Local Credit Markets and Firm Borrowing Costs*

Olivia Bordeu† Gustavo González‡ Maximiliano San Millán§ Marcos Soráq¶

November 21, 2026

Abstract

Using administrative data on the universe of bank loans to Chilean firms, we document that firm borrowing costs vary widely across cities. Among comparable firms and loans, average spreads differ by 196 basis points between cities at the 10th and 90th percentiles. Location accounts for about a third of the variance in city-average spreads, as much as loan and firm characteristics and more than borrower risk or bank identity. Location premia are higher in richer cities and in more concentrated credit markets, but these characteristics explain only about a fifth of their variation.

Key words: local credit markets, banks, interest rates.

JEL codes: G21, O16, R12.

*We are grateful to Milena Almagro, José Gabriel Carreño, Fernando Cirelli, Jonathan Dingel, Gene Grossman, Danial Lashkari, Eduardo Morales and audiences at the Central Bank of Chile, Banco de Portugal, Católica Lisbon, Nova SBE, Princeton University, the University of Chicago, and numerous conferences for helpful comments and suggestions. Esteban Aguilera, Sebastián Andalaft, Laura Carvajal, and Valeria Logan provided superb research assistance. We are especially grateful to José Gabriel Carreño for assisting us in running the codes at the Central Bank of Chile. The views expressed are those of the authors and do not necessarily reflect the views of the Central Bank of Chile or its board members. An earlier version was circulated under the title "Bank Competition and Investment Costs across Space".

†University of California-Berkeley, Haas School of Business, email: oliviabordeu@berkeley.edu

‡Pontificia Universidad Católica de Chile, email: gggonzal@uc.cl

§Banco Central de Chile, email: msanmillan@bcentral.cl

¶University of Illinois at Urbana-Champaign, email: msora@illinois.edu

1. Introduction

Access to capital is fundamental for investment and development. At the international level, a large literature has studied why interest rates are higher in some countries and their effect on growth.[1] While one could expect capital markets to be fully integrated within countries, a growing body of evidence suggests that credit markets are geographically segmented, motivating studies of how segmentation shapes market power (Aguirregabiria, Clark and Wang, 2025; Drechsler, Savov and Schnabl, 2017), branching decisions (Oberfield et al., 2024), and local development (Quincy and Xu, 2025). Due to data limitations, price differences between markets – a key implication of segmentation and a measure of its importance – have remained unmeasured.

The main goals of this paper are to quantify differences in interest rates across credit markets and to explore which local characteristics matter for interest rates. We show that in Chile, which does not impose restrictions on bank branching within the national territory and where banks are the main providers of credit, comparable firms pay borrowing costs that differ across cities by about as much as sovereign borrowing costs differ between Chile and the rest of Latin America. We find some evidence that location premia are higher in cities with more concentrated local credit markets – in line with oligopolistic market structure – and in richer cities; however, most of the differences in location premia remain unexplained by the variables suggested in the literature.

Given the importance of private-sector investment for local development, we focus on firm loans and set aside other instruments such as consumer loans or mortgages. Firm loans are also a setting where banks exercise considerable discretion over the terms of credit, since small-firm lending is relationship-based and draws on soft information, unlike more standardized consumer credit.[2] Because interest rates are sensitive to the characteristics of the borrowing firm and to the instrument used, the main empirical challenge is to disentangle location effects from firm sorting and differences in the type of instruments used across space.

To overcome this challenge, we exploit a rich administrative dataset from Chile that covers the

[1] Hassan and Zhang (2021) survey why interest rates can differ between countries, and Caselli and Feyrer (2007), Monge-Naranjo, Sánchez and Santaeulàlia-Llopis (2019) and Pellegrino, Spolaore and Wacziarg (2025) study international capital misallocation.

[2] See Petersen and Rajan (1994) and Berger and Udell (2002) on the role of lending relationships and soft information in small-firm finance, and Cerqueiro, Degryse and Ongena (2011) for direct evidence of discretion in loan rate setting.

universe of bank loans issued to firms between 2012 and 2018. Universal coverage is an important advantage of this dataset. Smaller firms are those most likely to be constrained by their local credit markets and yet, due to data limitations, most existing studies in the literature do not cover them. We can link our loan-level data with data on firms' employment and branch location to identify which firms are *local* firms, meaning that they operate in only one city. Most of our analysis focuses on interest rates paid by these types of firms, which we can link unambiguously to a city and, in Chile, are responsible for around half of total private-sector employment. The Chilean setting is well-suited to isolate the role of geographic segmentation of capital markets given that all banks are chartered nationally and headquartered in Santiago, but operate branches across the country with little evidence of geographic clustering (Bordeu, González and Sorá, 2026). This distinguishes the Chilean banking sector from that in other countries like the US, where a history of regulation has shaped banks' sorting patterns until today (Oberfield et al., 2024), and allows us to separate the role of location from the role of specific banks' geographic footprint.

In the raw data there is substantial geographic dispersion in the loan spreads faced by local firms on installment loans, which we argue below are the instruments better suited for firm investment. A loan spread is the loan interest rate minus a maturity-matched benchmark rate. City-average spreads weighted by loan amount differ by 241 basis points between the 25th and 75th percentiles and by 422 basis points between the 10th and 90th percentiles. We explain our focus on local firms and installment loans in Section 3. For scale, the amount-weighted average interest rate is 854 basis points. These differences are also substantial from an international perspective: Chile, one of the most developed and stable countries in Latin America, faces an average interest rate that is 223 basis points lower than the regional average based on the difference in average returns of the EMBI Global Diversified Index.

One key characteristic of the dataset is that we observe a rich set of loan and firm characteristics, including several measures of credit risk, for the universe of firms. These features distinguish these data from datasets used in previous studies, especially outside the US and Europe. In a first step, we estimate a linear model of loan spreads that accounts flexibly for firm and loan characteristics. Once we adjust for firm, loan, risk, and bank characteristics, the corresponding residual city-level gaps are 103 basis points between the 25th and 75th percentiles and 196 basis points between the

10th and 90th percentiles. These results suggest that differences in average loan spreads between cities go beyond demand-side differences in the type of firms borrowing in each city.

The location premia we estimate are identified from comparisons between cities conditional on observables. Unlike studies of location effects in wages, which typically follow workers who move between cities, we cannot rely on firms that move between locations. Three features of our setting nonetheless limit the scope for unobserved borrower characteristics to drive our results. First, our controls include the risk rating and the expected loss assigned by the bank that prices the loan, so any remaining borrower heterogeneity would have to be either unobserved by the lender or not reflected in its own risk assessment. Second, we include bank-by-quarter and bank-by-sector fixed effects, so location premia are identified from differences in the spreads that the same bank charges in different cities. Third, the incremental explanatory power of city fixed effects is similar across specifications with and without our estimated default probability, even though omitting it expands the sample.

