The Distributional Effects of Lending Rate Caps*

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Abstract

We estimate the financial and real effects of a lending rate cap introduced in Peru, affecting 26 percent of small business loans. Leveraging variation in exposure to the policy across loans, banks, and local credit markets, we find that the program reduced interest rates and generated substantial credit reallocation. In concentrated markets, highly treated banks replace risky borrowers with safe and new firms, which led to a net positive effect on credit and real outcomes. In contrast, the effect is negative in competitive locations where banks could not replace risky firms. This credit reallocation allowed highly treated banks to maintain their market share constant despite a 23 percentage-points decline in interest rates. Finally, we show that excluded risky borrowers had lower marginal revenue productivity of capital than the firms who benefited from more credit and lower rates. Consequently, the lending rate cap reduced capital misallocation in concentrated markets.

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1 Introduction

Small firms have limited access to formal credit in developing countries, and when they obtain a loan, it is usually granted at high interest rates. Thus, the regulation of lending rates is often floated in the political debate. Indeed, most developing countries have introduced or strengthened price regulations in bank credit markets over the last decade[1] arguing that these policies can reduce financial costs, expand credit, and improve the allocation of capital among small and young entrepreneurs. However, whether interest rate regulations can improve credit access and capital allocation is theoretically ambiguous.

From a standard industrial organization view, interest rate regulations can expand credit supply in concentrated markets by limiting banks' market power. However, when informational frictions dominate–as is common in developing economies–caps may exclude opaque firms that borrow at high interest rates to compensate lenders either for default risk or for the costs banks incur when building lending relationships. This exclusion could worsen capital misallocation if affected firms are highly productive.

We estimate the distributional and aggregate effects of lending rate caps on small firms by studying a reform implemented by the Central Bank of Peru in July 2021, which prohibited annualized interest rates above 83.4 percent for small business loans.

This setting is particularly relevant to understand the impact of interest rate regulations in emerging markets due to three main reasons. First, it is a big shock, capable of producing important general equilibrium effects. In the first half of 2021, 26 percent of small firm loans (6 percent of value) were originated at interest rates above the cap. Moreover, if we bring interest rates of loans originated before the regulation down to cap value, the annualized interest payment of small business loans would have declined by 8 percent. Second, the market of small business loans in our setting is similar to that of other developing countries in multiple dimensions. For example, on the supply side, Peru exhibits high levels of bank concentration, high interest rates, and a mix of traditional banks and micro-finance institutions competing for small firms. On the demand side, Peru exhibits high informality rates, which are common in other emerging markets and constitute a source of strong informational frictions. Third, Peru's long period of macroeconomic stability, characterized by low inflation and delinquency rates provides a unique opportunity to isolate the effects of the interest rate regulation.

[1]See, for example, Ferrari et al. (2018)

We use three main datasets provided by the Central Reserve Bank of Peru. First, we use loan-level data from the Interest Rates Report (*Reporte de Tasas de interés*), which includes information of loan origination at the bank-firm level in a monthly basis. We observe the value, duration, and annualized interest rate for all small firm loans between March and December 2021. Second, we use credit registry data from the Consolidated Report of Borrowers (*Reporte Consolidado de Deudores*), which includes information on the balance of loans at the bank-firm level in a monthly basis. We observe the value and repayment delay for all outstanding small firm loans between December 2019 and 2022. Additionally, this dataset includes information on the city where loans are originated and the industry of borrowers. Finally, we use data from tax records, which includes information on sales, employment, and capital, for the universe of firms in the formal economy in an annual basis from 2017 to 2023. Putting them together, our data allow us to trace the effects of lending rate caps on small firms' financial and real outcomes, estimating the role of credit access and capital allocation across different borrowers.

Three key patterns characterize the pre-reform credit market. First, micro and small-size loans–defined as those in the bottom two terciles of the loan size distribution–exhibited substantially higher interest rates than larger loans. Second, this premium was significantly larger in more concentrated local banking markets (measured by the Herfindahl-Hirschman Index) and for risky firms (those with a history of repayment delays exceeding 30 days in the year prior to the policy). Third, this high-rate, small-size loan segment was itself highly concentrated, dominated by a handful of specialized financial institutions. We classify the five banks most specialized in this segment as "highly treated", as they were disproportionately exposed to the lending rate cap.

We develop a stylized static model to guide our empirical analysis. In our baseline framework, a fixed number of banks with linear cost functions engage in Cournot competition over a continuum of small firms. Each firm has an investment project with an exogenous, firm-specific probability of failure or default. Consistent with our data, the model delivers an equilibrium interest rate that increases with the marginal cost of loan origination, the firm's default risk, and the degree of bank market power, which is summarized by the Herfindahl-Hirschman Index (HHI).

The model yields two testable implications. First, the lending cap makes it unprofitable to extend credit to high-risk firms–those with probability of failure greater than a given cutoff which is determined by the cap value and the cost of loan origination–leading to their exclusion from the market. Second, for a segment of moderate-risk firms–up to the exit cutoff–, lending remains profitable at the capped rate; leading to an expansion of credit at a lower cost. The model further predicts that the size of this benefited segment is strictly increasing in the degree of local market concentration.

Guided by our theoretical framework, we organize our empirical analysis in three blocks. We begin by estimating the average local credit market effect of the policy. We then test the role of bank market power and firm risk, documenting how banks reallocated credit in response to the regulation. Finally, we quantify the real economy impact of the policy and estimate the response of capital misallocation.

We start by estimating the average local credit market effect of the cap. To do so, we define credit markets at the city level, relying on the plausible assumption that small entrepreneurs depend on local lenders. We then aggregate our data and construct a city-level measure of treatment equal to the hypothetical decline in small firm interest payments had the policy been implemented pre-reform.[2] Our identification relies on the assumption that highly treated and low-treated cities would have followed parallel trends in the absence of the policy. We support this assumption with four key pieces of evidence. First, we plot event-study graphs showing no systematic differences between high- and low-treatment cities prior to the reform. Second, we document that our city-level treatment measure is driven by the geographical distribution of highly treated banks, a factor orthogonal to relevant industry and city-specific characteristics, as evidenced by a balance of covariates test. Third, we incorporate high-dimensionality fixed effects to absorb shocks at the industry, region, and city-size levels. Finally, we perform placebo tests by estimating the response of low-treated banks' outcomes across locations.

We find that cities with one standard deviation higher treatment experienced a 5 percentage-point decline in interest rates post-reform. However, the aggregate loan value remained statistically unchanged, masking two offsetting effects: a 5 percent contraction in micro-size credit that was completely counterbalanced by a 6 percent expansion in small and large loans. Our placebo test shows that neither interest rates nor credit evolved differently across low versus high treated locations for low-treated banks. Taken together, our results confirm that the policy successfully reduced interest rates. The absence of an effect on total lending indicates that banks fully offset the decline in constrained micro-size loans by rebalancing their portfolios

[2]This measure is inspired by the minimum wage literature. See, for example, Card and Krueger 2000; Dustmann et al. 2021, and references therein.

toward larger credit.

In the second part of the paper, we examine how bank competition and firm risk shape the impact of lending rate caps. We test two competing hypothesis regarding the role of bank competition. First, a standard industrial organization view formalized in our model implies that interest rate caps can increase credit supply by constraining bank market power. Second, an alternative perspective that emphasizes informational frictions and repeated interactions with borrowers (Stiglitz (1993), Petersen and Rajan (1995), Crawford et al. (2018)) implies that caps may reduce credit access by disrupting relationship lending.

We use the HHI to proxy for bank market power[3] and split cities accordingly. While in the average city the policy had null effects on aggregate credit, three key patterns emerge in the corss-section of markets with different HHI. First, small-size loans contract consistently across all markets. Second, bigger loans expand exclusively in concentrated markets, leading to an increase of 1.9 percent in total credit. Third, interest rates fall more sharply in cities with high concentration, as micro-size loans become a smaller share of banks' rebalanced portfolios. These findings strongly support the channel highlighted by our model: the lending rate cap improves aggregate credit conditions only in markets where banks exert market power. This result depends entirely on the reallocation from small-size loans to bigger credit, which is more likely to occur in concentrated markets. The reallocation of credit across differently affected segments and cities suggests that banks' internal capital markets are not defined at the local level. Instead, banks can flexibly move capital from competitive to concentrated cities when adjusting to the policy.

A central policy concern is that, by preventing risk-based pricing, lending rate caps may disproportionately exclude opaque borrowers–such as young and informal firms that pay high interest rates to compensate lenders for their greater risk. To investigate how firm risk shapes the impact of lending rate caps, we classify firms based on pre-regulation repayment behavior: those with any history of more than 30 day delays are grouped as ex-ante risky firms, while those without such delays are our ex-ante safe group. Consistent with interest rates pricing risk before the cap, we document that risky firms faced median interest rates of 100 percent, compared to just 50 percent for safe firms.

We estimate the response of total loans separately for risky, safe, and new borrowers. Our

[3] As we show in our descriptive analysis, interest rates are higher in concentrated markets even when controlling for loan-level observables.

results highlight the critical trade-off of price regulations in credit markets. While the total number of borrowers increase in concentrated markets, risky firms are excluded regardless of market concentration. Thus, the expansion of credit in concentrated markets is driven by treated banks replacing risky clients with safer incumbents and new borrowers. These findings underscore a key limitation of the policy: while they can expand credit where banks have market power, they disrupt credit access for high-risk firms everywhere.

This credit reallocation across firms and cities was critical for highly treated banks to adjust to the policy. We find that, at the country level, these banks reduced their weighted average interest rates by 23 percentage points. Despite this sharp decline, their market share remained constant at approximately 40 percent of clients and 27 percent of loan value. The ability to reallocate credit shielded highly treated banks from losing market share despite the policy successfully lowering the cost of credit for a segment of the market.

Having established how lending rate caps affect credit markets, we now estimate their real economy effects and focus on the response of capital misallocation, a key driver of aggregate productivity (Hsieh and Klenow 2009; Restuccia and Rogerson 2008; Bau and Matray 2023). Notice that the real impact is apriori unclear. First, firms that lose access to formal bank credit may substitute toward informal financing, thereby attenuating the real effects of the credit contraction. This is particularly important in our setting as informal credit is more prevalent among the very small, opaque firms most affected by the cap. Despite this type of credit not being recorded, exploring the response of real outcomes can shed light on the actual relevance of this margin of adjustment. Second, and more critically, the policy's real effect hinges on the productivity of the firms it excludes versus those it benefits. If the risky firms pushed out of the formal credit market are highly productive, the policy could actually dampen economic activity and increase misallocation, even if aggregate credit remains stable.

To analyze the real effects of the policy, we extend our conceptual framework to incorporate heterogeneity in firm productivity. Different from standard macroeconomic models with financial frictions where financial development policies that expand aggregate credit unambiguously boost output and improve capital allocation (Moll 2014; Midrigan and Xu 2014), a key implication of our framework is that a lending rate cap can have a positive or negative effect on economic activity even if credit expands.[4] This is because the policy induces a reallocation of

[4]Indeed, even capital misallocation and economic activity can respond in different directions to the introduction of a lending rate cap.

credit based on risk, not necessarily on productivity. Then, the impact on output and capital misallocation depends critically on the distribution of productivity among excluded riskier borrowers and benefited moderate-risk firms. If the excluded risky borrowers are, on average, more productive than the safer firms that gain credit, the policy will exacerbate capital misallocation and may reduce output. Conversely, if credit is reallocated toward more productive firms, the cap can improve aggregate efficiency and may expand output. This framework shifts our focus beyond credit markets to the question of whether the credit reallocation induced by the cap directs capital toward or away from its most productive uses.

