.

Table B.2: Column Progression: Risk-Sensitive Contract Design, Part I

Panel A. ln(Credit Line)

	(1)	(2)	(3)	(4)
GT3	0.360*** (8.96)	0.349*** (9.44)	0.331*** (7.87)	0.179*** (4.21)
Year-Month FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
City FE	No	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
Control FE	No	No	No	Yes
Observations	154,182	154,172	154,172	154,170
R^2	0.384	0.426	0.429	0.543

Panel B. Interest Spread

	(1)	(2)	(3)	(4)
GT3	-0.338*** (-3.34)	-0.400*** (-4.12)	-0.493*** (-4.53)	-0.442*** (-3.95)
Year-Month FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
City FE	No	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
Control FE	No	No	No	Yes
Observations	154,233	154,223	154,223	154,221
R^2	0.523	0.566	0.568	0.628

Table B.3: Column Progression: Risk-Sensitive Contract Design, Part II

Panel A. Interest Rate

	(1)	(2)	(3)	(4)
GT3	-0.315*** (-3.22)	-0.378*** (-4.06)	-0.464*** (-4.46)	-0.404*** (-3.77)
Year-Month FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
City FE	No	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
Control FE	No	No	No	Yes
Observations	154,233	154,223	154,223	154,221
R^2	0.579	0.617	0.619	0.670

Panel B. Maturity

	(1)	(2)	(3)	(4)
GT3	110.939*** (5.40)	63.272*** (2.84)	75.501*** (3.19)	49.014** (2.22)
Year-Month FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
City FE	No	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
Control FE	No	No	No	Yes
Observations	154,182	154,172	154,172	154,170
R^2	0.419	0.452	0.452	0.610

Notes: Loan-term FE are omitted in Panel B.

C Distance Robustness

This appendix keeps the distance-metric robustness exercise and a compact table of the pointwise GT3 effects that underlie the main-text distance-distribution figure.

C.1 Driving-Distance Robustness

Table C.1 replaces the baseline distance measure with routed driving distance in the interaction specifications for internal assessment and loan terms. The pattern is unchanged: the interaction is positive for assessment and credit quantity, and negative for loan pricing.

Table C.1: Driving-Distance Interactions for Internal Assessment and Loan Terms

Dep. Var.:	$\ln(\textit{Credit Line})$ (1)	Interest Rate (2)	Interest Spread (3)	$\ln(\textit{Income})$ (4)
GT3	−0.343** (−2.06)	1.118*** (3.75)	1.169*** (3.78)	−0.884** (−2.49)
log Driving Distance	−0.119*** (−20.44)	0.191*** (10.36)	0.191*** (10.28)	−0.205*** (−11.84)
GT3 × log Driving Distance	0.057*** (5.60)	−0.110*** (−3.82)	−0.114*** (−3.81)	0.150*** (7.62)
Constant	7.551*** (84.84)	5.923*** (30.62)	1.091*** (5.61)	16.704*** (73.60)
City × Year-Month FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Control FE	Yes	Yes	Yes	Yes
Observations	93,993	93,993	93,993	86,026
R^2	0.533	0.683	0.668	0.430

Notes: The interaction specifications from Table 16 are re-estimated after replacing $\ln(\textit{Distance})$ with log Driving Distance. Fixed effects and controls follow that table; column (4) omits Income-group FE.

C.2 Pointwise Effects

These pointwise effects translate the continuous $GT3 \times \ln(Distance)$ interaction into economic magnitudes at observed support points of the distance distribution. Table C.2 reports the pointwise GT3 effects that underlie Figure 6 in the main text.

Table C.2: Pointwise GT3 Effects Along the Distance Distribution

<i>Panel A. Common loan sample</i>				
Point	x	$\ln(Credit\ Line)$	Interest Rate	Interest Spread
x_0	0.0000	0.0831	0.3090**	0.3315**
p10	1.3433	0.1528	0.1708	0.1881
p25	2.4245	0.2089	0.0596	0.0727
p50	3.1507	0.2466*	-0.0151	-0.0048
p75	3.5910	0.2694**	-0.0604	-0.0518
p90	4.0897	0.2953**	-0.1117	-0.1051
p100	5.4649	0.3666***	-0.2532*	-0.2519*
Post GT3 max	5.8912	0.3888***	-0.2970**	-0.2974**

<i>Panel B. Income sample</i>		
Point	x	$\ln(Income)$
x_0	0.0000	0.1722
p10	1.6346	0.4256
p25	2.4245	0.5481*
p50	3.1507	0.6606**
p75	3.5777	0.7269**
p90	3.9705	0.7877***
p100	5.4649	1.0194***
Post GT3 max	5.8912	1.0855***

Notes: The table reports the pointwise GT3 effects $\hat{\beta}_{GT3} + x\hat{\beta}_{GT3 \times \ln(Distance)}$ underlying Figure 6. Panel A uses the common loan sample for credit line and pricing outcomes, while Panel B uses the income sample. Rows p10 through p90 use percentiles of the corresponding pre GT3 distance distribution; p100 is the corresponding pre GT3 maximum; the final row is the post GT3 maximum. The table is the numerical counterpart to Figure 6. Stars are based on pointwise linear-combination tests using the variance matrix from Table 16.