To quantify the extent of between-city variance in spreads attributable to local components, we follow the methodology in Card, Rothstein and Yi (2025). We find that 7.4% of the variance in city-specific mean spreads net of month effects can be attributed to differences in the identity of the banks that lend in each city; 34.0% to differences in firm and loan characteristics such as size of the firm in terms of sales and maturity of the loan, and 23.0% to differences in firms' risk classifications between cities. The remaining 35.7% is accounted for by city effects, the component of spreads common to all loans in a city conditional on these characteristics. Without loan-amount weights, the share of city effects is 27.8% and remains the largest of the four.

In the second part of this paper we explore which characteristics of the local credit market are associated with the local component of interest rates identified before. We find that more concentrated local credit markets are associated with higher interest rates: cities where firms borrow from fewer banks exhibit larger location premia, and so do cities with a higher Herfindahl–Hirschman index, although the latter association is less precisely estimated. Both patterns are consistent with a role for banks' local market power, but the number of banking relationships is itself an equilibrium outcome and we read these associations as descriptive. More economically developed cities also display higher rates, whereas our proxy for the quality of judicial institutions is not significantly related to the local component. Taken together, these local characteristics account for about a fifth of the variation in

the estimated location premia, leaving most of it unexplained.

Our results contribute to the literature in finance and industrial organization studying the boundary of credit markets. Petersen and Rajan (2002) show, using survey data from the United States, that information technology allowed borrowers to locate increasingly farther away from their lenders since the 1970s. However, Nguyen (2019) analyzes US data from 1999–2012 and finds that branch closures led to substantial and persistent reductions in small business lending at the census tract level, suggesting that despite technological change, proximity still matters. The local nature of credit markets underlies empirical studies in finance (Crawford, Pavanini and Schivardi, 2018; Degryse and Ongena, 2005; Drechsler, Savov and Schnabl, 2017; Whited and Zhao, 2021) and industrial organization (Aguirregabiria, Clark and Wang, 2025). Our contribution to this literature is to document interest rate differences between cities and the role for market power, which are predictions of these models. Relative to previous studies, our coverage of small local firms allows us to capture the importance of local credit markets precisely for the firms that are unlikely to have alternative funding options.

While we focus on the local component of interest rates, recent studies have leveraged loan-level datasets to study differences in interest rates more broadly. Gilchrist, Sim and Zakrajšek (2013) studied differences in bond spreads for large US firms, while Amiti et al. (2026), Faria-e Castro, Jordan-Wood and Kozlowski (2025) and Ferreira and Kozeniauskas (2025) cover a broader set of financial instruments and firms using US and Portuguese data. We discuss differences between their results and ours in Section 3.

2. Context and Data Sources

Chile has a well-developed financial system in which banks serve as the primary providers of credit. Between 2012 and 2018, the level of credit to the private sector was comparable to that in high-income countries, with banks providing nearly 80% of this credit. Survey data reveal that firms of all sizes rely heavily on banks, making Chile a well-suited application to study the determinants of geographic differences in the cost of borrowing using data from bank loans (see Section A.1 and Section A.2).

All banks operating in Chile are nationally chartered, with headquarters located in Santiago and branch networks spread throughout the country. Importantly, there are no geographic restrictions on where banks are allowed to open branches. The regulatory approval process for opening a new branch focuses primarily on the solvency of the bank, rather than the location of the branch. Some countries, most notably the US, historically imposed limits on banks' geographic expansion. Chile has neither such regulations nor major regional banks, offering a useful benchmark for studying geographic segmentation when no bank is tied to a specific region.

Our geographic unit of analysis is the administrative notion of municipality, which we call cities. Municipalities often encompass a local labor market with the exception of Santiago, the capital of the country, which groups 34 metropolitan municipalities. Given our focus on geographic segmentation of credit markets and the observation that Santiago municipalities are smaller and much closer to each other than the rest of the municipalities in the country, we drop Santiago from most of our analysis.

In the second part of the paper we focus on the determinants of the local component of interest rates. One of our candidate mechanisms for the role of space in interest rates is concentration among suppliers of credit. Our focus on banks' market power is motivated by the low number of banks competing in the average Chilean city. During 2012–2018, the average number of banks per city fluctuated between 4.2 and 4.7, while the median remained stable at 3 for all years. Although the national HHI in the loan market fluctuated around 1650, local markets were significantly more concentrated. The average across local indices fluctuated around 3300 (see Section A.3).

2.1. Data

Our main dataset is administrative loan-level data from 2012–2018, collected by the Financial Market Commission (CMF).[3] As part of its mandate to oversee the proper functioning, development and stability of Chilean financial markets, the CMF collects detailed loan-level data from financial

[3]This study was developed within the scope of the research agenda conducted by the Central Bank of Chile (CBC) in economic and financial affairs of its competence. The CBC has access to anonymized information from various public and private entities, by virtue of collaboration agreements signed with these institutions. To secure the privacy of workers and firms, the CBC mandates that the development, extraction and publication of the results should not allow the identification, directly or indirectly, of natural or legal persons. Officials of the CBC processed the disaggregated data. All the analysis was implemented by the authors and did not involve nor compromise the Chilean IRS (SII) or the CMF. The information contained in the databases of the Chilean IRS is of a tax nature originating in self-declarations of taxpayers presented to the Service; therefore, the veracity of the data is not the responsibility of the Service.

institutions under its regulatory oversight. We restrict our analysis to loans that private non-financial firms take from commercial banks, denominated in Chilean pesos, not associated with any public guarantee, and with maturities of at least three days. We keep fixed-interest-rate loans and exclude loans issued by *BancoEstado*, the only state-owned commercial bank in Chile.

The dataset includes two measures of loan risk. The first is a categorical firm-level risk rating assigned by banks when a firm applies for a loan. For large firms, banks conduct individual assessments, classifying them into one of 16 risk categories: A1–A6 (low risk), B1–B4, and C1–C6 (high risk). For smaller firms, the risk is assessed after the banks classify firms with similar characteristics together. The second measure of risk is the expected loss on each loan, reflecting the bank's projection of potential default costs. Crucially for our analysis, these measures are provided by the bank in charge of pricing the loan. In Tables 2 and 3, we also include our own estimate of the probability of default, constructed using a probit model with lagged firm characteristics. Appendix A.4 describes its construction and shows that the contribution of city fixed effects for local firms remains similar when this control is omitted and the sample expands.

We complement these data with VAT records obtained from the Chilean tax authority. This database contains monthly information on sales and intermediate purchases by all firms, which is used to construct firm-level controls in the analysis below.