We test our model predictions using firm-level tax records for small businesses between 2017 and 2023. First, we find that real outcomes mirror the credit reallocation documented earlier: in concentrated markets, firm sales and capital increase by 9 and 11 percent, respectively, whereas in competitive markets, they contract by 4 and 5 percent. To directly assess allocative efficiency, we compute a standard measure of capital misallocation–the dispersion of the log marginal revenue product of capital (MRPK)–within city-industry cells. Our results show that capital misallocation declines in concentrated markets and increases in competitive ones. This provides evidence that pre-existing bank competition is a critical determinant of whether price regulations improve or worsen the allocation of capital in the economy.

To provide further evidence on these distributional effects, we track firms borrowing in the pre-reform period, between March and June 2021, and match them to annual tax records reported from 2017 to 2023. We rank firms by pre-reform MRPK within industries[5] and split them into high and low MRPK depending on whether they are above or below the industry median (Bau and Matray 2023). We start documenting that, while 40 percent of firms paying above-cap rates exhibited high MRPK, just 30 percent of firms paying below-cap rates did. This aligns with financial friction models where firms operate at high-MRPK levels due to credit constraints (e.g., Buera and Shin 2013; Moll 2014).

We provide firm-level evidence on the distributional effects of price regulations by comparing firms borrowing just above and just below the cap, before and after the reform. Our findings show that, on average, firms borrowing above the cap evolve similarly than those borrowing below in terms of capital and sales. However, conditioning on high-MRPK firms, those borrowing above the cap accumulated 19 percent more capital after the regulation, compared with similar firms borrowing below the cap. On the other hand, conditioning on low-MRPK firms, those

[5]We implicitly assume that small firms share the same Cobb-Douglas production function within industries.

borrowing above the cap exhibited a 19 percent decline in capital. We find null effects on sales among high-MRPK firms, consistent with capital investments preceding output gains, and a 38 percent contraction of sales among low-MRPK borrowers. These results indicate that rate caps improved capital allocation among incumbent borrowers by redirecting resources toward highly productive firms.

Our paper analyzes how lending rate caps reshape credit markets and economic outcomes. By studying the introduction of a cap that affected 26 percent of small firm loans in Peru, we show that these policies can create important distributional effects: while lowering interest rates, they systematically exclude risky firms and expand credit to safer entrepreneurs only in concentrated cities. Furthermore, caps can improve capital allocation by redirecting resources to high-productivity firms in concentrated credit markets.

Literature Review. We contribute to two main areas of research. First, we contribute to the literature that studies the effects of price regulations in credit markets (Benmelech and Moskowitz 2010; Rigbi 2013; Agarwal et al. 2014; Madeira 2019; Cuesta and Sepúlveda 2021; Galenianos and Gavazza 2022; Cherry 2025; Nelson 2025; Kuroishi et al. 2025). We contribute by estimating the role of firm risk and bank market power in the transmission of lending rate caps to small businesses in an emerging market. The literature indicates that informational frictions generate credit rationing (Stiglitz and Weiss 1981). In this context, banks need to build relationship lending to expand credit (Petersen and Rajan 1994), and then, market power can actually have positive effects on credit (Petersen and Rajan 1995; Crawford et al. 2018). Thus, lending rate caps might reduce credit supply in both concentrated and competitive locations. We provide evidence that bank concentration mediates banks' ability to reallocate credit away from risky firms and towards safe and new borrowers, which is instead consistent with bank market power generating under-provision of credit before the policy.

Our documented credit reallocation across loan-size bins and firms also suggests that banks face frictions to raise capital, as highlighted in previous research (Stein 1998; Jayaratne and Morgan 2000; Jiménez et al. 2012). Furthermore, the reallocation of credit across cities with different levels of concentration indicates that banks' capital markets are geographically integrated (Becker 2007; Cortés and Strahan 2017). We also contribute to the literature documenting a trade-off between economic growth and financial stability in the context of pro-competitive policies in the banking sector (Corbae and Levine 2025; Carlson et al. 2022). In our setting, banks' ability to reallocate credit mitigates this trade-off. Indeed, in highly concentrated markets where such reallocation is feasible, financial stability measured as delinquency rates improves while economic activity expands.

Second, our paper contributes to the literature of finance and development (Burgess and Pande 2005; Banerjee and Duflo 2014; Bruhn and Love 2014; Ponticelli and Alencar 2016; Garber et al. 2021; Fonseca and Van Doornik 2022; Fonseca and Matray 2024; Quincy and Xu 2025). We contribute by studying the effects of lending rate caps, a policy widely used in emerging markets, but whose impact on small firm dynamism is *a priori* unclear. Using administrative data, we document that firm risk and bank market power interact and shape the aggregate impact of the policy, consistent with recent empirical evidence highlighting the negative effects of bank concentration in developing countries (Joaquim et al. 2020; Burga and Céspedes 2021).

We relate to the well-documented literature showing that small businesses in emerging markets borrow at high interest rates that cannot be explained by default (Banerjee 2003). Our paper shows that these firms operate with high marginal returns, consistent with macro-development models with financial frictions (Banerjee and Moll 2010; Itskhoki and Moll 2019). Moreover, we estimate the response of capital misallocation in the context of small firms. In this line, our paper relates to the literature studying the role of financial frictions in driving misallocation in emerging economies (Hsieh and Klenow 2009; Restuccia and Rogerson 2008; Banerjee and Moll 2010; Buera and Shin 2013; Moll 2014; Midrigan and Xu 2014; Bau and Matray 2023; Joaquim and Sandri 2020; Cavalcanti et al. 2023). We contribute by providing empirical evidence that lending rate caps can reduce capital misallocation in concentrated markets by redirecting credit towards productive firms. We document how the distribution of borrowers over the triplet productivity, risk, and interest rate shifts after the implementation of the cap.

The rest of the paper is organized as follows. Section 2 provides a description of the data. Section 3 presents our conceptual framework and section 4 describes our empirical setting. Section 5 reports our results and section 6 concludes.

2 Data and Institutional Background

2.1 Data

We use three main datasets provided by the Central Reserve Bank of Peru to estimate the impact of lending rate caps on small businesses loans.

1. Interest rate report. We use loan-level data from the *Reporte de Tasas de Interés*, which includes bank-firm level information on loans at origination. We observe the value, duration, and annualized interest rate on every small firm credit granted by all banks established in Peru, in a monthly basis, between March and December 2021. We also observe the city where loans are originated, the industry where firms operate, a unique borrower identifier used for bank regulation purposes, and a unique firm tax identifier. We use this dataset for two main objectives. First, we construct measures of treatment at different levels of aggregation such as loan, bank, and city. Second, we estimate the impact of lending rate caps on interest rates, loan origination, and number of borrowers.

2. Credit registry data. We use loan-level data from the *Reporte Crediticio de Deudores*, which includes information on outstanding debt at the bank-firm level. We observe the value and days of repayment delay for all loans, in a monthly basis, between December 2019 and 2022. As in our previous dataset, we also observe the city where loans are originated, the industry where firms operate, a unique borrower identifier used for bank regulation purposes, and a unique firm tax identifier. We use this dataset to classify borrowers in three categories: incumbent safe, incumbent risky, and new clients, and estimate the reallocation of credit across these categories within industry and city bins.

3. Tax reports. We use firm-level data from tax files, which include information on sales, employment, and capital, for the universe of firms in the formal economy. This annual panel of firms is available between 2017 and 2023. Additionally, we observe the city and industry that firms report to the Tax Agency, as well as a unique tax identifier that allows us to merge all our datasets. We use this data to estimate the effects of lending rate caps on small firm real outcomes and to quantify the response of capital misallocation.

2.2 The market of small business loans

Lending rate caps were implemented for all small firm credit. Before discussing the policy implementation, we briefly describe this segment of the market. Small firm credit includes all loans granted to firms whose total bank debt is below USD 80 thousand[6]. Table 1 reports summary statistics of the value, duration, and annualized interest rate of small business loans in the pre-reform period. The average loan size is USD 2 559, while the median value is USD 811. These loans are usually short-term, with an average and median duration of around one year.[7] Finally, these loans tend to be granted at high annualized interest rates, which average 65 percent. If we weight by loan size, the average duration and annualized interest rate are around 2 years and 30 percent, respectively, which indicates that bigger loans exhibit significantly longer duration and lower interest rates.

The are 41 financial institutions providing small firm credit, including traditional banks and micro-finance institutions (MFIs).[8] Table 2 reports market shares using pre-reform data. There are 9 traditional banks that represent 39 percent of the market, in terms of value, and 32 MFIs that account for the remaining 61 percent. MFIs play a key role in this market, with 4 of them ranked at the top 5.[9] Moreover, these institutions usually offer small-size loans, thus, their market share in terms of number of clients is even higher, reaching 76 percent. Finally, we can observe that the market of small firm credit is highly concentrated, with only 5 institutions attending 74 percent of firms. Throughout the text, we will refer to traditional banks and microfinance institutions as banks.

2.3 Interest rates in the cross-section

We provide a descriptive analysis on the drivers of interest rates in our data. Notice that, in principle, interest rates could reflect inflation and default rates. However, inflation fluctuated between 1.4 and 4.7 percent, while delinquency rates among small business loans ranged from 4.7 to 8.8 percent in our sample period. Thus, none of them can account for the observed interest rates in our setting. We use our detailed administrative data to test the role of loan

[6]We consider an exchange rate of PEN 3.50 per USD, which is the average exchange rate in 2020.

[7]It is worth noticing that duration refers to the length of the repayment period, which is done in a monthly basis and starts one month after origination.

[8]MFIs are small, usually local lenders, specialized in providing small-size loans.

[9]This contrasts with the market of large firm loans, where five traditional banks account for more than 90 percent of the market, and MFIs provide a negligible share.

size, bank market power, and firm risk by estimating the following OLS regression:

$$\begin{aligned} r_{\ell ibt} = \beta_1 \text{MS Loan}_\ell + \beta_2 \text{HHI}^{\text{MS}}_{c(i)} + \beta_3 \text{Risky}_i + \beta_4 \text{MS Loan}_\ell \times \text{HHI}^{\text{MS}}_{c(i)} \\ + \beta_5 \text{MS Loan}_\ell \times \text{Risky}_i + \delta_t + \delta_{j(i)} + \delta_{s(i),r(i),c(i)} + u_{\ell ibt} \end{aligned} \tag{1}$$

Where $r_{\ell ibt}$ denotes the interest rate on loan ℓ granted by bank b to firm i in month t. We define micro-size and small-size loans MS Loan_ℓ as an indicator variable equal to one if the loan value is below USD 1 061 thousand, which is the percentile 66th of the pre-reform small firm loan-size distribution.[10] HHI^{MS}_c represents the Herfindahl-Hirschman index (HHI) of city c considering micro-size and small-size loans only, and is our proxy to test the role of bank market power in shaping interest rates. We define Risk_i as an indicator variable equal to one if firm i exhibited 30 or more days of repayment delay at least once in 2020. This is our proxy for firm risk. Finally, δ denotes fixed effects at different levels such as time, firm industry j, and firm size s interacted with risk r and city c.

Our results are reported in Table 3. Column (1) shows that interest rates on small-size loans are, on average, 44 percentage points higher than interest rates on bigger loans, even after controlling for currency and time fixed effects. This result is not accounted for industry specific characteristics either, as shown in column (2). Column (3) indicates that bank competition and firm risk also play a role. One standard deviation (SD) higher HHI is associated with 8 percentage points higher interest rates, and ex-ante risky firms pay, on average, 15 percentage points higher rates.

We further study the role of market concentration and firm risk by interacting these variables with loan size. Column (4) shows that small-size loans are originated at 21 percentage points higher interest rates, on average. However, small-size loans originated in cities with one SD higher HHI exhibit an additional increase of 6 percentage points in interest rates. Moreover, interest rates increase by 9 additional percentage points when grated to ex-ante risky firms. Finally, column (5) saturates our specification and shows that bank concentration and firm risk play a key role in shaping interest rates of small-size loans, even after controlling for loan size, firm risk, and city fixed effects. Overall, our results suggest that the interaction of loan-size with market power and firm risk is key to understand the cross-section of interest rates in Peru.