D Industry Heterogeneity

This appendix restores the one digit-industry split that complements the grouped B2B-versus-B2C evidence in Table 5. To preserve statistical power, the table reports industries with at least 3,000 loan observations.

Table D.1: Difference-in-Differences Estimates by One-Digit Industry

Panel A.

Dep. Var.: $\ln(\textit{Credit Line})$	A	C	E	F	G
GT3	0.120 (0.71)	0.116*** (3.18)	0.066 (1.06)	0.238*** (3.93)	0.096 (1.18)
Constant	5.898*** (65.09)	6.690*** (288.44)	6.557*** (225.11)	6.562*** (180.88)	6.534*** (150.01)
Year-Month FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Control FE	Yes	Yes	Yes	Yes	Yes
Observations	3,484	34,370	11,453	63,386	3,681
R^2	0.603	0.647	0.537	0.525	0.702

Panel B.

Dep. Var.: $\ln(\textit{Credit Line})$	H	I	L	O
GT3	0.064 (0.69)	0.821*** (6.26)	0.160* (1.68)	0.164 (1.38)
Constant	6.425*** (122.85)	6.471*** (55.63)	6.750*** (114.02)	6.376*** (97.23)
Year-Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Control FE	Yes	Yes	Yes	Yes
Observations	4,761	7,077	4,514	3,574
R^2	0.580	0.475	0.636	0.541

Notes: Columns are separate difference in differences regressions of $\ln(\textit{Credit Line})$ within one digit industry subsamples. Specifications follow the preferred loan level credit line model, except industry FE are omitted by construction. Industry-code definitions follow GB/T 4754 (2017).

E Stacked Difference-in-Differences Robustness

This appendix reports stacked difference in differences estimates for the core quantity, pricing, and bank-assessed-income outcomes. Each stack is centered on a GT3 rollout cohort, using an event window from 24 months before to 25 months after the cohort specific rollout month. The stacked regressions compare the adopting cohort with not yet treated provinces in the same event time window and absorb cohort specific fixed effects. The four tables below use the same four column fixed effect progression: cohort specific year month and bank fixed effects; then cohort specific city fixed effects; then cohort specific industry fixed effects; and finally cohort specific borrower and loan control fixed effects.

Figure E.1 reports the corresponding stacked DID event-study coefficients for the credit-line outcome.