Panel A of Table 1 presents summary statistics by loan type. Factoring loans, which allow firms to obtain liquidity by selling their receivables to banks, are the most common. These loans tend to be small, reinforcing their role in short-term liquidity management rather than long-term investment. Installment loans are the second most common type and are widely used, as shown by the number of firms borrowing under this category. These loans are significantly larger in amount and have longer maturities, making them better suited for investment. Given our focus on differences in interest rates that matter for firms' investment in physical capital and productive purposes, we focus on installment loans in the variance decomposition exercise.

Lack of spatial arbitrage in interest rates should be particularly relevant for firms that operate in a single city and therefore face fewer options. In most of our empirical analysis we focus on these local firms, which contributed 51% of private-sector employment in 2018. Panel B of Table 1 shows summary statistics from the subsample of local firms. Compared to the full sample, local firms

Table 1: Summary Statistics by Loan Type (2012–2018)

	Count			Amount		Interest Rate			Maturity		Sales	
	Loans	Cities	Firms	Mean	Median	Mean	W. Mean	Median	Mean	Median	Mean	Median
A. All Firms												
Factoring	2,215,984	267	7,635	17.0	0.5	762	623	679	2	2	4139.1	149.0
Installments	221,514	299	30,744	341.6	91.1	1052	642	938	10	3	565.8	79.3
Real Estate	11,216	143	1,039	1008.7	299.1	635	445	545	3	2	3132.2	594.8
Foreign Trade	7,814	151	961	712.1	228.4	676	562	638	6	4	3748.0	689.9
B. Local Firms												
Factoring	297,994	254	5,251	23.2	3.1	1030	854	893	2	2	414.3	88.8
Installments	119,330	298	22,834	139.6	56.0	1226	854	1175	12	4	161.6	57.8
Real Estate	3,066	111	488	250.4	86.8	844	579	757	5	2	485.4	195.6
Foreign Trade	1,757	91	357	397.2	181.8	777	604	706	7	6	913.0	257.0

Notes: Minor loan categories are omitted from this table. Maturity is denominated in months, and both Loan Amount and Firm Sales are denominated in thousands of USD at market exchange rates. Sales statistics count each firm-year once within the set of firms using each loan type. Interest rates are expressed in basis points. In the column *W. Mean* we compute the average interest rate weighted by the amount of each loan. Sample restricted to non-Santiago-based, non-financial-sector, fixed-rate, private-bank loans, 2012–2018.

face higher interest rates and borrow smaller amounts, consistent with their generally smaller size. However, as in the broader dataset, installment loans remain the primary credit instrument for larger borrowing needs.

The local installment-loan sample in Table 1 comprises 119,330 loans issued to 22,834 firms in 298 cities. Tables 2 and 3 require all regression covariates, including predicted default probability, whose construction relies on lagged firm financial information unavailable for some firm-years. Together with the other estimation requirements, this reduces the installment-loan sample from 221,514 to 161,482 observations for all firms and from 119,330 to 76,853 for local firms. Omitting predicted default probability retains 118,946 local installment loans, as reported in Appendix A.4. For the variance decomposition in Table 4, we use this broader sample and drop cities with fewer than 20 loans or fewer than 3 borrowing firms, where city fixed effects are noisy. The resulting sample contains 118,296 loans in 235 cities.

As we do not observe the specific bank branch in which a firm took a specific loan, in what follows, we will assume that local firms conduct their financial activities in the city where they operate. Reassuringly, 87% of firm loans are issued by banks with branches in the city of the borrowing firm. In addition, to the extent that firms seek loans outside of their city, they are likely doing so to access

lower interest rates. As a result, any measurement error introduced by this assumption would likely bias our estimates toward understating the true differences in interest rates across cities.

3. Firm Interest Rates across Space

3.1. The Determinants of Interest Rates for Firm Loans

We begin our analysis of interest rates by estimating equation (1),

$$s_{\ell ft} = \beta_0 + \beta_{m(t)} + \gamma' risk_t^{\ell f} + \alpha' X_t^{\ell f} + \beta^{b(\ell)\times q(t)} + \beta^{b(\ell)\times s(f)} + \beta^{c(f)} + \epsilon_{\ell ft}, \tag{1}$$

using the subsample of loans described in the previous section. The outcome variable, $s_{\ell ft}$, is the spread between the interest rate charged for loan ℓ extended to firm f in period t and the yield of a bond with a similar maturity in the same month.[4] The purpose of focusing on these spreads, instead of the rates directly, is to absorb variation in credit conditions that affect all instruments simultaneously across cities, such as movements in the monetary policy rate.

On the right-hand side, we include a month fixed effect that captures variation in macroeconomic conditions that may affect spreads for all types of firms and loans. Risk is captured in the second variable, $risk_t^{\ell f}$, a vector that includes the bank-assessed risk category, expected loss, delinquent debt, cumulative debt with the bank, and our predicted default probability. We include one fixed effect for each of the 16 categories comprising our categorical measure of risk. The term $X_t^{\ell f}$ encompasses the decile of the firm in terms of sales, the type of loan, the size of the loan, and fixed effects for maturity groups. We include fixed effects for the interaction between the bank issuing the loan and the quarter of issuance, $\beta^{b(\ell)\times q(t)}$, which capture variation across periods and banks. We also include a set of fixed effects for the interaction between the bank and the sector of the firm, $\beta^{b(\ell)\times s(f)}$, which capture sectoral specialization of banks.

Our last set of fixed effects, and our main object of interest, are city fixed effects for the city in

[4]The data includes the day on which the loan was issued. We use $q(t)$ and $m(t)$ to denote the quarter and month in which the loan was issued, respectively. Spreads are constructed using the interbank rate for loans with maturities up to one year. For longer maturities, they are based on yields of Chilean sovereign bonds denominated in pesos: 2-year bonds for loans with maturities between 1–3 years, 5-year bonds for loans between 3–5 years, and 10-year bonds for loans over 5 years.

which the firm operates $\beta^{c(f)}$. These capture any other determinants of interest rates related to the borrowing firm's geographic location.

In Tables 2 and 3, we provide a first approximation to the explanatory power of each of the variables on the right-hand side of equation (1). We focus on the increase in the R^2 as we add the variables in the right-hand side of equation (1) sequentially. The incremental contribution depends on the order in which controls are added (Gelbach, 2016). In these regressions, observations are weighted by loan amount.

Table 2 shows the results using data from all firms. Panels A and B show the results using all types of loans or installment loans, respectively. As mentioned, installment loans are of particular interest because they are the instrument better suited for firm investment. In both cases, the risk variables have the strongest explanatory power. With the methodological caveat of the previous paragraph in mind, the amount of variation attributable to the firm's location is small; for installment loans, it is roughly half the effect of bank-sector specialization.