Finally, we show that interest rates and concentration over the loan-size distribution are

[10] We use this cutoff because average interest rates decline significantly in the top tercile. As we present below, Figure 2 plots the distribution of interest rates for each decile of the loan size distribution showing this pattern.

closely related. To illustrate this point, Figure 1 plots the weighted average interest rate for each decile of the loan-size distribution against two proxies of bank competition. The circle size denotes how big is each decile in terms of loan value, with the biggest circle referring to the top decile and the smallest to the bottom decile. The dashed line separates micro and small-size loans (right) from large credit (left). Panel (a) shows that the market of micro and small-size loans is highly concentrated. Around 85 percent of smaller loans, at the bottom four deciles, are offered by only three financial institutions.[11] Interestingly, this measure of concentration strongly correlates with interest rates. In contrast, only 45 percent of large loans are provided by the three largest financial institutions competing in those bins. Panel (b) plots interest rates on HHI for each decile and shows a similar patterns. This evidence suggests that the market of small firm credit is highly segmented based on loan-size and competition varies substantially across the loan-size distribution.

2.4 Lending rate cap and bank exposure

The Central Reserve Bank of Peru established a lending rate cap for small firm credit since July 2021. This cap defined a maximum annualized interest rate of 83.4 percent for new loans, and represented an important change in the structure of small firm lending. For example, around 26 percent of loans were granted at interest rates above the cap between March and June 2021, before the policy was implemented. These loans represented 6 percent in terms of value, and if we bring interest rates on every loan originated in the pre-reform period down to the cap, the total annualized interest payment of small businesses would have declined by 8 percentage points. Thus, the new regulation reshaped the landscape of small firm credit markets.

Figure 3 plots monthly statistics of the distribution of interest rates for the universe of small business loans originated between March and December 2021. Each box shows the percentiles 10th, 25th, 50th, 75th, and 90th of the distribution of interest rates, while the red diamonds represent the average interest rate. First, we can notice that the distribution of interest rates compresses from above after the regulation of interest rates. While the 75th percentile was around 100 percent in the pre-reform period, it dropped to the cap value of 83.4 percent after the reform. The observed bunching of 25 percent of loans originated at the cap value after the reform is suggestive evidence of market power. On the other hand, the median and percentiles

[11] For a given decile, we compute the value of loans originated by each financial institution between March and June 2021, and then compute the share of the three largest ones within the decile.

25th and 10th did not change. Furthermore, we can see a reduction in the average interest rate from 65 to 53 percent. We plot the distribution of loan-size and loan-duration in Figure 4. The average and median loan-size increased by 9 and 7 percent after the reform, respectively, while the average and median duration remained constant.

As we discussed in the previous subsection, the market of small firm credit is highly segmented with few banks specialized in micro and small-size loans with high interest rates. We measure the hypothetical decline in annualized interest payments necessary to satisfy the regulation in the pre-reform period for each bank. We find that only 5 banks are highly exposed to the policy, with exposures above 1 percent.[12] These highly treated banks represent around 40 percent of the total value of small firm credit and are specialized in micro and small-size loans. For example, while micro and small-size loans represent 19 percent of low treated banks' portfolios, they account for more than 50 percent of highly treated banks' lending.

3 Conceptual Framework

3.1 Entrepreneurs

There is a continuum of entrepreneurs with measure one that are risk-neutral and invest in a risky project with firm-specific probability of success $1 - \sigma$. When the project succeed, entrepreneurs use their stock of capital to produce according to the following technology:

$$y = zk^{\alpha}$$

where z is productivity and $\alpha \in (0, 1)$ captures decreasing marginal returns, both are common across firms. If the project fails, entrepreneurs exit the market. Firms borrow to finance the stock of capital taking the cost of debt r^{ℓ} as given. Thus, entrepreneurs maximize expected profits as follows:

$$\pi(z, \sigma) = \max_{k} \ (1 - \sigma) \times \left\{ zk^{\alpha} - r^{\ell}k \right\}$$

For a given interest rate, we have the following credit demand:

[12] Bank exposure ranges from 0 to 30 percent. Due to data restrictions, we can only provide descriptive statistics related to interest rates considering at least five banks.

$$Q(r^\ell) = (\alpha z)^{\frac{1}{1-\alpha}}\, {r^\ell}^{-\frac{1}{1-\alpha}} \tag{2}$$

Notice that our decreasing returns parameter α shapes the demand elasticity. When marginal returns to capital decline more slowly (α is closer to one), credit demand is more sensitive to increases in interest rates.

3.2 Banks

The financial sector includes N banks that are heterogeneous in their marginal cost of raising funds c_b and compete a la Cournot. Banks can observe firm risk and take the demand function $Q(r^\ell)$ as given. Thus, for a given level of firm risk, bank b chooses the amount of credit $Q_b(\sigma)$ that maximizes expected profits as follows:

$$\max_{Q_b(\sigma)} \left\{(1-\sigma)\, r^\ell(Q(\sigma)) - c_b\right\} Q_b(\sigma)$$

where $Q(\sigma) = \sum_b Q_b(\sigma)$ is the total supply of credit and $r^\ell(Q)$ is the inverse demand function consistent with equation (2). Assuming a symmetric Cournot equilibrium, interest rates are given by:

$$r^\ell(\sigma) = \frac{c}{(1-\sigma)\,(1-(1-\alpha)\times \text{HHI})} \tag{3}$$

where $\text{HHI} = \sum_b \left(\frac{Q_b}{Q}\right)^2$ and $c = \sum_b \frac{Q_b}{Q} \times c_b$. Thus, interest rates increase with firm risk and market concentration. Moreover, if firm demand of credit is more inelastic, banks can exert more market power and interest rates become more sensitive to HHI. Finally, interest rates increase with bank marginal cost of providing credit.

The market equilibrium is a set of prices $\left\{r^\ell(\sigma)\right\}$ and quantities $\{Q_b(\sigma), k(\sigma), y(\sigma)\}$ such that: (i) Firms take prices r^ℓ as given, and choose capital k to maximize expected profits, leading to the aggregate credit demand function defined by equation (2), and (ii) Banks take demand and competitors' strategies as given, and choose $Q_b(\sigma)$ to maximize expected profits, leading to the interest rate function defined by equation (3).

In equilibrium, aggregate output is given by:

$$Y = \Lambda \times z^{\frac{1}{1-\alpha}} \times \int (1-\sigma)^{\frac{1}{1-\alpha}}\, dF_{(z,\sigma)}$$

where $\Lambda = \left\{\frac{\alpha(1-[1-\alpha]\times\text{HHI})}{c}\right\}^{\frac{\alpha}{1-\alpha}}$. Notice that aggregate output depends negatively on credit market concentration. Furthermore, it also depends on the distribution of firm risk. If this distribution is more concentrated towards high levels of risk, then aggregate output is lower.

3.3 Lending Rate Cap

Our symmetric equilibrium will change once lending rate caps are introduced. Let $\overline{r}$ denote the interest rate cap. First, notice that for low levels of risk and market concentration, interest rates from equation (3) are below the cap. We define the function $\sigma^B(\text{HHI})$ representing the maximum level of risk, for a given HHI and loan origination cost, such that interest rates in the market equilibrium are not greater than the cap.

$$\sigma^B(\text{HHI}) = 1 - \frac{c}{\overline{r} \times (1 - (1-\alpha) \times \text{HHI})} \tag{4}$$

Thus, the cap affects pricing among firms with risk above σ^B. For this group of firms, banks will charge the maximum interest rate $\overline{r}$ only if it is profitable to do so. We define the maximum level of risk σ^E such that, if banks set interest rates at the cap value, total profits are non-negative:

$$\sigma^E = \frac{\overline{r} - c}{\overline{r}} \tag{5}$$

Thus, our symmetric Cournot equilibrium with a lending rate cap leads to the following interest rate schedule:

$$\overline{r}^\ell(\sigma) = \begin{cases} \emptyset & \text{for } \sigma \geq \sigma^E \\ \overline{r} & \text{for } \sigma \in (\sigma^B, \sigma^E) \\ \dfrac{c}{(1-\sigma)\,(1-(1-\alpha)\times\text{HHI})} & \text{for } \sigma \leq r^B \end{cases} \tag{6}$$

This new equilibrium yields two key implications that we test in our empirical analysis. First, the lending rate cap excludes high-risk borrowers with $\sigma > \sigma^E$. If the cap is too tight or the distribution of firms is concentrated among the riskiest clients, more borrowers are excluded from credit markets and the cap can reduce aggregate credit. Second, firms with moderate risk $\sigma \in (\sigma^B, \sigma^E)$ enjoy lower interest rates and obtain more credit after the cap. Furthermore, the number of benefited firms increases in highly concentrated markets, as we can notice from equation (4), where σ^B is decreasing in HHI.

4 Empirical approach

We estimate the impact of lending rate caps following a local credit market approach. We define credit markets at the city level.[13] This layer of aggregation is crucial to explore how banks reallocate credit across firms, industries and cities, which allows us to test the role of credit market concentration and firm risk in shaping the impact of lending rate caps. Moreover, this setting enables us to estimate the response of aggregate outcomes such as capital misallocation.

We define our city-level treatment as the hypothetical decline in annualized interest payments necessary to bring interest rates on loans originated in city c, between March and June 2021, down to the cap.[14] Specifically, we compute the following measure:

$$\text{Treatment}_c = \frac{\sum_{i \in c} \ell_{it} \times \max\{r_{it} - \overline{r}, 0\}}{\sum_{i \in c} \ell_{it} \times r_{it}} \times 100 \tag{7}$$

Where ℓ_{it} denotes the value of small firm loans granted to firm i in month t, r_{it} is the interest rate charged on those loans, and $\overline{r}$ is the lending rate cap. This variable captures how binding the policy was in a given city.

Figure 5 plots the distribution of treatment, and shows that it is highly right-skewed. The average treatment is 5 percent and the standard deviation is 7 percent. Moreover, half of cities exhibit treatment below 0.4 percent, and a quarter of them have treatment above 7 percent. We quantify the effects of lending rate caps by comparing the evolution of multiple outcomes, before and after the regulation, in cities that were differently treated by the policy, estimating the following difference-in-differences equation:

$$Y_{ct} = \beta_t \times \text{Treatment}_c + \delta_c + \delta_t + u_{ct} \tag{8}$$

Where Y_{ct} denotes an outcome variable in city c and time t such as interest rates and loan value. We include city fixed effects δ_c to control for pre-determined time-invariant characteristics

[13] Cities are defined at the province level. Peru has 196 provinces, 157 of which have branches. Our results are robust to the narrowest possible definition of cities at the district level. Around 400 out of 1896 districts have branches.

[14] This measure is inspired by the minimum wage literature. See for example Card and Krueger (1994), Draca, Machin, and Van Reenen (2011), Dustmann et al. (2021), and references therein.

of local credit markets, and time fixed effects δ_t to control for aggregate shocks. Standard errors are clustered at the city level. Our coefficient of interest is β_t, which captures the monthly effect of being one standard deviation more treated. We identify this parameter by comparing cities that are differently exposed to the policy, before and after the regulation of interest rates.

