

# Local Credit Markets and Firm Borrowing Costs\*

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## 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 is the largest single component of the variance in city-average spreads, ahead of borrower risk, loan and firm characteristics, and bank identity. Spreads are higher in richer cities and in cities with more loan concentration across banks, although these characteristics explain less than a fifth of the total variation in location premia.

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

**JEL codes:** G21, O16, R12.

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# 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.<sup>1</sup> 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.<sup>2</sup> 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 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

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

<sup>2</sup>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.

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 rates faced by local firms on installment loans, which we argue below are the instruments better suited for firm investment. Weighted city averages differ by 241 basis points between the 25th and 75th percentiles and by 422 basis points between the 10th and 90th percentiles. We elaborate on these decisions and show average interest rate differences between cities for all instruments in Section 3. These are substantial differences relative to the amount-weighted average interest rate of 854 basis points and even 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 interest rates 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 the average interest rate between cities go beyond demand-side differences in the type of firms borrowing in each city.

To quantify the extent of between-city variance in interest rates 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 rates can be attributed to differences in the identity of the banks that lend in each city; 33.9% 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. Crucially, 35.7% of the variance in average rates remains unexplained and, in our linear model, is attributed to a local component unrelated to all other covariates.

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 with a higher Herfindahl–Hirschman index and fewer banking relationships per firm exhibit larger location premiums, consistent with a role for banks’ local market power. 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 roughly a fifth of the variation in the estimated location premiums.

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 4.3 and 4.6, while the median remained stable at 3 for all years. Although the national HHI in the loan market fluctuated around 1620, local markets

were significantly more concentrated. The average across local indices fluctuated around 3200 (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).<sup>3</sup> 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 institutions under its regulatory oversight. We restrict our analysis to loans that private 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 [Section A.4](#), we complement our risk measures with our own estimate of default probabilities using a probit specification in the panel following all loans through maturity. Including the estimated probability of default makes a negligible difference for our outcomes of interest conditional on our categorical risk measures, validating the content of the latter as measures of risk.

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

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<sup>3</sup>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 Central Bank of Chile processed the disaggregated data. All the analysis was implemented by the authors and did not involve nor compromise the 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.

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 |
| <i>A. All Firms</i>   |           |        |        |        |        |               |         |        |          |        |        |        |
| 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  |
| <i>B. Local Firms</i> |           |        |        |        |        |               |         |        |          |        |        |        |
| 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: 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.

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 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 number of loans in our baseline sample is 119,330, issued to 22,834 firms in 298 cities. The results in Table 3 show a slightly lower number of observations given that we require all variables in the table to be non-missing. Given our focus on location premia later on, we

implement a final restriction to the sample for the analysis in Table 4 and drop cities with fewer than 20 loans or fewer than 3 borrowing firms, which represent 0.54% of the observations in the sample and where the estimated city fixed effects are noisy. This step leads the number of cities in our sample to drop from 298 to 235.

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),

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

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  $\ell$  extended to firm  $f$  in period  $t$  and the yield of a bond with a similar maturity in the same month.<sup>4</sup> 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 both a risk categorization of the firm and the

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<sup>4</sup>The data includes the day on which the loan was issued. We refer to  $q(t)$  and  $y(t)$  as the quarter and year at which the loan was issued. 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.

expected loss on the loan. 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 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. As it is well known, this approach understates the contribution of the variables added later, providing a conservative lower bound on the contribution of space to interest rate variation (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.

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. The contribution of city fixed effects to the  $R^2$  for installment loans almost doubles compared to the full sample and, as shown in Panel B of Table 3, is similar to the contribution of the bank-sector match in the subsample of installment loans. 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.<sup>5</sup>

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<sup>5</sup>Blickle, Parlato and Saunders (2026) document that large U.S. 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

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 $\times$ Quarter FE |                    |           |           | ✓         | ✓         | ✓         |                                 |         |         | ✓       | ✓       | ✓       |
| Bank $\times$ 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   |
| $\Delta R^2$             | 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.  $\Delta R^2$  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. Panel B restricts to installment loans.

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 $\times$ Quarter FE |                    |         |         | ✓       | ✓       | ✓       |                                 |         |         | ✓       | ✓       | ✓       |
| Bank $\times$ 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   |
| $\Delta R^2$             | 0.016              | 0.422   | 0.089   | 0.040   | 0.015   | 0.016   | 0.029                           | 0.413   | 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.  $\Delta R^2$  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 exclude the predicted default probability (`p_default`). 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 with a far more parsimonious specification, 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.<sup>6</sup>

charge systematically lower rates than non-specialized lenders on otherwise similar loans.

<sup>6</sup>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.

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 3.2](#) our focus is explaining between-loan variation in the full sample of loans, while in [Section 3.3](#) we study between-city variation in the average interest rate, the main focus of the paper.