Table 2: Incremental R^2: All Firms

	Panel A: All Loans						Panel B: Installment Loans Only					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Risk controls		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
Loan & firm controls			✓	✓	✓	✓			✓	✓	✓	✓
Bank × Quarter FE				✓	✓	✓				✓	✓	✓
Bank × Sector FE					✓	✓					✓	✓
City FE						✓						✓
R^2	0.015	0.477	0.544	0.583	0.601	0.615	0.045	0.538	0.597	0.639	0.657	0.666
ΔR^2	0.015	0.462	0.067	0.039	0.018	0.013	0.045	0.493	0.059	0.042	0.017	0.009
N	2,162,044	2,162,044	2,162,044	2,162,044	2,162,044	2,162,044	161,482	161,482	161,482	161,482	161,482	161,482

Notes: Each column adds a set of controls to the previous specification. ΔR^2 reports the increase in R^2 relative to the previous column. Within each panel, all columns are estimated on the common sample used by the richest specification. All regressions use loan-amount weights. Sample covers non-Santiago, non-financial-sector, fixed-rate, private-bank loans, 2012–2018. Risk controls include predicted default probability. Panel B restricts to installment loans.

In Table 3, we repeat the analysis focusing on local firms, for which the mapping between firm and city is unambiguous. While the main contribution is still coming from risk-related factors, the role of location is stronger for these firms. For installment loans, city fixed effects add 1.8 percentage points to the R^2, roughly twice their contribution in the full sample and somewhat more than the 1.3 percentage points contributed by the bank-sector match. Bank specialization by sector, which the bank-sector match arguably captures, has received considerable attention in the literature as a driver

of the interest rates firms face on their loans.[5]

Table 3: Incremental R^2: Local Firms

	Panel A: All Loans						Panel B: Installment Loans Only					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Risk controls		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
Loan & firm controls			✓	✓	✓	✓			✓	✓	✓	✓
Bank × Quarter FE				✓	✓	✓				✓	✓	✓
Bank × Sector FE					✓	✓					✓	✓
City FE						✓						✓
R^2	0.016	0.440	0.531	0.573	0.585	0.603	0.029	0.462	0.564	0.605	0.618	0.636
ΔR^2	0.016	0.424	0.090	0.042	0.013	0.018	0.029	0.434	0.101	0.041	0.013	0.018
N	316,578	316,578	316,578	316,578	316,578	316,578	76,853	76,853	76,853	76,853	76,853	76,853

Notes: Each column adds a set of controls to the previous specification. ΔR^2 reports the increase in R^2 relative to the previous column. Within each panel, all columns are estimated on the common sample used by the richest specification. All regressions use loan-amount weights. Sample covers non-Santiago, non-financial-sector, fixed-rate, private-bank loans issued to local firms, 2012–2018. Risk controls include predicted default probability. Panel B restricts to installment loans.

In recent studies, Ferreira and Kozeniauskas (2025), Amiti et al. (2026) and Faria-e Castro, Jordan-Wood and Kozlowski (2025) estimate equations similar to equation (1) using data from Portugal and the United States. The main focus of these studies is interest rate dispersion more broadly, without a focus on location. The R^2 in our regressions is in the same range as theirs despite including fewer fixed effects and controls, and we find a larger role for firms' risk. In the US context, Amiti et al. (2026) and Faria-e Castro, Jordan-Wood and Kozlowski (2025) study loans of more than $1 million issued by the largest US banks between 2012 and 2024. A key distinction of our paper is that we include all loans.[6]

Given the methodological limitations of the previous approach, we turn to an approach based on Card, Rothstein and Yi (2025) to study the role of location in explaining variation in interest rates. In Section 3.3 our focus is explaining between-loan variation, while in Section 3.4 we study between-city variation in average loan spreads, the main focus of the paper.

[5] Blickle, Parlatore and Saunders (2026) document that large US banks concentrate their lending in a small set of industries and offer more generous loan terms, including lower interest rates, to borrowers in their preferred industry. Blickle et al. (2025) provide a complementary information-based pricing mechanism and show that specialized lenders charge systematically lower rates than non-specialized lenders on otherwise similar loans.

[6] Table 9 in Appendix Section A.5 repeats the analysis on the subsample of large loans (relative to the Chilean market). On that subsample, the R^2 is approximately 0.6 and the contribution of city fixed effects is similar to that in our baseline sample.

3.2. Variance Decomposition

We estimate equation (1) via weighted OLS on local installment loans, omitting predicted default probability to retain the broader sample described in Section 2. Appendix A.4 reports the corresponding incremental-R^2 results: city fixed effects add 1.6 percentage points, compared with 1.8 percentage points in Table 3. Their contribution thus remains similar across these specifications and samples. We retain all other risk controls. With our estimates at hand, we define the de-meaned spread $\delta_\ell \equiv s_{\ell ft} - \hat{\beta}_0 - \hat{\beta}_{m(t)}$. This object captures the spread after netting out the overall and monthly means.

We split the demeaned spreads into four additive terms and a residual: a risk-pricing component $\hat{\gamma}^{r(\ell)} \equiv \hat{\gamma}' risk_t^{\ell f}$, a component capturing the pricing of other covariates $\hat{\gamma}^{x(\ell)} \equiv \hat{\alpha}' X_t^{\ell f}$, a bank component $\hat{\gamma}^{b(\ell)} \equiv \hat{\beta}^{b(\ell)\times q(t)} + \hat{\beta}^{b(\ell)\times s(f)}$, and a location premium $\hat{\gamma}^c_{c(f)} \equiv \hat{\beta}^{c(f)}$. By construction,

$$\delta_\ell = \hat{\gamma}^{r(\ell)} + \hat{\gamma}^{x(\ell)} + \hat{\gamma}^{b(\ell)} + \hat{\gamma}^c_{c(f)} + \hat{\epsilon}_\ell, \tag{2}$$

and the OLS residual $\hat{\epsilon}_\ell$ is orthogonal to each of the four components. The location premium $\hat{\gamma}^c_c$ captures differences in the conditional mean spread across cities, given all other covariates. This fixed effect could, in principle, capture differences in unobserved characteristics of the borrowers as well as characteristics of the local credit market. Because the firms in our sample operate in a single city, we cannot separate the two using firms that move between locations, as the literature on location effects in wages does with workers. Three features of our specification limit the scope for the former interpretation. First, we observe the risk assessment made by the issuing bank on each loan, so the relevant borrower characteristics would have to be unobserved not only by us as econometricians but by the lending bank as well, or observed by the bank but not reflected in its risk rating or expected loss. Second, the bank fixed effects imply that location premia are identified from differences in the spreads charged by the same bank across cities. Third, the contribution of city fixed effects to the R^2 is similar across specifications with and without our estimated default probability, despite the different samples (see Appendix A.4). We cannot rule out, however, that banks price soft information that is not recorded in their risk measures and that differs systematically across cities.