Our identification relies on the assumption that, absent the policy, highly treated cities would have evolved in parallel trends with low-treated locations. We provide evidence supporting our identifying assumption in four ways. First, we plot clean event-study graphs showing that treatment has null effects before the regulation. Second, we show that our treatment measure is highly related to treated banks' geographical footprint. Moreover, we document that cities are comparable in multiple dimensions in a covariate balance test. Third, we include time-varying fixed effects at the region and city-size level to control for any region-specific shock and city size specific trends. Additionally, we use our detailed data to estimate a city $\times$ industry specification that allows us to control for time-varying shocks taking place at the industry level. The full set of fixed effects is included in the following specification:

$$Y_{jct} = \beta_t \times \text{Treatment}_c + \delta_{jc} + \delta_{jt} + \delta_{q(c),t} + \delta_{r(c),t} + u_{jct} \tag{9}$$

Where Y_{jcrt} denotes an outcome variable in industry j, city c, and time t. This specification includes time-invariant city-industry fixed effects δ_{jc} and time-varying fixed effects at the industry, region, and city-size levels, denoted by δ_{jt}, δ_{rt}, and $\delta_{q(c)t}$, respectively. Thus, we identify the impact of lending rate caps within industry $\times$ city-size $\times$ region bins, which allows us to control for multiple shocks that may correlate with our city-level measure of treatment. Fourth, we conduct a placebo test by considering only low-treated banks in our estimation. By doing so, we provide evidence that our effects are not driven by any city nor industry specific shock affecting small firm loans around the policy implementation date.

5 Results

Guided by our conceptual framework, we organize our empirical analysis in three blocks. First, we estimate the average local credit market effect of the policy. Second, we test the role of bank market power and firm risk, documenting how banks reallocated credit in response to the regulation. Third, we quantify the real economy impact of the policy and estimate the response of capital misallocation.

5.1 Financial Effects

We start by estimating the response of interest rates. Our results are reported in Table 4. Column (1) shows that one standard deviation (SD) higher treatment led to a 5 percentage points reduction in interest rates in our baseline specification (8) which includes city and time fixed effects.

A potential threat to our identification is that the exposure of cities might not be random. Instead, it could be driven by industry, region, or city specific characteristics that can partially explain the different evolution of interest rates in more versus less treated locations. Figure 6 shows that city-level treatment is actually strongly correlated with highly treated banks' geographical presence. Since bank presence is typically related to long-term considerations, we find implausible that our measure of treatment is related to city-specific shocks. Figure 7 presents the result of our covariate balance test showing that differently treated cities are comparable in multiple dimensions related to industry and labor force composition, as well as financial deepening.

To further deal with this threat to identification, we disaggregate our data and estimate equation (9), which includes time-varying fixed effects at the industry, region, and city-size levels. Our result are reported in column (4) and shows a similar decline in interest rates, indicating that our results are not related to alternative shocks occurring around the policy implementation. Figure 8 plots the monthly treatment effect of lending rate caps on interest rates. Panel (a) shows that cities with higher treatment experience a rapid and persistent contraction in interest rates in the post-reform period. Consistent with our identifying assumption, our event study graph shows no evidence of pre-trends.

Another potential threat to identification is that highly treated cities could be exposed to different shocks around the policy implementation date. Despite this being untestable by definition, we provide evidence against this possibility by splitting city-level interest rates into the contribution of highly treated banks and low treated ones, as follows:

$$r_{ct} \equiv \frac{\sum_{i \in c} \mathrm{L}_{ict} \times r_{ict}}{\mathrm{L}_{ct}} = \frac{\sum_{i \in HTB \cap c} \mathrm{L}_{ict} \times r_{ict}}{\mathrm{L}_{ct}} + \frac{\sum_{i \in LTB \cap c} \mathrm{L}_{ict} \times r_{ict}}{\mathrm{L}_{ct}}$$

Where the first component is the contribution of highly treated banks to the city-level interest rate, and the second component is the contribution of low treated banks. We estimate the effect of our treatment measure on each component and report our results in columns (2) and (3) of Table 4. Our estimates indicate that the decline in interest rates is totally explained by highly treated banks. On the other hand, the contribution of interest rates charged by low treated institutions on the city-level interest rate remained constant after the policy. We do the same decomposition using our city×industry data and report our results in columns (5) and (6) showing that highly treated banks fully account for the reduction in interest rates. Thus, we find implausible that our estimation results could be driven by city-level shocks taking place around the policy implementation.

Panels (b) and (c) of Figure 8 plot the monthly treatment effect of lending rate caps on the contribution of high and low treated banks to the city-level interest rate. We observe that interest rates charged by highly treated banks exhibit a rapid and persistent decline after the policy implementation, while low treated banks charge similar interest rates before and after the introduction of the lending rate cap. Both figures show no evidence of pre-trends, which is consistent with our identifying assumption.

We then estimate the response of loan origination. We create a balanced panel and use the mid-point growth rate of loan value, relative to the city × industry average, as our dependent variable in equation (9).[15] This methodology has appealing properties such as capturing both, intensive and extensive margins, and ensuring that our estimates aggregate at any higher level (Fonseca and Matray 2024; Matray et al. 2024; Beaumont et al. 2025). Column (4) of Table 5 shows that, despite the large decline in interest rates presented above, higher treatment is associated with a statistically insignificant response of loan value. We then split loans into two groups, motivated by our descriptive analysis presented in Section 2, and study whether banks reallocate credit within local credit markets. Specifically, we decompose our mid-point growth rate into the contribution of micro-size and small-size and large loans as follows:

$$\frac{\mathrm{L}_{ct} - \overline{\mathrm{L}}_c}{(\mathrm{L}_{ct} + \overline{\mathrm{L}}_c)/2} = \frac{\mathrm{L}_{ct}^{M} - \overline{\mathrm{L}}_c^{M}}{(\mathrm{L}_{ct} + \overline{\mathrm{L}}_c)/2} + \frac{\mathrm{L}_{ct}^{SL} - \overline{\mathrm{L}}_c^{SL}}{(\mathrm{L}_{ct} + \overline{\mathrm{L}}_c)/2}$$

Where the super-index M and SL indicate micro-size loans, and small-size and large loans, respectively. Then, the first component represents the contribution of micro-size loans–typically

[15]Specifically, our mid-point growth rate is $\frac{\mathrm{L}_{jct} - \overline{\mathrm{L}}_{jc}}{(\mathrm{L}_{jct} + \overline{\mathrm{L}}_{jc})/2}$, where L_{jct} denotes the value of loans originated in industry j, city c, and month t, and $\overline{L}_{jc}$ denotes its average value.

granted by few banks at high interest rates–to the mid-point growth-rate of total loans in city c and industry j. We estimate the response of each component and report our results in columns (5) and (6). We find that banks also reallocate credit from micro-size towards bigger loans within local credit markets. While the contribution of small-size loans decline by 0.2 percent, the contribution of bigger loans increase by 1.1 percent. Columns (1) to (3) show the results of estimating our *naive* specification (8) that considers city-level data incorporating only city and time fixed effects. We find similar patterns, null effects on total lending, and credit moving away from micro-size towards bigger loans.

Once again, we deal with the potential concern that cities could be exposed to a different shock around the policy implementation by computing the contribution of highly treated banks and low treated ones to the city-level mid-point growth rate. We do so for micro-size and bigger loans, separately. If our identifying assumption is valid, the response of credit should be entirely driven by highly treated banks. We report our results in Table 6. Column (1) shows that higher treatment leads to a 5.4 percent decline in micro-size loans, and column (2) indicates that highly treated banks explain 4.1 percentage points of this reduction. Column (4) shows that small-size and large loans increase by 6.1 percent, and column (5) indicates that highly treated banks account for 4.8 percentage points. Moreover, columns (3) and (6) document that the contribution of low treated banks is not statistically significant in either group of loans. Thus, our estimation results show that the reallocation of credit is fully driven by highly treated banks and are not related to any city-specific shock.

We plot event study graphs associated to the average response of loan value in Figure 9. Our event study graphs support our identifying assumption showing no evidence of pre-trends. In the next subsections, we will test the role of bank market power and firm risk in driving the average response of credit reported above.

5.2 Bank Market Power and Firm Risk

Bank market power. Our local credit market approach allows us to dig deeper into the mechanisms through which lending rate caps affect aggregate lending. We start by analyzing the role of bank market power. To do so, we compute the Herfindahl-Hirschman Index (HHI) of local credit markets and estimate the following equation where HHI is demeaned and standardized:

$$Y_{ct} = (\beta + \gamma \times \text{HHI}_c) \times \text{Treatment}_c \times \text{Post}_t + \lambda \times \text{HHI}_c \times \text{Post}_t + \delta_c + \delta_t + u_{ct} \quad (10)$$

Estimating this equation requires enough variation in market concentration across differently treated cities. Since treatment is strongly correlated with highly treated banks' geographical footprint, we have substantial variation in market concentration across differently treated locations. Figure 10 presents a scatter plot of city-level treatment and HHI. We can observe that the correlation between these variables is close to zero. Thus, we have enough variation to estimate equation (10).

We report our results in Table 7. Column (1) shows that highly treated cities experience a 4.5 reduction in interest rates. Additionally, interest rates decline more in concentrated markets, around 0.8 percentage points more in cities whose HHI is one SD above the median. Column (2) reports the response of loan value. We find that, while the average response of credit is statistically insignificant, credit grows in highly concentrated markets. One standard deviation higher concentration leads to a 1.9 percent expansion in credit. Our findings are consistent with a standard industrial organization view, as credit expansion occurs only in highly concentrated markets.

As we discussed before, credit reallocation is critical to maintain aggregate credit constant. We then explore the role of bank market power in shaping credit reallocation. Columns (3) and (4) of Table 7 report the response of the contribution of micro-size and bigger loans, respectively. We can see that, while micro-size loans decline in all locations, independently on their level of bank competition, the expansion of bigger loans only occurs in cities that are highly concentrated. Such reallocation leads to a lower share of micro-size loans which is consistent with the stronger decline of interest rates presented in column (1).

Our results indicate that market power shapes the impact of lending rate caps, consistent with our stylized framework. In highly concentrated markets, lending rate caps reduce interest rates and expand credit supply because banks can rebalance their portfolios away from micro-size loans towards small-size and large credit. On the other hand, in more competitive markets, lending rate caps can reduce interest rates but at the cost of reducing credit supply of micro-size loans that cannot be reallocated.

Firm risk. We now study the role of firm risk. In principle, if markets are competitive, interest rates might reflect loan origination costs and firm risk. Thus, a lending rate cap might exclude risky firms that can only borrow at high interest rates. To test the role of this hypothesis, we define risky firms as those who experience more than 30 days of repayment delay at least once in 2020, and safe firms as those who never experience such delay. It is worth noting that this measure is defined for firms with active lending relationships in 2020. Figure 11 plots the distribution of interest rates for these groups. Consistent with interest rates reflecting firm risk, we find that the median interest rate on loans granted to ex-ante safe borrowers is 50 percent, while loans offered to ex-ante risky firms exhibit a median interest rate of 100 percent.

We test the role of firm risk by estimating equation (8) using the number of firms and the share of risky borrowers as our dependent variables. We report our results in Table 8. Column (1) shows that the regulation of interest rates had null effects on the number of borrowers. Additionally, column (2) indicates that the number of borrowers increases in concentrated markets, consistent with the response of loan value. Columns (3) and (4) show that the share of risky borrowers declines significantly in treated locations after the reform, independently on the degree of bank concentration. Our results indicate that lending rate caps harm risky borrowers, excluding them from credit markets, while lenders provide more credit to new borrowers and safe incumbents in concentrated cities.

Finally, we study the implications of lending rate caps for aggregate firm performance in bank credit markets. It is important to underscore that reallocating credit towards bigger loans might be inefficient for multiple reasons. First, it might increase firm leverage, increasing risk-taking incentives. Second, bank expertise in providing micro-size credit might not be transferable to the market of bigger loans. Thus, credit reallocation can lead to an increase in the pool of new risky borrowers that are not captured by our measure of ex-ante risk. Finally, even in the absence of these channels, the regulation of lending rates might reduce bank charter value, increasing bank risk-taking incentives (Corbae and Levine 2025; Carlson et al. 2022).