## 3.2. Variance decomposition

We estimate [equation \(1\)](#) via weighted OLS on the subsample of local firms, using only installment loans. 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  $\hat{\gamma}^{c(f)} \equiv \hat{\beta}^{c(f)}$ . By construction,

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

and the OLS residual  $\hat{\epsilon}_\ell$  is orthogonal to each of the four components. The location premium  $\hat{\gamma}^c$  captures differences in the conditional mean in interest rates 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. Given that we observe the risk assessment made by the issuing bank on each loan, for the former interpretation to be driving our results, the unobservable characteristics should have been unobservable not only for us as econometricians but for the lending bank as well.

The interquartile range in the distribution of  $\hat{\gamma}^c$  across cities is 103 bp, and between percentiles 10 and 90 is 196 basis points. Relative to spreads of 241 and 422 basis points for raw city averages, respectively, these results indicate that controls remove roughly half of the raw dispersion.

Taking weighted variances of [equation \(2\)](#) yields

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

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

$$\sum_{k \neq j} \text{Cov}(\hat{\gamma}^j, \hat{\gamma}^k).$$

The focus of this paper is on differences in average interest rates 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

$$\bar{\delta}_c = \bar{\gamma}_c^r + \bar{\gamma}_c^x + \bar{\gamma}_c^b + \hat{\gamma}^c \quad (3)$$

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. 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  |
| <i>A. Variance components (SD and share of total variance)</i>            |            |        |            |        |
| Bank effects                                                              | 39.1       | 0.074  | 83.8       | 0.046  |
| Risk covariates                                                           | 49.6       | 0.230  | 91.4       | 0.169  |
| Other covariates                                                          | 79.5       | 0.339  | 183.5      | 0.375  |
| City effects                                                              | 85.1       | 0.357  | 45.6       | 0.022  |
| Residual                                                                  |            |        | 209.3      | 0.388  |
| <i>B. Covariance components (correlation and share of total variance)</i> |            |        |            |        |
| Bank & risk                                                               | 0.165      | 0.020  | -0.013     | -0.002 |
| Bank & covariates                                                         | -0.107     | -0.020 | -0.131     | -0.036 |
| Bank & city                                                               | 0.261      | 0.054  | 0.079      | 0.005  |
| Risk & covariates                                                         | 0.788      | 0.192  | 0.639      | 0.190  |
| 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 \(2025\)](#).

Average interest rates differ between cities. In the local installment-loan sample used for the variance decomposition, the gap between percentiles 10 and 90 of loan-amount-weighted city averages 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  $\delta_c$  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 rates. Around 35% of the differences are captured by the city fixed effects. Understanding which characteristics of the local credit market covary with  $\hat{\gamma}^c$  is the focus of [Section 4](#).

### 3.4. 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](#).

Most loan-level results align with the weighted version of the analysis. The main distinction is that there is an increased role for the correlation between the risk-city and bank-city components, which becomes the second-strongest correlation. This suggests that firm sorting on the basis of risk matters more for smaller firms and for firms that tend to borrow smaller amounts. The results from the city-level analysis are mostly unchanged compared to the weighted version of the analysis. While the role of bank differences between cities grows considerably, the local component remains the most important.

## 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  $\beta^c$ . In this section, we delve deeper into what characterizes high-interest rate locations.

**Local characteristics.** We relate the estimated location premiums 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 \(2025\)](#). *Income* is the city’s GDP per capita, averaged over 2012–2018; 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. *Location risk* 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 concentration* ( $HHI_c$ ) 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

$$\hat{\beta}_c = \kappa_0 + \kappa_1 \text{Income}_c + \kappa_2 \text{LocationRisk}_c + \kappa_3 \text{HHI}_c + \kappa_4 \text{BanksPerFirm}_c + \kappa_5 \text{JudicialDelay}_c + \nu_c. \quad (4)$$

Because  $\hat{\beta}_c$  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)<br>Unweighted    | (2)<br>Inv. SE         |
|----------------|----------------------|------------------------|
| GDP per capita | 8.256***<br>(2.070)  | 9.239***<br>(1.848)    |
| GDP volatility | -4.905<br>(80.95)    | -16.80<br>(72.94)      |
| Bank HHI       | 0.00758<br>(0.00423) | 0.00899**<br>(0.00341) |
| Banks per firm | -227.2***<br>(42.40) | -150.8***<br>(43.56)   |
| Judicial delay | 0.0641<br>(0.119)    | 0.0368<br>(0.0941)     |
| Constant       | 82.45<br>(92.51)     | -15.21<br>(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  $\hat{\beta}_c$  (in basis points). Columns weight cities equally (1) and by the inverse standard error of  $\hat{\beta}_c$  (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 precision-weighted coefficient on the HHI implies that a city with an HHI 1,000 points higher carries a location premium about 9 basis points larger. The complementary measure, banks per firm, enters negatively throughout, consistent with the same interpretation. Richer cities carry higher local premiums: a one-thousand-2021-USD increase in GDP per capita is associated with roughly 9 basis points higher spreads. A natural interpretation of this finding is that demand for loans may be higher in these cities. 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 slightly less than 20% of the cross-city variation in  $\hat{\beta}_c$ .

## 5. Conclusion

We show that average interest rates 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. Location premia are higher in richer cities and 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. These associations are descriptive, however, and the local characteristics we consider account for only around one-fifth of the variation in location premiums.

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.