The interquartile range in the distribution of $\hat{\gamma}^c_c$ across cities is 103 bp, and between percentiles

10 and 90 is 196 basis points. Compared with gaps of 241 and 422 basis points in raw city-average spreads, respectively, these results indicate that controls remove roughly half of the raw dispersion.

Taking weighted variances of equation (2) yields

$$\mathrm{Var}(\delta) = \sum_j \mathrm{Var}(\hat{\gamma}^j) + 2\sum_{j<k} \mathrm{Cov}(\hat{\gamma}^j, \hat{\gamma}^k) + \mathrm{Var}(\hat{\epsilon}),$$

where $j, k \in \{r, x, b, c\}$. We attribute to each component its total contribution $\mathrm{Var}(\hat{\gamma}^j) + \sum_{k \neq j} \mathrm{Cov}(\hat{\gamma}^j, \hat{\gamma}^k)$.

The focus of this paper is on differences in average loan spreads between cities. To delve deeper into the factors driving differences in such averages, we take the within-city average of each component in equation (2), using loan amounts as weights. Given that we use the same weights we used in the regression and we include city fixed effects, the within-city average of the residual $\hat{\epsilon}_\ell$ is zero, and the average demeaned spread satisfies

$$\overline{\delta}_c = \overline{\gamma}^r_c + \overline{\gamma}^x_c + \overline{\gamma}^b_c + \hat{\gamma}^c_c \tag{3}$$

Our distinction between the role of location in equation (2) and equation (3) follows the literature on the role of location in wages (Card, Rothstein and Yi, 2025). In that context, location explains a small share of individual wages yet a large share of differences in average wages across cities. We begin by discussing the results from equation (2) but, given our focus on geographic segmentation, focus on the results from equation (3) as our main results.

3.3. Loan-Level Results

The last two columns in Table 4 show the variance decomposition at the loan level. Panel A reports, for each component, the standard deviation and the contribution to total variance, including covariance terms. As in the R^2 analysis above, the main takeaway is that risk and covariates are the primary determinants of interest rates. The contribution of city fixed effects is slightly above 2%, around half of the total contribution of bank-related fixed effects.

Panel B focuses on the correlation between components. Quantitatively, the main element is the positive covariance between risk and other firm and loan characteristics, capturing, for example, that

smaller firms tend to be more risky. The second most important element is the negative correlation between bank fixed effects and firm covariates, capturing that smaller firms tend to sort to banks that charge lower interest rates. We do not find strong evidence of firm sorting across cities by risk in this specification.

At the loan level, idiosyncratic borrower and loan characteristics are more important drivers of interest rates, as expected. However, understanding the extent to which differences in prices are driven by supply-side factors is important to determine whether the market is allocating loans efficiently. As we argued above, our city fixed effects are likely to be driven by supply-side differences between cities.

Table 4: Variance Decomposition of Interest Rate Spreads

	City level		Loan level	
	SD	Share	SD	Share
Spread (bp)	180.0	1.000	336.1	1.000
A. Variance components (SD and share of total variance)				
Bank effects	39.1	0.074	83.8	0.046
Risk covariates	49.6	0.230	91.3	0.169
Other covariates	79.6	0.340	183.5	0.375
City effects	85.1	0.357	45.6	0.022
Residual			209.3	0.388
B. Covariance components (correlation and share of total variance)				
Bank & risk	0.165	0.020	-0.012	-0.002
Bank & covariates	-0.106	-0.020	-0.131	-0.036
Bank & city	0.261	0.054	0.079	0.005
Risk & covariates	0.788	0.192	0.638	0.189
Risk & city	0.370	0.096	0.037	0.003
Covariates & city	0.280	0.117	-0.003	-0.000
N	235		118,296	

Notes: Decomposition following Card, Rothstein and Yi (2025). Sample: installment loans to local firms outside Santiago, 2012–2018, in cities with at least 20 loans and 3 borrowing firms.

3.4. City-Level Results

Average loan spreads differ between cities. For installment loans to local firms in the cities retained for the variance decomposition, the gap between percentiles 10 and 90 of city-average spreads weighted

by loan amount is 422 basis points, and the gap between percentiles 25 and 75 is 241 basis points. Naturally, the characteristics of firms and loans differ between cities.

The first and second columns in Table 4 show a variance decomposition of $\overline{\delta}_c$ across cities following the same definitions we used for the loan-level analysis. There are differences between cities in terms of the firm characteristics of the borrowing firms and, in particular, their risk profiles. Differences in risk and other covariates across cities explain 23% and 34%, respectively, of the differences in average local spreads net of month effects. Around 36% of the differences are captured by the city fixed effects. Understanding which characteristics of the local credit market covary with $\hat{\gamma}_c^c$ is the focus of Section 4.

3.5. Unweighted Version

In our previous analysis we weighted observations by loan amount both when estimating equation (1) and when taking the within-city average of the components in equation (2). We repeat the analysis dropping weights from both steps. The results are shown in Table 10 in the Appendix Section A.6.

At the loan level, the contribution of city effects is essentially unchanged, at about 2% of the variance. The main difference is that bank effects become more important: their share rises from 4.6% to 11.7%, and the negative correlation between bank effects and other covariates found in the weighted analysis disappears. The correlation between the risk and city components doubles but remains small, at 0.08.

The larger role of banks carries over to the city level. Differences in the identity of lending banks account for 22.6% of the variance in city-average spreads, compared with 7.4% in the weighted analysis. The shares of other covariates and of city effects fall to 26.3% and 27.8%, respectively, while the share of risk is unchanged at 23%. The local component remains the largest, although by a narrower margin. Since the unweighted analysis gives more weight to small loans, these results suggest that bank identity matters more for the pricing of smaller loans.

4. What Characterizes High-Interest-Rate Cities?

Our analysis allowed for variation in interest rates across space unexplained by variation in demand-side variables, which we captured with location fixed effects $\hat{\gamma}_c^c$. In this section, we delve deeper into what characterizes high-interest-rate locations.

Local characteristics. We relate the estimated location premia to city-level characteristics. The first two summarize the local economy and are built from gridded estimates of local GDP in constant 2021 USD from Rossi-Hansberg and Zhang (2025). *GDP per capita* is averaged over 2012–2018 and measured in thousands of constant 2021 USD; we aggregate each 0.25° cell to the municipality by weighting its GDP and population by the share of the cell's area that falls within the municipality, and divide aggregated GDP by aggregated population. *GDP volatility* is the standard deviation of the municipality's annual log GDP growth over 2012–2022, computed from the same series for cities with at least five annual growth observations.

The next two measures capture the competitiveness of the local credit market. *Bank HHI* is a Herfindahl–Hirschman index that we measure within our estimation sample of fixed-rate installment loans and take the median across years. *Banks per firm*, the average number of distinct bank relationships per firm in the city, is a complementary measure of local market power.