To test the relevance of these channels, we quantify the response of non-performing loans (NPL) after the policy. We use our credit registry data that includes information on the balance of loans to compute the share of credit that exhibits 30 or more days of repayment delay in each local credit market. Given that small firm credit is paid on a monthly basis, and loan repayment starts immediately the month after loan origination, the share of NPL responds rapidly to financial conditions. Our results are reported in columns (5) and (6) of Table 8. We find that higher treatment is associated with a reduction of 0.4 percentage points in the share of NPL, suggesting that firm and bank risk-taking incentives play a minor role. Moreover, this reduction is not related to market concentration, which indicates that potential losses in market expertise when reallocating credit are minimal. Thus, local credit markets become safer after the implementation of lending rate caps, which is consistent both with the exit of risky borrowers and reduction in cost of credit.

Our documented reallocation of credit across firms and cities was critical for highly treated banks to adjust to the policy. Panel (a) in Figure 12 plots the weighted average interest rate relative to March 2021. The dark connected line shows that small firm loans are originated at 13 percentage points lower interest rates after the policy, and this contraction is fully driven by highly treated banks, as we can observe in the solid blue line.

Panel (b) shows that, despite the large decline in interest rates, highly treated banks maintain their market share constant at 38 percent in terms of number of borrowers and 27 percent in terms of total value. Figure 13 plots the growth rate of micro-size, small-size, and large loans, separately. We observe a reduction of around 30 percent in micro-size loans that is totally offset by an expansion of around 50 percent in small-size and large loans. Figure 14 shows that the share of small-size loans within highly treated banks' portfolios declined sharply from 19 to 10 percent. Thus, banks ability to reallocate credit was crucial for the policy to reduce interest rates without affecting aggregate credit.

5.3 Real Effects

In the previous subsections, we documented that the lending rate cap led to substantial credit reallocation, generating winners and losers in credit markets. In this section, we estimate the real impact of this policy and show that it depends critically on how productive are firms that lose credit access relative to those who benefit from more credit and lower rates.

5.3.1 Conceptual framework

We start by extending our conceptual framework to underscore the role of the correlation between productivity and risk. Entrepreneur are now heterogeneous not only in terms of risk but also in productivity z. Our aggregate credit demand for a given risk level σ becomes:

$$Q(r^\ell, \sigma) = \alpha^{\frac{1}{1-\alpha}} r^{\ell^{-\frac{1}{1-\alpha}}} \int_z z^{\frac{1}{1-\alpha}} f(z, \sigma) dz \tag{11}$$

The banking sector is similar as before. Banks engaged in Cournot competition only observe firm risk and take the aggregate demand as given. Thus, interest rates without and with the cap are similar to those in equations (3) and (6), respectively. Aggregate output without the cap is given by:

$$Y = \Lambda \times \int_z \int_\sigma \tilde{y}(z, \sigma) dF_{(z,\sigma)}$$

where $\tilde{y}(z, \sigma) \equiv ((1-\sigma)z)^{\frac{1}{1-\alpha}}$. Notice that higher market power leads to a reduction in aggregate TFP as captured by Λ. In a perfectly competitive market, firms would borrow at lower interest rates which allow them to operate at a bigger scale.

As we showed before, the cap harms some borrowers excluding them from credit markets, while it benefits others who will enjoy more credit and lower interest rates. Thus, aggregate output with the cap is given by:

$$Y_R = \Lambda \times \left[\underbrace{\int_z \int_0^{\sigma^B} \tilde{y}(z, \sigma) dF_{(z,\sigma)}}_{\text{Unaffected}} + \underbrace{\int_z \int_{\sigma^B}^{\sigma^E} (1 + \omega(\sigma)) \, \tilde{y}(z, \sigma) dF_{(z,\sigma)}}_{\text{Benefited}} + \underbrace{\int_z \int_{\sigma^E}^{1} 0 dF_{(z,\sigma)}}_{\text{Excluded}} \right]$$

where $\omega(\sigma) \equiv \left[\frac{c/(1-\sigma)}{\bar{r}(1-(1-\alpha)\text{HHI})}\right]^{\frac{\alpha}{1-\alpha}} - 1$. Thus, the impact of the lending rate cap on aggregate output Δ is given by:

$$\Delta = \Lambda \times \left[\int_z \int_{\sigma^B}^{\sigma^E} \omega(\sigma) \tilde{y}(z, \sigma) dF_{(z,\sigma)} - \int_z \int_{\sigma^E}^{1} \tilde{y}(z, \sigma) dF_{(z,\sigma)} \right]$$

Where the first term captures the gains from lower interest rates among moderate-risk firms and the second term captures the loss of excluding riskier firms from credit markets. Thus, the correlation between risk and productivity is crucial to understand the real effects of lending rate caps. If highly productive firms are more concentrated over moderate-risk values (i.e., stayers benefited from lower rates), then the first term will dominate and the cap expands aggregate output. On the other hand, if highly productive firms are actually the riskiest ones (i.e., firms excluded from credit market), then the second term will dominate and the cap reduces output.

5.3.2 Empirical results

A key challenge when using tax reports is that the definition of small firm credit based on outstanding debt does not depend on any real outcome observed in tax files. We overcome this by keeping all natural person with business, a firm tax category that relies heavily on small firm credit. Then, we aggregate our annual tax reports to the city level and estimate equation (10) using sales and capital as our dependent variables.

Table 9 shows our results. We can observe that bank concentration also shapes the response of real outcomes. Columns (1) and (4) show the average response of sales and capital, respectively. These effects are small and statistically insignificant. On the other hand, columns (2) and (5) show the effect of the interaction between treatment and a demeaned standardized measure of HHI. We can see that the degree of competition also determines the real impact of lending rate caps. While the responses of sales and capital are insignificant in locations with the average HHI, higher treatment leads to a 7 percent increase in sales in cities with one standard deviation higher concentration relative to the mean. Capital accumulation explains this effect, increasing by 10 percent in concentrated locations. Our results are consistent with the expansion of credit documented in the previous section. Figure 15 plots event-study graphs associated to the average effect of treatment interacted with HHI showing no evidence of pre-trends.

This response of capital and sales suggests that benefited firms are productive enough to completely offset the negative effect on excluded risky borrowers in concentrated markets. We now estimate the response of capital misallocation. We define the marginal revenue productivity of capital for firm i operating in industry j as follows:

$$\mathrm{MRPK}_{ij} = \alpha_j \frac{Y_{ij}}{K_{ij}} \propto \frac{Y_{ij}}{K_{ij}}$$

This definition of marginal revenue productivity assumes that small firms belonging to the same industry j operate the same Cobb-Douglas technology with capital share α_j. Then, we define capital misallocation as the variance of log MRPK (Hsieh and Klenow 2009; Restuccia and Rogerson 2008; Bau and Matray 2023). We compute this variance at the city $\times$ industry level and estimate how it responds to the regulation. Columns (8) and (9) show that the dispersion of MRPK increases in competitive markets–where credit conditions tighten after the regulation–but declines significantly in concentrated cities, where financial conditions improve.

5.3.3 Firm-level evidence of distributional effects

We use our micro-data to estimate the response of firm-level outcomes and provide further evidence on the distributional effects of lending rate caps among incumbent borrowers. We start by providing descriptive statistics of the distribution of interest rates, firm risk, and marginal revenue productivity of capital. We focus on firms that obtain a loan in our pre-reform period from March to June 2021 and group them in two bins according to whether the observed interest rate is above or below the cap. Then, we merge these firms with those reporting outstanding debt in our credit registry between 2019 and 2020, and classify them in ex-ante safe and risky firms, as we did in the previous section. Finally, we merge these firms with tax records for those reporting taxes between 2019 and 2020 and rank firms operating in the same industry according to their MRPK (Bau and Matray (2023)).[16]

Table 10 shows the distribution of firms borrowing below and above the lending rate cap in the pre-reform period for different levels of marginal revenue productivity of capital and risk status. First, we can observe that ex-ante risky firms are more likely to borrow above the cap. While less than 10 percent of ex-ante safe small borrowers pay interest rates above the cap, around 26 percent of ex-ante risky borrowers borrow at interest rates above the cap. Second, we can observe that firms borrowing above the cap are more likely to exhibit high MRPK. Around 30 percent of small borrowers paying interest rates below the cap are high MRPK and around 40 percent of small firms borrowing above the cap are high MRPK.

To explore how lending rate caps affect capital allocation, we define our treatment measure as a dummy variable equal to one for firms borrowing at rates above the cap before the policy implementation. Then, we estimate the response of firm-level sales and capital by comparing firms right above the cap with firms below the cap, before and after the regulation. Specifically,

[16]It is worth noticing that focusing on firms reporting taxes reduces the sample size, among other reasons due to the high levels of informality. However, we still have an important number of firms (around 30,000), and 12 percent of them borrow at interest rates above the cap.

we estimate the following equation:

$$\ln Y_{ijct} = \beta \times \text{Above}_i \times \text{Post}_t + \delta_i + \delta_{x(i)t} + \delta_{jt} + \delta_{ct} + u_{ijct} \tag{12}$$

where the dependent variable measures the log of sales and capital, Above_i is an indicator variable equal to one for firms borrowing right above the cap, and δ's represent time-invariant firm fixed effects and time-varying industry j, city c, and firm size bins $x(i)$ fixed effects.

We report our results in Table 11. Columns (1) and (2) show that the impact of borrowing above the cap is null and statistically insignificant for the average firm. We explore the distributional effects in columns (3) to (6). We can see that high-MRPK firms accumulate 19 percent more capital after the reform, while their sales' expansion is statistically insignificant, suggesting that the impact of capital accumulation on sales might take time. On the other had, low-MPRK firms shrink, reducing capital by 19 percent. Overall, our firm-level estimates suggest that lending rate caps improved the allocation of capital in concentrated markets.

6 Conclusions

Small firms have limited credit access in developing countries, and when they obtain a loan, it is usually granted at high interest rates. Thus, price regulations in credit markets are often floated in the political debate. Despite the widespread adoption of this policy, there is little empirical evidence on how lending rate caps affect small firms' credit access and capital misallocation. In this paper, we study the effects of a lending rate cap in Peru that affected 26 percent of small business loans.

We find that the policy reduced interest rates without lowering total credit. However, this null response hides substantial heterogeneous effects across loans, firms, and credit markets. While risky firms systematically lose credit access, banks expand lending to safe and new firms in concentrated credit markets. This credit reallocation allowed highly treated banks to maintain their market share constant despite a 23 percentage-points decline in interest rates. Excluded risky borrowers had lower marginal revenue productivity of capital than the firms who obtained more credit at low rates. Consequently, the lending rate cap reduced capital misallocation in concentrated markets.

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Tables

Table 1: Characteristics of Small Firm Credit

	Loan size (USD) (1)	Duration (days) (2)	Interest rates (percent) (3)
Average	2559	346	65
Weighted by loan-size		748	31
SD	6997	289	41
Median	811	364	52
Obs.	1,348,108	1,348,108	1,348,108

Notes. This table provides summary statistics using loans originated between March and June 2021, before the policy was implemented. Loan size is the value of loans expressed in USD, duration is the length of loan repayment expressed in days, and interest rates are expressed in percentage points.

Table 2: Financial Institutions in Small Firm Credit Market

	Market share	
	Value	Num. Firms
	(1)	(2)
TB 1	24.0	21.8
MFI 1	10.9	30.8
MFI 2	10.3	9.7
MFI 3	7.6	6.4
MFI 4	6.1	4.9
Total TB	38.7	23.6
Total MFI	61.3	76.3

Notes. This table shows the market share of the 5 biggest financial institutions in the market of small firm credit. Column (1) computes the market shares using loan value and column (2) uses number of firms. We separate traditional banks (TB) from micro-finance institutions (MFI).