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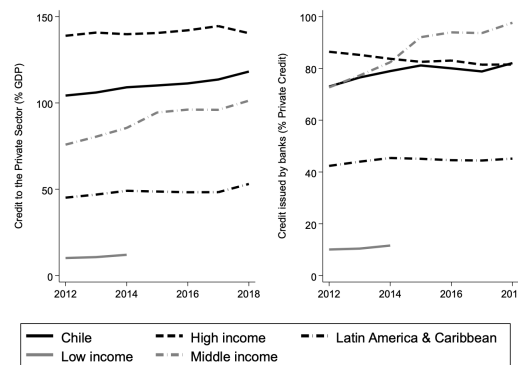
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## A. Appendix

### 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)

| <i>Firm size</i> | 2015 ELE             |                                 |                      |
|------------------|----------------------|---------------------------------|----------------------|
|                  | % borrows from banks | % biggest loan comes from banks | % private employment |
| Micro            | 57.1                 | 16.7                            | 7.7                  |
| Small            | 66.4                 | 29.6                            | 39.3                 |
| Medium           | 77.7                 | 42.1                            | 21.9                 |
| Large            | 80.5                 | 50.4                            | 30.1                 |

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 |
|---------------------------------------------------|------|------|------|------|------|------|------|
| <i>A.</i>                                         |      |      |      |      |      |      |      |
| <i>City-Bank Pairs</i>                            | 391  | 384  | 386  | 366  | 366  | 345  | 345  |
| <i>Cities</i>                                     | 85   | 86   | 83   | 83   | 83   | 82   | 80   |
| <i>B. Year-on-year change (excluding mergers)</i> |      |      |      |      |      |      |      |
| New city-bank pairs                               | 4    | 8    | 5    | 0    | 0    | 1    | 1    |
| Disappearing city-bank pairs                      | 15   | 4    | 20   | 1    | 1    | 2    | 9    |
| <i>C. Banks per City</i>                          |      |      |      |      |      |      |      |
| Mean                                              | 4.6  | 4.6  | 4.6  | 4.4  | 4.4  | 4.2  | 4.3  |
| Standard Deviation                                | 3.6  | 3.5  | 3.5  | 3.1  | 3.1  | 2.7  | 2.7  |
| Median                                            | 3    | 3    | 3    | 3    | 3    | 3    | 3    |
| <i>D. Herfindahl-Hirschman Index</i>              |      |      |      |      |      |      |      |
| National                                          | 1678 | 1662 | 1619 | 1625 | 1643 | 1678 | 1664 |
| Average across local indices                      | 3519 | 3505 | 3317 | 3318 | 3318 | 3248 | 3069 |
| Median across local indices                       | 3159 | 3098 | 2785 | 2728 | 2690 | 2599 | 2545 |

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. Adding an estimate of the default probability

Our baseline controls for borrower risk rely on the bank-assessed risk category together with continuous provisioning and indebtedness measures. As a robustness check, we augment these controls with a predicted probability of default estimated outside the loan-pricing regression. Specifically, we estimate 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, and use it to predict a default probability for each firm-year. We then add this predicted default probability to the risk controls and repeat the incremental  $R^2$  analysis on local firms. Because the default probability requires firm financials that are not available for every loan, this exercise is run on a somewhat smaller sample than the baseline. Table 8 shows that the results are nearly unchanged: city fixed effects continue to raise the  $R^2$  by about 1.8 percentage points in the richest specification, confirming that the local component is not an artifact of incompletely controlling for borrower risk.

Table 8: Incremental  $R^2$ : Local Firms, with 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 $\times$ Quarter FE |                    |         |         | ✓       | ✓       | ✓       |                                 |        |        | ✓      | ✓      | ✓      |
| Bank $\times$ Sector FE  |                    |         |         |         | ✓       | ✓       |                                 |        |        |        | ✓      | ✓      |
| City FE                  |                    |         |         |         |         | ✓       |                                 |        |        |        |        | ✓      |
| $R^2$                    | 0.016              | 0.440   | 0.531   | 0.573   | 0.586   | 0.603   | 0.029                           | 0.462  | 0.564  | 0.605  | 0.618  | 0.636  |
| $\Delta R^2$             | 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.  $\Delta R^2$  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. 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 analysis in the main text 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 $\times$ Quarter FE |                    |        |        | ✓      | ✓      | ✓      |                                 |        |        | ✓      | ✓      | ✓      |
| Bank $\times$ 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  |
| $\Delta R^2$             | 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.  $\Delta R^2$  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  |
| <i>Variance components (SD and share of total variance)</i>            |            |        |            |        |
| Bank effects                                                           | 73.8       | 0.225  | 149.8      | 0.117  |
| Risk covariates                                                        | 51.6       | 0.233  | 134.1      | 0.180  |
| Other covariates                                                       | 75.8       | 0.263  | 219.9      | 0.313  |
| City effects                                                           | 82.3       | 0.278  | 57.1       | 0.021  |
| Residual                                                               |            |        | 277.2      | 0.369  |
| <i>Covariance components (correlation and share of total variance)</i> |            |        |            |        |
| 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).