Finally, *Judicial delay* proxies for the efficiency of local contract enforcement. We measure it as the average duration, in days, of resolved civil commercial cases—contract enforcement, insolvency, and related business matters—over 2015–2018, computed at the Court of Appeals level and assigned to cities through each court's territorial jurisdiction. Higher values indicate slower local courts.

We then estimate

$$\begin{aligned}\hat{\gamma}_c^c = \kappa_0 &+ \kappa_1 \,\text{GDP per capita}_c + \kappa_2 \,\text{GDP volatility}_c \\ &+ \kappa_3 \,\text{Bank HHI}_c + \kappa_4 \,\text{Banks per firm}_c \\ &+ \kappa_5 \,\text{Judicial delay}_c + \nu_c.\end{aligned} \tag{4}$$

Because $\hat{\gamma}_c^c$ is itself estimated with sampling error that varies across cities, we report both an unweighted specification and a specification that weights cities by the inverse standard error of the

estimated fixed effect. Table 5 shows the results.

Table 5: City Fixed Effects and Local Characteristics

	(1) Unweighted	(2) Inv. SE
GDP per capita	8.256***	9.239***
	(2.070)	(1.848)
GDP volatility	-4.905	-16.80
	(80.95)	(72.94)
Bank HHI	0.00758	0.00899**
	(0.00423)	(0.00341)
Banks per firm	-227.2***	-150.8***
	(42.40)	(43.56)
Judicial delay	0.0641	0.0368
	(0.119)	(0.0941)
Constant	82.45	-15.21
	(92.51)	(80.07)
Observations	235	235
R^2	0.200	0.169
Adjusted R^2	0.182	0.151

Notes. The dependent variable is the estimated city fixed effect $\hat{\gamma}_c^c$ (in basis points). GDP per capita is measured in thousands of constant 2021 USD. Columns weight cities equally (1) and by the inverse standard error of $\hat{\gamma}_c^c$ (2). Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Local credit-market concentration is positively associated with the location premium. The clearest evidence comes from banks per firm, which enters negatively and is significant in both specifications: location premia are lower in cities where firms borrow from more banks. Because the number of banking relationships is itself an equilibrium outcome, we read this association as descriptive. The HHI points in the same direction. Its coefficient is similar across the two specifications but is less precisely estimated when cities are weighted equally: it is significant at the 10% level in the unweighted specification ($p \approx 0.07$) and at the 1% level in the precision-weighted one. The precision-weighted estimate implies that a city with an HHI 1,000 points higher carries a location premium about 9 basis points larger. Richer cities carry higher local premia: a one-thousand-2021-USD increase in GDP per capita is associated with roughly 9 basis points higher spreads. This sign is not what one would expect

if location premia mainly reflected less developed local credit markets. While we cannot distinguish between them with our data, one possible interpretation is that demand for loans is higher in these cities; another is that GDP per capita proxies for omitted local factors, such as the cost of operating bank branches. By contrast, neither local GDP volatility nor judicial delay is significantly related to the location premium in either specification. Overall, the local characteristics jointly explain about a fifth of the cross-city variation in $\hat{\gamma}_c^c$, so most of the variation in location premia remains unexplained.

5. Conclusion

We show that average loan spreads differ widely between Chilean cities. The gap between the 10th and 90th percentiles of city average spreads is 422 basis points and remains 196 basis points after controlling for firm, loan, risk, and bank characteristics. City effects account for between 28% and 36% of the variance in city-average spreads, depending on whether loans are weighted by amount. Location premia are higher in cities where bank lending is more concentrated and lower in cities where firms borrow from more banks, patterns that are consistent with local market power. They are also higher in richer cities, a pattern for which we do not have a clear explanation. These associations are descriptive, however, and the local characteristics we consider account for only about a fifth of the variation in location premia.

Our results align with previous studies of local credit markets that postulated oligopolistic competition between banks. The extent of differences we documented in this paper can serve as a quantitative target for future studies aiming to quantify the importance of geographic segmentation of credit markets for welfare and productivity. Moreover, understanding why credit markets remain local to some extent — given technological advances — as well as distinguishing among candidate mechanisms that account for the remaining variation in location premia are natural avenues for future research.

References

Aguirregabiria, Victor, Robert Clark, and Hui Wang. 2025. "The Geographic Flow of Bank Funding and Access to Credit: Branch Networks, Synergies, and Local Competition." *American Economic Review*, 115(6): 1818–1856.

Amiti, Mary, Anil K. Kashyap, Anna Kovner, and David E. Weinstein. 2026. "Why Do Firms Pay Different Interest Rates on Their Bank Loans?" Working paper. February 9, 2026.

Berger, Allen N., and Gregory F. Udell. 2002. "Small Business Credit Availability and Relationship Lending: The Importance of Bank Organisational Structure." *The Economic Journal*, 112(477): F32–F53.

Blickle, Kristian, Cecilia Parlatore, and Anthony Saunders. 2026. "Specialization in Banking." *Journal of Finance*, 81(3): 1531–1572.

Blickle, Kristian, Zhiguo He, Jing Huang, and Cecilia Parlatore. 2025. "Information-Based Pricing in Specialized Lending." *Journal of Financial Economics*, 172: 104135.

Bordeu, Olivia, Gustavo González, and Marcos Sorá. 2026. "Bank Branches and the Allocation of Capital across Cities." Working paper (February 16, 2026).

Card, David, Jesse Rothstein, and Moises Yi. 2025. "Location, Location, Location." *American Economic Journal: Applied Economics*, 17(1): 297–336.

Caselli, Francesco, and James Feyrer. 2007. "The Marginal Product of Capital." *The Quarterly Journal of Economics*, 122(2): 535–568.

Cerqueiro, Geraldo, Hans Degryse, and Steven Ongena. 2011. "Rules versus Discretion in Loan Rate Setting." *Journal of Financial Intermediation*, 20(4): 503–529.

Crawford, Gregory S., Nicola Pavanini, and Fabiano Schivardi. 2018. "Asymmetric Information and Imperfect Competition in Lending Markets." *American Economic Review*, 108(7): 1659–1701.

Degryse, Hans, and Steven Ongena. 2005. "Distance, Lending Relationships, and Competition." *The Journal of Finance*, 60(1): 231–266.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2017. "The Deposits Channel of Monetary Policy." *The Quarterly Journal of Economics*, 132(4): 1819–1876.

Faria-e Castro, Miguel, Samuel Jordan-Wood, and Julian Kozlowski. 2025. "An Empirical Analysis of the Cost of Borrowing." Federal Reserve Bank of St. Louis Working Paper 2024-016.

Ferreira, Miguel H., and Nicholas Kozeniauskas. 2025. "Beyond Risk: Firm Financing and Interest Rates." Unpublished manuscript.