Table 3: Interest Rates in the Cross-Section of Loans

	Interest Rates				
	(1)	(2)	(3)	(4)	(5)
MS Loans	44.23***	38.70***	36.61***	21.55***	
	(0.06)	(0.06)	(0.05)	(0.15)	
$\text{HHI}_c^{\text{MS Loans}}$			7.95***	4.46***	
			(0.03)	(0.04)	
Risky			15.38***	9.25***	
			(0.08)	(0.14)	
MS Loans × $\text{HHI}_c^{\text{MS Loans}}$				5.51***	3.83***
				(0.05)	(0.05)
MS Loans × Risky				8.78***	6.13***
				(0.17)	(0.16)
Fixed Effects					
Time	✓	✓	✓	✓	✓
Firm Industry	✗	✓	✓	✓	✓
Size, Risk, and City	✗	✗	✗	✗	✓
Observations	1,378,745	1,360,904	1,360,904	1,360,904	1,360,903

Notes. This table shows our results from estimating equation (1). Column (1) reports our baseline specification controlling for time fixed effects. Columns (2)-(4) include industry fixed effects, and column (5) includes size, risk, and city fixed effects. MS Loans is a dummy variable equal to one for micro-size and small-size loans, whose value is below USD 1061, which is the 66th percentile of the pre-reform loan size distribution. $\text{HHI}_{\text{MS Loans}}$ is the Herfindahl-Hirschman index of micro and and small-size loans in city c, and is standardized. Risky is a dummy variable equal to one for firms that experienced repayment delays of 30 or more days at least once in 2020. Robust standard errors are in parenthesis. *, **, and *** denote 10, 5, and 1 percent statistical significance, respectively.

Table 4: Average Effect of Lending Rate Caps on Interest Rates

	Province-level			Province × Industry-level		
	All	HTB	LTB	All	HTB	LTB
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treatment}_c \times \text{Post}_t$	-5.092***	-5.201***	0.109	-4.260***	-4.742***	0.482**
	(0.340)	(0.372)	(0.106)	(0.281)	(0.312)	(0.216)
Fixed Effects						
Province	✓	✓	✓	✗	✗	✗
City-size × Month	✓	✓	✓	✓	✓	✓
HHI-group × Month	✓	✓	✓	✓	✓	✓
Province × Industry	✗	✗	✗	✓	✓	✓
Industry × Month	✗	✗	✗	✓	✓	✓
Region × Month	✗	✗	✗	✓	✓	✓
Observations	1,548	1,548	1,548	120,828	120,828	120,828

Notes. This table reports our results from estimating equation (8). City-level interest rates are weighted by loan value. Treatment_c is the standardized percent decline in interest payments necessary to bring all loans originated between March and June 2021 down to the lending rate cap. Post_t is an indicator variable equal to one after June 2021. Columns (1) to (3) estimate equation (8) incorporating city and time fixed effects, and columns (4) to (6) estimate equation (9) including industry, region, and city-size fixed effects. All specifications include standardized HHI interacted with Post_t. HTB refers to the contribution of highly treated banks to the city-level interest rates, and LTB denotes the contribution of low treated banks. Standard errors are clustered at the city level. *, **, and *** denote 10, 5, and 1% statistical significance, respectively.

Table 5: Average Effect of Lending Rate Caps on Total Loans

	Province-level			Province × Industry-level		
	MPGR	Contr. micro-size	Contr. small & large	MPGR	Contr. micro-size	Contr. small & large
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treatment}_c \times \text{Post}_t$	0.016	-0.003***	0.019*	0.009	-0.002***	0.011*
	(0.010)	(0.001)	(0.010)	(0.006)	(0.000)	(0.006)
Fixed Effects						
Province	✓	✓	✓	✗	✗	✗
City-size × Month	✓	✓	✓	✓	✓	✓
HHI-group × Month	✓	✓	✓	✓	✓	✓
Province × Industry	✗	✗	✗	✓	✓	✓
Industry × Month	✗	✗	✗	✓	✓	✓
Region × Month	✗	✗	✗	✓	✓	✓
Observations	1,570	1,570	1,570	182,080	182,080	182,080

Notes. This table reports our results from estimating equation (8). Treatment_c is the standardized percent decline in interest payments necessary to bring all loans originated between March and June 2021 down to the lending rate cap. Post_t is an indicator variable equal to one after June 2021. Columns (1) to (3) estimate equation (8) incorporating city and time fixed effects, and columns (4) to (6) estimate equation (9) including industry, region, and city-size fixed effects. All specifications include standardized HHI interacted with Post_t. Contr. micro-size refers to the contribution of micro-size loans to city-level loan growth, and Contr. small & large denotes the contribution of small-size and large loans. Micro-size loans are those whose value is within the bottom tercile of the pre-reform loan-size distribution (below USD 575). Standard errors are clustered at the city level. *, **, and *** denote 10, 5, and 1% statistical significance, respectively.

Table 6: Average Effect of Lending Rate Caps on Total Loans

	Micro-size loans			Small & Large loans		
	Mid-point growth rate	Contr. HTB	Contr. LTB	Mid-point growth rate	Contr. HTB	Contr. LTB
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treatment}_c \times \text{Post}_t$	-0.054***	-0.041***	-0.012	0.061***	0.048***	0.013
	(0.015)	(0.005)	(0.014)	(0.015)	(0.003)	(0.015)
Fixed Effects						
Province	✓	✓	✓	✓	✓	✓
City-size × Month	✓	✓	✓	✓	✓	✓
HHI-group × Month	✓	✓	✓	✓	✓	✓
Observations	1,550	1,550	1,550	1,570	1,570	1,570

Notes. This table reports our results from estimating equation (8). Treatment_c is the standardized percent decline in interest payments necessary to bring all loans originated between March and June 2021 to the lending rate cap. Post_t is an indicator variable equal to one after June 2021. Columns (1) to (3) focus on micro-size loans and columns (4) to (6) estimate the response of small and large loans. Micro-size loans are those whose value is within the bottom tercile of the pre-reform loan-size distribution (below USD 575). All specifications include standardized HHI interacted with Post_t. Contr. HTB refers to the contribution of highly treated banks to city-level loan growth, and Contr. LTB denotes the contribution of less treated banks. Highly treated banks are those whose exposure is above 1 percent. Standard errors are clustered at the city level. *, **, and *** denote 10, 5, and 1% statistical significance respectively.

Table 7: Lending Rate Caps and Bank Market Power

	Interest rate	Value of loans		
		Mid-point growth rate	Contr. micro-size	Contr. small & large
	(1)	(2)	(3)	(4)
Treatment$_c$ × Post$_t$	-4.553***	0.002	-0.003**	0.005
	(0.165)	(0.014)	(0.002)	(0.013)
Treatment$_c$ × HHI$_c$ × Post$_t$	-0.715***	0.019*	0.000	0.018*
	(0.121)	(0.010)	(0.001)	(0.010)
Fixed Effects				
Province	✓	✓	✓	✓
City-size × Month	✓	✓	✓	✓
HHI-group × Month	✓	✓	✓	✓
Observations	1,546	1,570	1,570	1,570

Notes. This table reports our results from estimating equation (10). Treatment$_c$ is the standardized percent decline in interest payments necessary to bring all loans originated between March and June 2021 down to the lending rate cap. Post$_t$ is an indicator variable equal to one after June 2021. HHI is expressed in standard deviations from the mean. All specifications include standardized HHI interacted with Post$_t$. Contr. micro-size refers to the contribution of micro-size loans to city-level loan growth, and Contr. small & large denotes the contribution of small-size and large loans. Micro-size loans are those whose value is within the bottom tercile of the pre-reform loan-size distribution (below USD 575). Standard errors are clustered at the city level. *, **, and *** denote 10, 5, and 1% statistical significance respectively.

Table 8: Lending Rate Caps and Firm Risk

	Num. of firms		Share of risky firms		Share of NPL	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment$_c\times$ Post$_t$	-0.001	-0.014	-0.003***	-0.002**	-0.004**	-0.005***
	(0.010)	(0.014)	(0.001)	(0.001)	(0.002)	(0.001)
Treatment$_c\times$ HHI$_c\times$ Post$_t$		0.018*		-0.001		-0.001
		(0.010)		(0.001)		(0.001)
Fixed Effects						
Province	✓	✓	✓	✓	✓	✓
City-size × Month	✓	✓	✓	✓	✓	✓
HHI-group × Month	✓	✓	✓	✓	✓	✓
Observations	1,570	1,570	1,548	1,548	2,826	2,826

Notes. This table reports our results from estimating equation (10). Treatment$_c$ is the standardized percent decline in interest payments necessary to bring all loans originated between March and June 2021 to the lending rate cap. Post$_t$ is an indicator variable equal to one after June 2021. HHI is expressed in standard deviations from the mean. All specifications include standardized HHI interacted with Post$_t$. Risky firms are those who have experienced more than 30 days of repayment delay at least once in 2020. NPL refers to non performing loans which is the outstanding debt with more than 30 days of repayment delay. Standard errors are clustered at the city level. *, **, and *** denote 10, 5, and 1% statistical significance respectively.

Table 9: Real Effects of Lending Rate Caps

	Capital			Sales			Var [ln($Sales/Capital$)]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment$_c$× Post$_t$	-0.034	0.005	-0.051**	-0.023	0.005	-0.036**	0.028	0.007	0.047**
	(0.023)	(0.019)	(0.021)	(0.019)	(0.021)	(0.017)	(0.021)	(0.027)	(0.021)
Treatment$_c$× HHI$_c$× Post$_t$		0.101***			0.070**			-0.053	
		(0.037)			(0.035)			(0.043)	
Treatment$_c$× High HHI$_c$× Post$_t$			0.112***			0.090**			-0.126**
			(0.043)			(0.042)			(0.055)
Fixed Effects									
Province × Industry	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Region × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
City-size × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
HHI-group × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	22,367	22,367	22,367	22,367	22,367	22,367	22,367	22,367	22,367

Notes. This table reports our results from estimating equation (10). We consider natural person with businesses and aggregate outcomes up to the city level. Treatment$_c$ is the standardized percent decline in interest payments necessary to bring all loans originated between March and June 2021 to the lending rate cap. Post$_t$ is an indicator variable equal to one after 2020. HHI is expressed in standard deviations from the mean. Standard errors are clustered at the city level. *, **, and *** denote 10, 5, and 1% statistical significance respectively.

Table 10: Distribution of Interest Rates, Risk, and MRPK

	Ex-ante Safe			Ex-ante Risky		
	Low	Middle	High	Low	Middle	High
	(1)	(2)	(3)	(4)	(5)	(6)
Below cap	7 679	7 673	7 482	785	869	819
Above cap	821	731	904	270	258	319

Notes. This table shows the distribution of firms across different bins of interest rates, risk, and MRPK. We consider natural person with business obtaining a small business loan between March and June 2021, and reporting taxes in 2020.

Table 11: Distributional Effects of Lending Rate Caps

	All Small Firms		High-MRPK		Low-MRPK	
	Capital	Sales	Capital	Sales	Capital	Sales
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Above}_i \times \text{Post}_t$	0.070	-0.118	0.193*	0.025	-0.186*	-0.379**
	(0.079)	(0.103)	(0.113)	(0.133)	(0.105)	(0.172)
Fixed Effects						
Firm	✓	✓	✓	✓	✓	✓
Size-Year	✓	✓	✓	✓	✓	✓
City-Year	✓	✓	✓	✓	✓	✓
Industry-Year	✓	✓	✓	✓	✓	✓
Observations	23,050	21,614	12,176	11,918	10,866	9,346

Notes. This table reports our results of estimating equation (12) in concentrated markets. We consider all natural person with businesses that obtained a loan between May and June 2021 and compare them in 2022 versus 2019. Above_i is a dummy variable equal to one for firms borrowing above the cap and zero otherwise. Standard errors are clustered at the firm level. *, **, and *** denote 10, 5, and 1% statistical significance respectively.