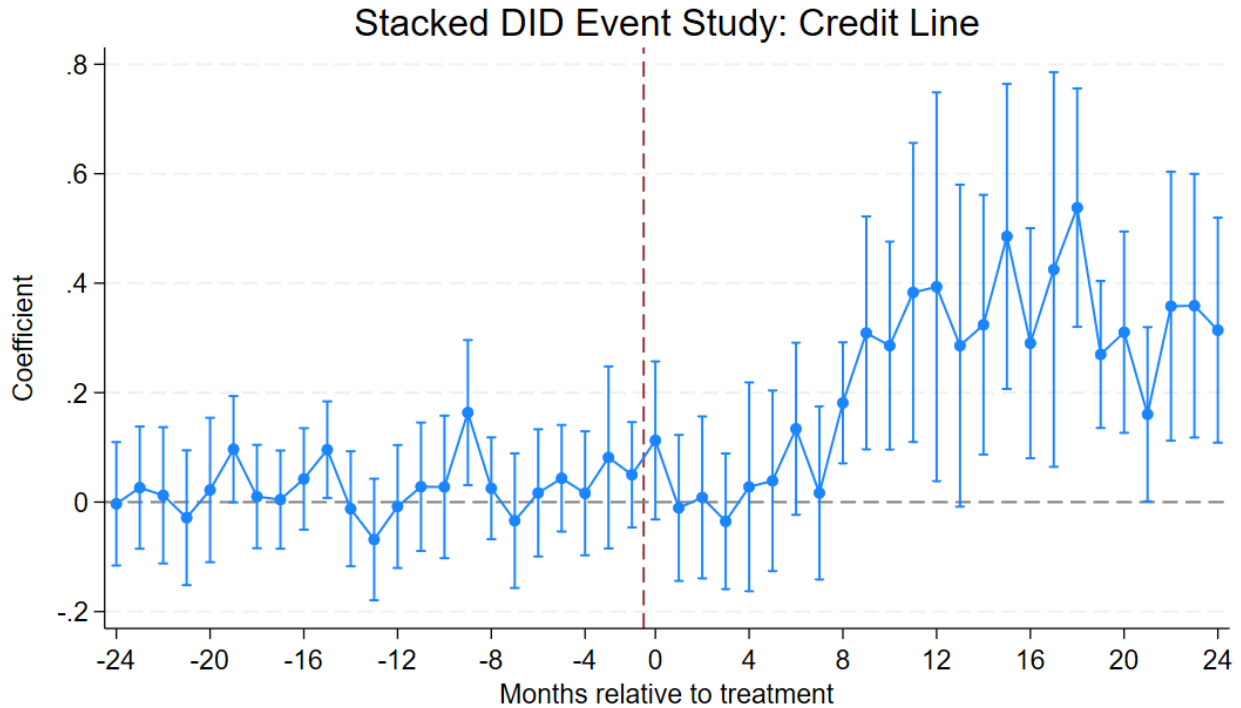


Figure E.1: Stacked DID Event Study: Credit Line

Notes: The figure plots stacked DID event-study coefficients for the credit-line outcome, with event time measured in months relative to GT3 rollout.

Table E.1: Stacked DID Column Progression: Credit Line

Dep. Var.:	$\ln(\textit{Credit Line})$			
	(1)	(2)	(3)	(4)
GT3	0.382*** (5.46)	0.180*** (4.64)	0.176*** (4.55)	0.108*** (3.33)
Constant	6.286*** (438.92)	6.297*** (1286.51)	6.298*** (1295.08)	6.301*** (1600.54)
Cohort $\times$ Year-Month FE	Yes	Yes	Yes	Yes
Cohort $\times$ Bank FE	Yes	Yes	Yes	Yes
Cohort $\times$ City FE	No	Yes	Yes	Yes
Cohort $\times$ Industry FE	No	No	Yes	Yes
Cohort $\times$ Control FE	No	No	No	Yes
Observations	401,141	400,760	400,759	400,721
R^2	0.292	0.396	0.399	0.535

Notes: The table reports stacked difference in differences estimates for the credit line outcome. The stacked design and fixed effect progression are described above.

Table E.2: Stacked DID Column Progression: Interest Rate

Dep. Var.:	Interest Rate			
	(1)	(2)	(3)	(4)
GT3	−0.399** (−2.51)	−0.325*** (−3.63)	−0.329*** (−3.68)	−0.188** (−2.17)
Constant	8.757*** (253.33)	8.753*** (760.94)	8.753*** (765.90)	8.746*** (763.13)
Cohort × Year-Month FE	Yes	Yes	Yes	Yes
Cohort × Bank FE	Yes	Yes	Yes	Yes
Cohort × City FE	No	Yes	Yes	Yes
Cohort × Industry FE	No	No	Yes	Yes
Cohort × Control FE	No	No	No	Yes
Observations	401,223	400,841	400,840	400,799
R^2	0.239	0.372	0.377	0.455

Notes: The table reports stacked difference in differences estimates for the contractual nominal interest rate. The stacked design follows Appendix E.

Table E.3: Stacked DID Column Progression: Interest Spread

Dep. Var.:	Interest Spread			
	(1)	(2)	(3)	(4)
GT3	−0.435*** (−2.66)	−0.330*** (−3.69)	−0.334*** (−3.73)	−0.206** (−2.34)
Constant	3.636*** (105.12)	3.631*** (312.66)	3.631*** (315.00)	3.624*** (310.97)
Cohort × Year-Month FE	Yes	Yes	Yes	Yes
Cohort × Bank FE	Yes	Yes	Yes	Yes
Cohort × City FE	No	Yes	Yes	Yes
Cohort × Industry FE	No	No	Yes	Yes
Cohort × Control FE	No	No	No	Yes
Observations	401,223	400,841	400,840	400,799
R^2	0.355	0.467	0.471	0.538

Notes: The table reports stacked difference in differences estimates for Interest Spread. The stacked design follows Appendix E.

Table E.4: Stacked DID Column Progression: Bank-Assessed Income

Dep. Var.:	$\ln(Income)$			
	(1)	(2)	(3)	(4)
GT3	0.124** (2.53)	0.158*** (2.70)	0.154*** (2.67)	0.168*** (2.79)
Constant	15.152*** (801.97)	15.149*** (1427.18)	15.150*** (1434.42)	15.149*** (1427.13)
Cohort $\times$ Year-Month FE	Yes	Yes	Yes	Yes
Cohort $\times$ Bank FE	Yes	Yes	Yes	Yes
Cohort $\times$ City FE	No	Yes	Yes	Yes
Cohort $\times$ Industry FE	No	No	Yes	Yes
Cohort $\times$ Control FE	No	No	No	Yes
Observations	356,702	356,321	356,320	356,292
R^2	0.147	0.206	0.216	0.235

Notes: The table reports stacked difference in differences estimates for bank assessed borrower income. The stacked design follows Appendix E; column (4) omits internal Income-group FE and Credit-score FE.