Gelbach, Jonah B. 2016. "When Do Covariates Matter? And Which Ones, and How Much?" *Journal of Labor Economics*, 34(2): 509–543.

Gilchrist, Simon, Jae W. Sim, and Egon Zakrajšek. 2013. "Misallocation and Financial Market Frictions: Some Direct Evidence from the Dispersion in Borrowing Costs." *Review of Economic Dynamics*, 16(1): 159–176.

Hassan, Tarek A., and Tony Zhang. 2021. "The Economics of Currency Risk." *Annual Review of Economics*, 13: 281–307.

Monge-Naranjo, Alexander, Juan M. Sánchez, and Raül Santaeulàlia-Llopis. 2019. "Natural Resources and Global Misallocation." *American Economic Journal: Macroeconomics*, 11(2): 79–126.

Nguyen, Hoai-Luu Q. 2019. "Are Credit Markets Still Local? Evidence from Bank Branch Closings." *American Economic Journal: Applied Economics*, 11(1): 1–32.

Oberfield, Ezra, Esteban Rossi-Hansberg, Nicholas Trachter, and Derek T. Wenning. 2024. "Banks in Space." National Bureau of Economic Research NBER Working Paper 32256.

Pellegrino, Bruno, Enrico Spolaore, and Romain Wacziarg. 2025. "Barriers to Global Capital Allocation." *The Quarterly Journal of Economics*, 140(4): 3067–3131.

Petersen, Mitchell A., and Raghuram G. Rajan. 1994. "The Benefits of Lending Relationships: Evidence from Small Business Data." *Journal of Finance*, 49(1): 3–37.

Petersen, Mitchell A., and Raghuram G. Rajan. 2002. "Does Distance Still Matter? The Information Revolution in Small Business Lending." *The Journal of Finance*, 57(6): 2533–2570.

Quincy, Sarah, and Chenzi Xu. 2025. "Branching Out: Capital Mobility and Long-Run Growth." National Bureau of Economic Research (NBER) Working Paper 34457.

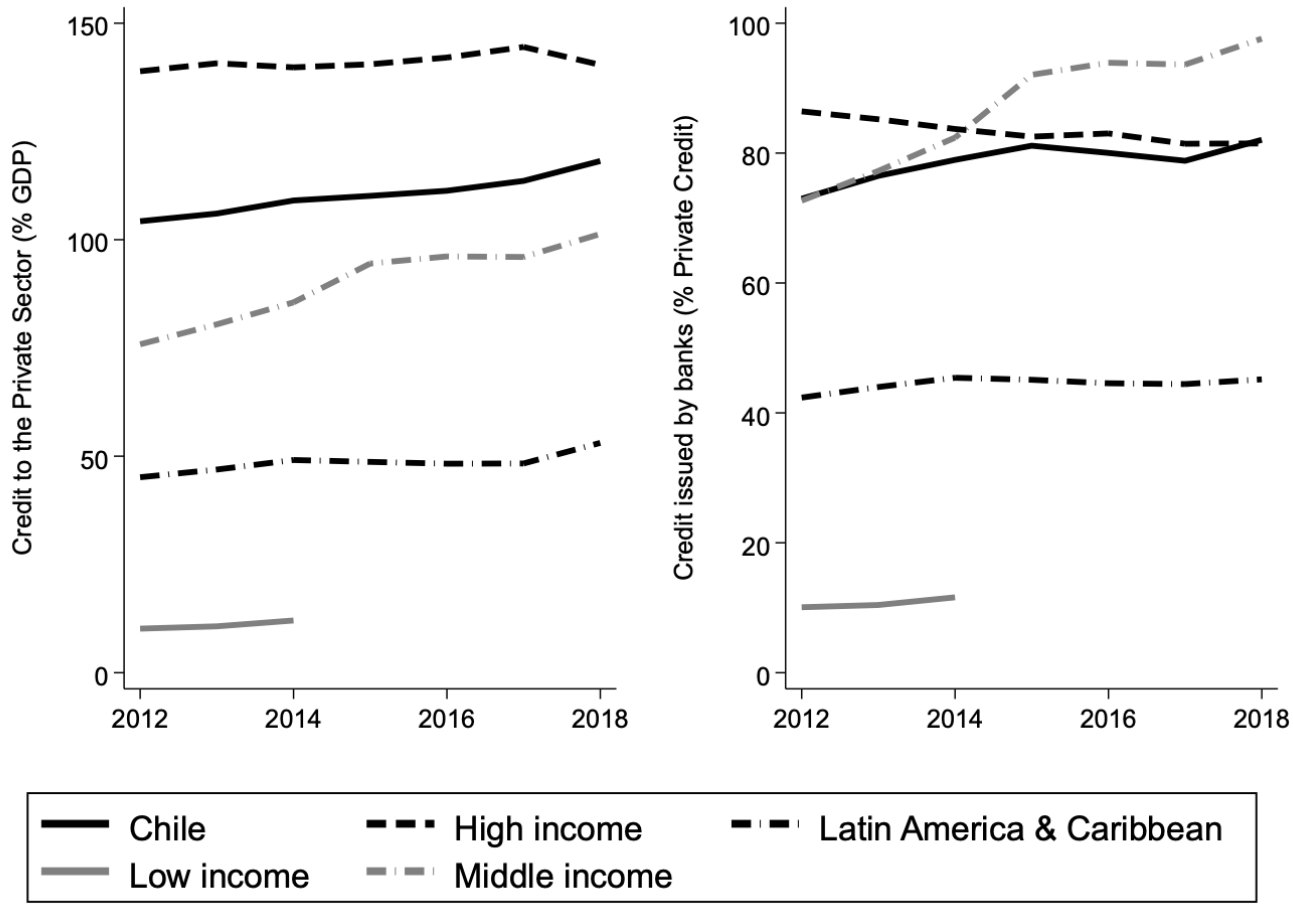
Rossi-Hansberg, Esteban, and Jialing Zhang. 2025. "Local GDP Estimates Around the World." National Bureau of Economic Research Working Paper 33458.

Whited, Toni M., and Jake Zhao. 2021. "The Misallocation of Finance." *The Journal of Finance*, 76(5): 2359–2407.

A. Appendix

A.1. Chile's Financial Development

Figure 1 below shows the evolution of the two indicators of financial development mentioned in the main text.



Source and notes: Authors' calculations using public data from the World Bank.

Figure 1: Financial development

A.2. The Importance of Banks for Domestic Credit in Chile

We analyze firm-level data from the 2015 *Encuesta longitudinal de empresas* (ELE), a nationally representative survey that includes a module on firms' sources of credit. We calculate the percentage of private firms that borrow from banks and the percentage of firms for which banks constitute the primary source of credit. We exclude Santiago. The first two columns of Table 6 show that banks are the main source of credit for large private firms.