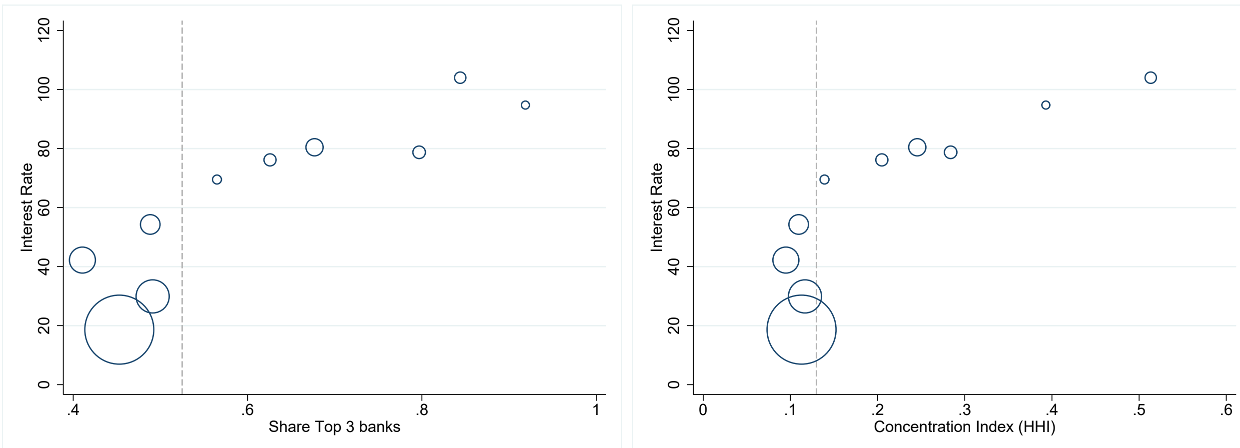
Table 12: Distributional Effects of Lending Rate Caps

	All Small Firms		High-MRPK		Middle-MRPK		Low-MRPK	
	Capital	Sales	Capital	Sales	Capital	Sales	Capital	Sales
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Above$_i$	0.070	-0.118	0.286**	0.147	-0.242**	-0.191	-0.139	-0.462*
	(0.079)	(0.103)	(0.145)	(0.165)	(0.123)	(0.167)	(0.129)	(0.236)
Fixed Effects								
Firm	✓	✓	✓	✓	✓	✓	✓	✓
Size-Year	✓	✓	✓	✓	✓	✓	✓	✓
City-Year	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year	✓	✓	✓	✓	✓	✓	✓	✓
Observations	23,050	21,614	7,504	7,398	8,982	8,596	6,530	5,246

Notes. This table reports our results of estimating equation (12) in concentrated markets. We consider firms that obtained a loan between May and June 2021 and compare them in 2022 versus 2019. Above$_i$ is a dummy variable equal to one for firms borrowing above the cap and zero otherwise. Standard errors are clustered at the firm level. *, **, and *** denote 10, 5, and 1% statistical significance respectively.

Figures

Figure 1: Interest rates and size-bin specific characteristics

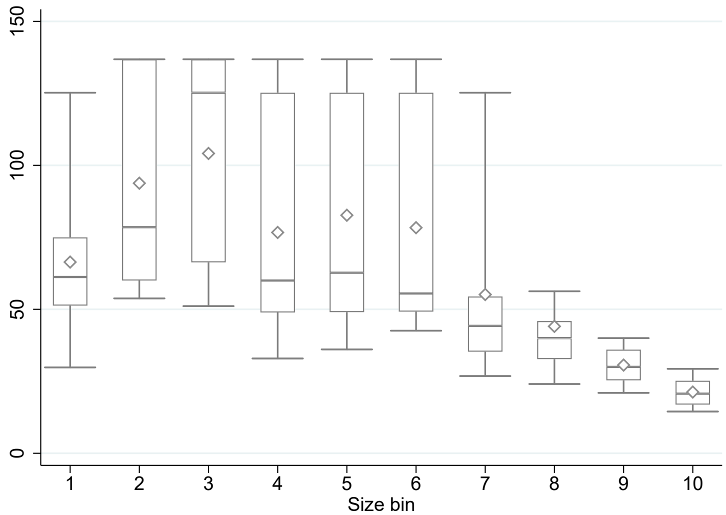


(a) Share top 3 banks

(b) Concentration Index

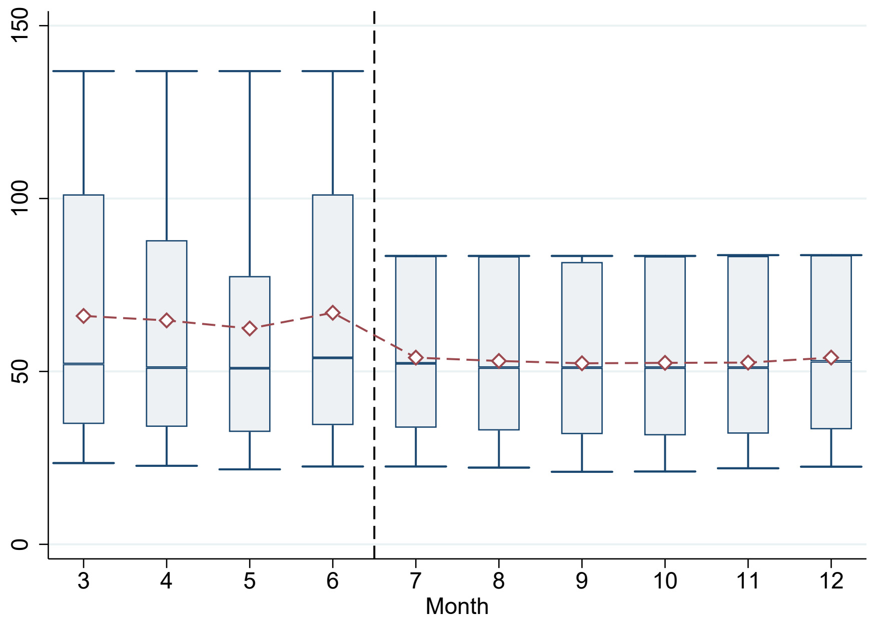
Notes. This figure reports the weighted average interest rate and two proxies for bank competition in each loan-size decile of small business loans. Panel (a) considers the share of the 3 largest banks, while Panel (b) considers bank concentration, defined as those with the largest market share, both are calculated for each loan size-bin. The size of the circles represent the size of the bin. The dashed line separates bigger loans (to the left) and small and medium size loans (to the right).

Figure 2: Distribution of Interest Rates by Loan-Size Decile



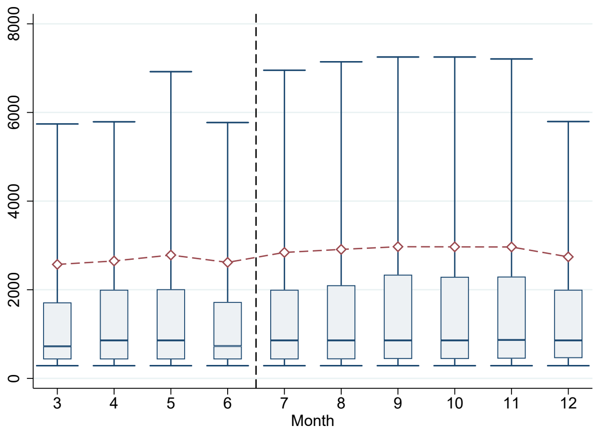
Note: This figure plots the distribution of annualized interest rates for each decile of the loan-size distribution. Boxplots show the percentiles 10th, 25th, 50th, 75th, and 90th, while the diamonds represent the average interest rate.

Figure 3: Distribution of Interest Rates

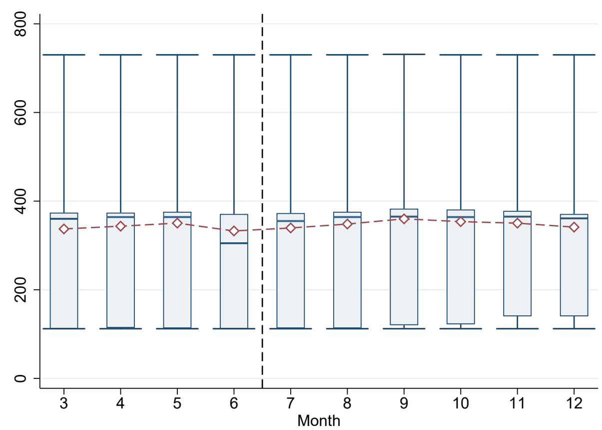


Note: This figure shows the distribution of annualized interest rates in 2021. Each box plots the percentiles 10th, 25th, 50th, 75th, and 90th of the distribution of interest rates corresponding to each month from March to December 2021. The connected red diamonds show the simple average interest rate.

Figure 4: Distribution of Loan Size and Duration



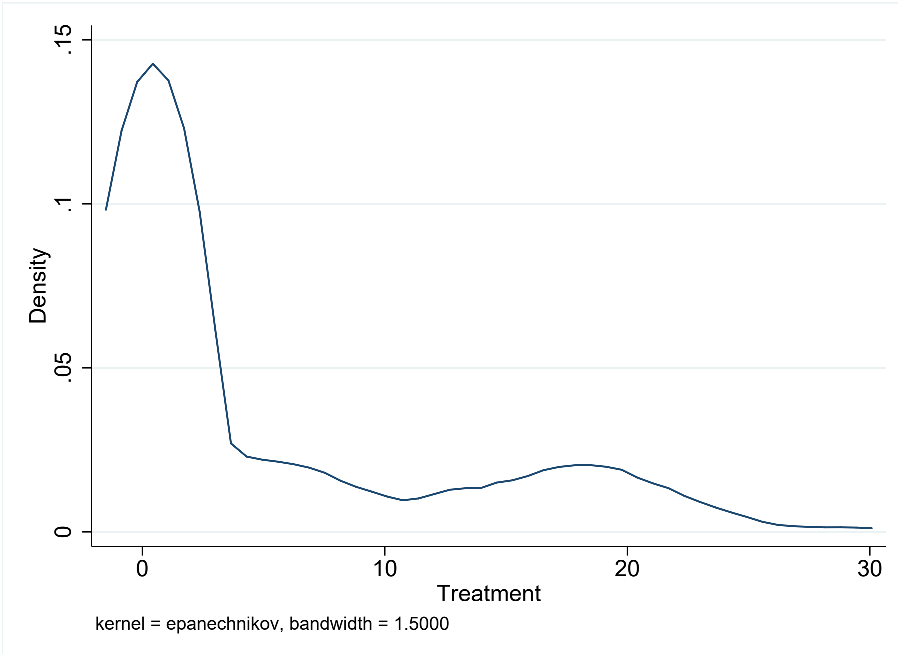
(a) Loan Size



(b) Loan Duration

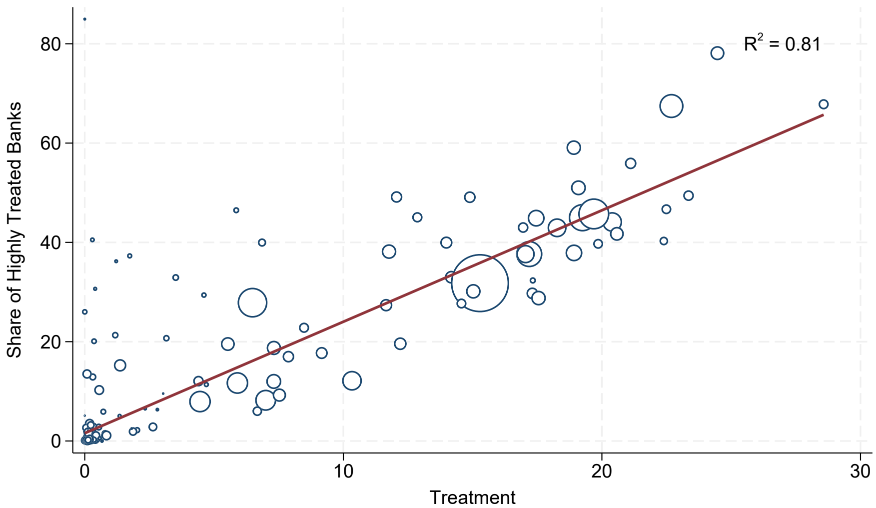
Note: This figure shows the distribution of loan size and duration in 2021. Boxplots show the percentiles 10th, 25th, 50th, 75th, and 90th, while the diamonds represent the average interest rate.