Table 6: Credit sources for firms (excluding Santiago)

Firm size	2015 ELE		
	% borrows from banks	% biggest loan comes from banks	% private employment
Micro	57.2	16.8	7.7
Small	66.4	29.6	39.4
Medium	77.8	42.1	21.9
Large	80.5	50.4	31.0

Source and notes: Authors' calculations using data from the *Encuesta longitudinal de empresas.*

A.3. The Network of Bank Branches

The following results rely on publicly available data on loans aggregated at the city-bank level from the CMF. For Panels A-C we exclude *BancoEstado* from the sample and count city-bank pairs where a bank has a positive value of outstanding loans in a given year. For Panel B we exclude new city-bank pairs that can be attributed either to the merger between *Itaú* and *Corpbanca* in 2014 or the merger between *BBVA* and *Scotiabank* in 2018. For calculating market shares in Panel D we consider *BancoEstado* but exclude cities where it was the only active bank.

Table 7: Bank Network outside the Metropolitan Region

	2012	2013	2014	2015	2016	2017	2018
A.							
City-Bank Pairs	391	384	386	366	366	345	345
Cities	85	86	83	83	83	82	80
B. Year-on-year change (excluding mergers)							
New city-bank pairs	4	8	5	0	0	1	1
Disappearing city-bank pairs	15	4	20	1	1	2	9
C. Banks per City							
Mean	4.6	4.5	4.7	4.4	4.4	4.2	4.3
Standard Deviation	3.6	3.5	3.5	3.1	3.1	2.8	2.8
Median	3	3	3	3	3	3	3
D. Herfindahl–Hirschman Index							
National	1679	1663	1619	1625	1644	1678	1665
Average across local indices	3519	3505	3318	3319	3318	3248	3069
Median across local indices	3159	3099	2785	2728	2690	2599	2546

Source and notes: Authors' calculations using data from the CMF. Panels A-C exclude *BancoEstado.*

Notice that the number of cities in this Table is substantially lower than the number of cities we recover from the loan-level data, as the data is more aggregated in the public data we use to construct Table 7.

A.4. Excluding Predicted Default Probability

The risk controls in Tables 2 and 3 include a predicted probability of default alongside the bank-assessed risk category and continuous provisioning and indebtedness measures. We estimate this probability using a discrete-time hazard (probit) model of firm default as a function of lagged firm

characteristics—the debt-to-sales ratio, firm age and its square, the wage bill, value added per worker, log sales, and sales growth—together with sector and year fixed effects. Because the required financial information is unavailable for some firm-years, including this control reduces the estimation sample.

Table 8 repeats the local-firm analysis without predicted default probability, retaining all other controls and loan-amount weights. Omitting this control expands the installment-loan sample from 76,853 to 118,946 observations. City fixed effects add 1.6 percentage points to the R^2, compared with 1.8 percentage points in Table 3; the corresponding contributions for all loan types are also 1.6 and 1.8 percentage points. The contribution of location remains similar across these specifications and samples, motivating our use of the broader sample for the variance decomposition.

Table 8: Incremental R^2: Local Firms, without Predicted Default Probability

	Panel A: All Loans						Panel B: Installment Loans Only					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Risk controls		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
Loan & firm controls			✓	✓	✓	✓			✓	✓	✓	✓
Bank × Quarter FE				✓	✓	✓				✓	✓	✓
Bank × Sector FE					✓	✓					✓	✓
City FE						✓						✓
R^2	0.016	0.438	0.527	0.567	0.582	0.598	0.029	0.442	0.541	0.586	0.602	0.618
ΔR^2	0.016	0.422	0.089	0.040	0.015	0.016	0.029	0.412	0.099	0.045	0.016	0.016
N	433,222	433,222	433,222	433,222	433,222	433,222	118,946	118,946	118,946	118,946	118,946	118,946

Notes: Each column adds a set of controls to the previous specification. ΔR^2 reports the increase in R^2 relative to the previous column. Within each panel, all columns are estimated on the common sample used by the richest specification. All regressions use loan-amount weights. Sample covers non-Santiago-based, non-financial-sector, fixed-rate, private-bank loans issued to local firms, 2012–2018. Risk controls exclude predicted default probability, allowing a larger sample than in Table 3. Panel B restricts to installment loans.

A.5. Big Loans

The 75th percentile of loan amounts among local firms is 43,134 USD. Table 9 repeats the specification in Table 3, including predicted default probability, over the subsample of loans larger than 43,134 USD.

A.6. Unweighted Version

Table 10 below repeats the analysis in the main text without weighting observations by loan amount.

Table 9: Incremental R^2: Local Firms, Large Loans

	Panel A: All Loans						Panel B: Installment Loans Only					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Risk controls		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
Loan & firm controls			✓	✓	✓	✓			✓	✓	✓	✓
Bank × Quarter FE				✓	✓	✓				✓	✓	✓
Bank × Sector FE					✓	✓					✓	✓
City FE						✓						✓
R^2	0.025	0.397	0.490	0.541	0.552	0.574	0.039	0.427	0.518	0.566	0.579	0.602
ΔR^2	0.025	0.373	0.093	0.051	0.012	0.022	0.039	0.388	0.091	0.048	0.013	0.023
N	78,383	78,383	78,383	78,383	78,383	78,383	47,676	47,676	47,676	47,676	47,676	47,676

Notes: Each column adds a set of controls to the previous specification. ΔR^2 reports the increase in R^2 relative to the previous column. Within each panel, all columns are estimated on the common sample used by the richest specification. All regressions use loan-amount weights. Sample restricted to local firms with loan amounts at or above the 75th percentile of the local loan amount distribution (43,134 USD), 2012–2018. Panel B restricts to installment loans.

Table 10: Variance Decomposition of Interest Rate Spreads (Unweighted)

	City level		Loan level	
	SD	Share	SD	Share
Spread (bp)	179.4	1.000	456.5	1.000
Variance components (SD and share of total variance)				
Bank effects	73.8	0.226	149.8	0.117
Risk covariates	51.6	0.233	134.0	0.180
Other covariates	75.8	0.263	220.0	0.313
City effects	82.3	0.278	57.1	0.021
Residual			277.2	0.369
Covariance components (correlation and share of total variance)				
Bank & risk	0.283	0.067	0.079	0.015
Bank & covariates	-0.022	-0.008	-0.009	-0.003
Bank & city	0.139	0.053	0.081	0.007
Risk & covariates	0.676	0.164	0.588	0.166
Risk & city	0.263	0.069	0.079	0.006
Covariates & city	0.033	0.013	-0.014	-0.002
N	235		118,296	

Notes: Decomposition following Card, Rothstein and Yi (2025).