Figure 5: Density of City Exposure to Lending Rate Caps



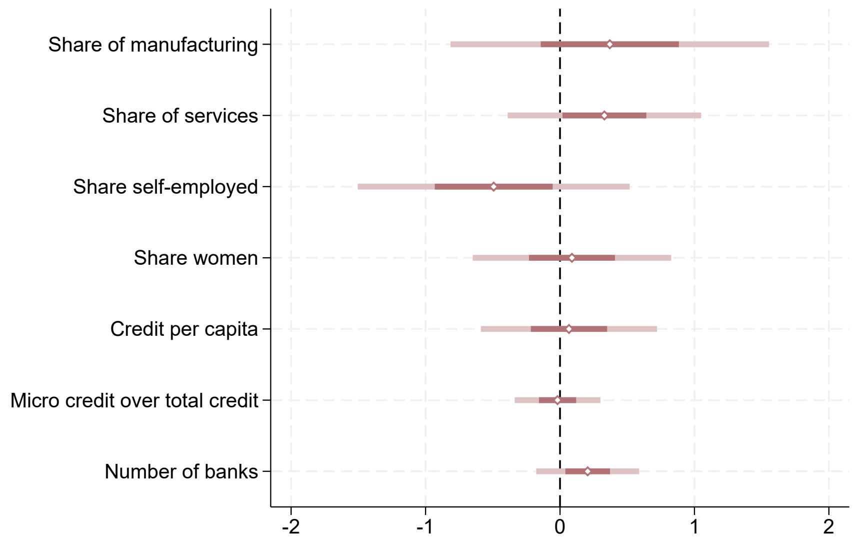
Note: This figure shows the distribution of treatment defined as the percentage decline in annualized interest payments of small business loans required to satisfy the regulation of lending rates between March and June 2021, as defined in equation (7).

Figure 6: City treatment and presence of highly treated banks



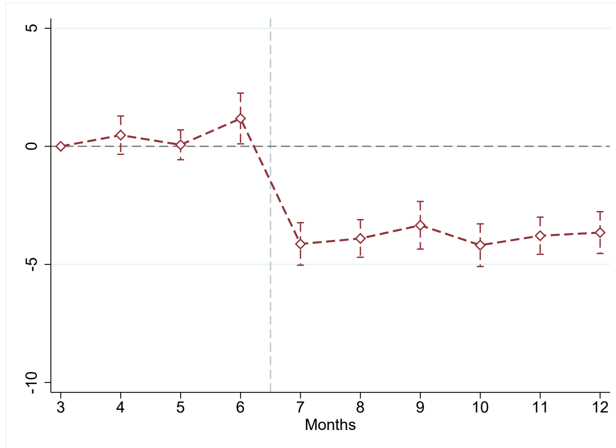
Note: This figure plots the relationship between treatment and highly treated banks' market share across cities. Treatment is the standardized decline in annualized interest payments necessary to satisfy the regulation between March and June 2021. Highly treated banks are those whose exposure is above 1 percent.

Figure 7: Covariate Balance Test

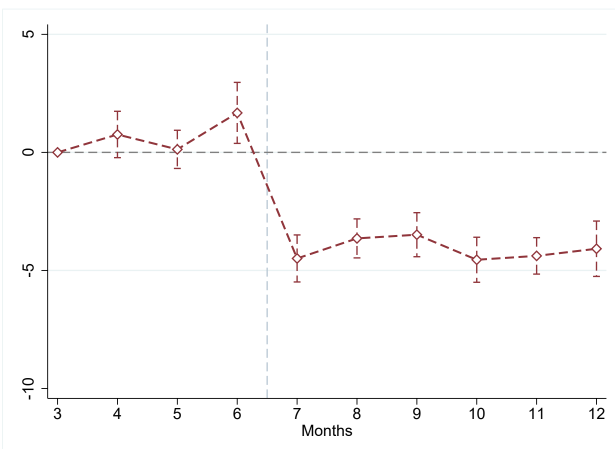


Note: This figure shows coefficient estimates along with 95% confidence intervals (darker bars) and 99% confidence intervals (lighter bars) for the impact of a one standard deviation increase in city treatment across different variables. All variables are standardized to have zero mean and a standard deviation of one. We control for city size measured as population terciles. Shares are defined as the fraction of workers with the underlying characteristic in a given location.

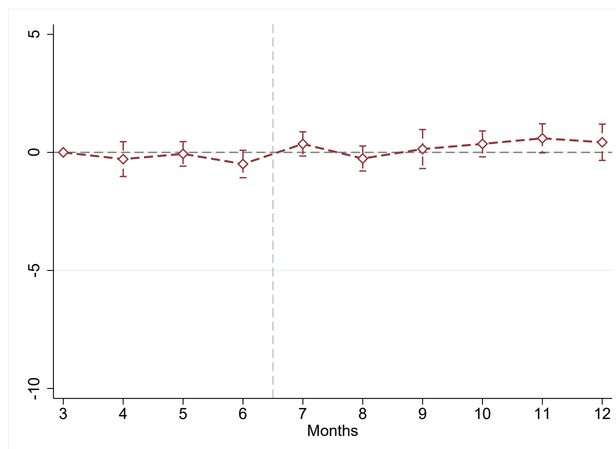
Figure 8: Event Study Graphs for the Average Effect of Lending Rate Caps on Interest Rates



(a) Interest rates



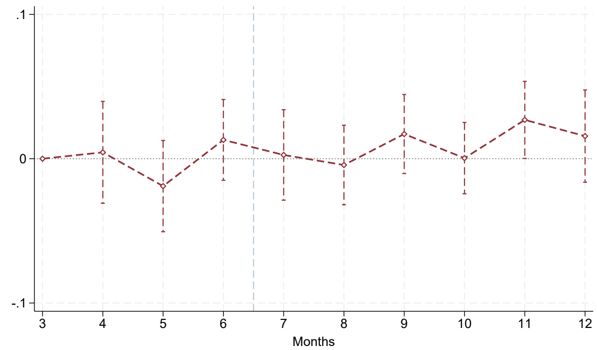
(b) Highly Treated Banks



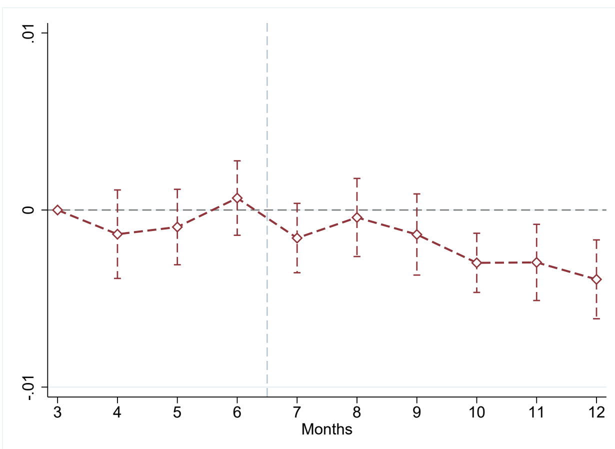
(c) Low Treated Banks

Notes. This figure reports the event study graph for the average city-level effects of lending rate caps on interest rates, using equation (9). Treatment_c is the standardized decline in annualized interest payments necessary to satisfy the regulation between March and June 2021. Highly treated banks are those whose exposure is above 1 percent. The policy was implemented in June 2021. Each dot is the coefficient on the interaction between treatment and month fixed effects. The confidence interval is at the 95% level. Standard errors are clustered by city.

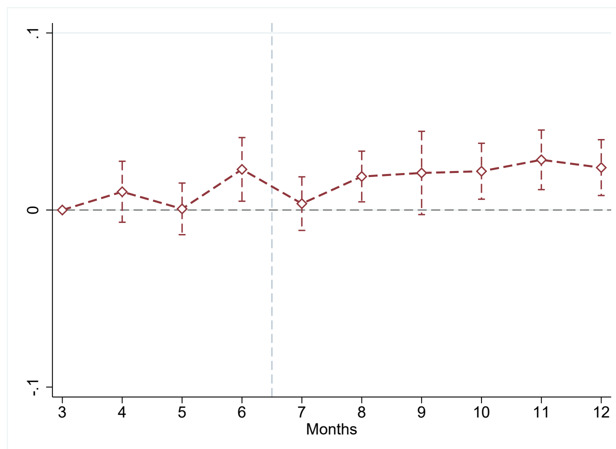
Figure 9: Event Study Graphs for the Average Effect of Lending Rate Caps on Loan Value



(a) Loan Value



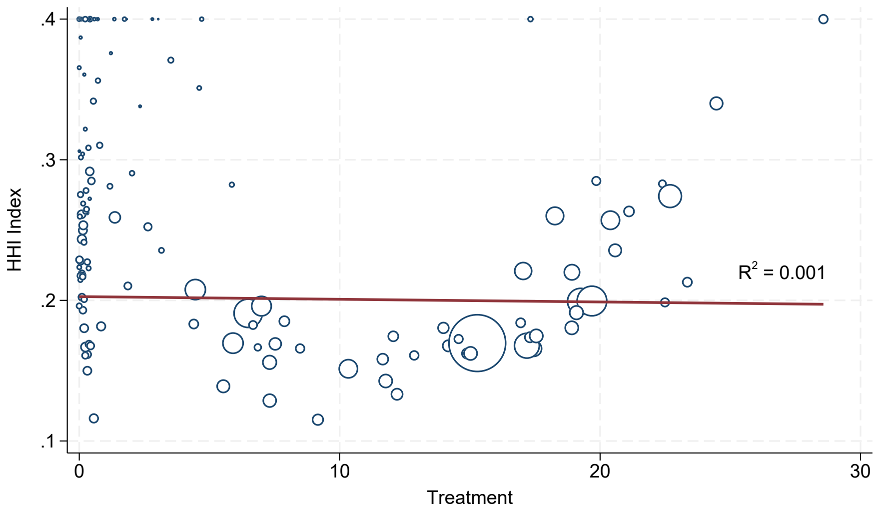
(b) Contr. micro-size loans



(c) Contr. small & large loans

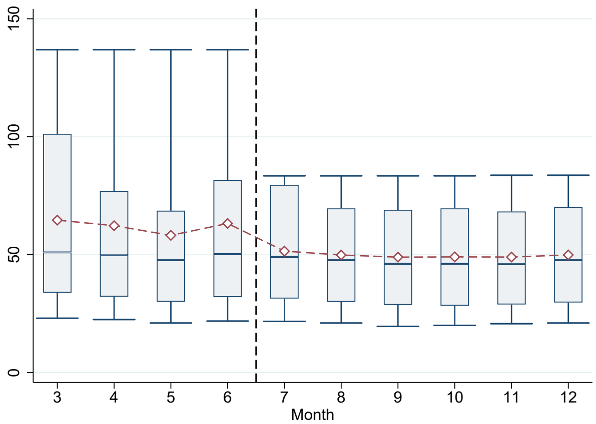
Notes. This figure reports the event study graph for the average city-level effects of lending rate caps on interest rates, using equation (9). Treatment$_c$ is the standardized decline in annualized interest payments necessary to satisfy the regulation between March and June 2021. Micro-size loans are those whose value is within the bottom tercile of the pre-reform loan-size distribution (below USD 575). The policy was implemented in June 2021. Each dot is the coefficient on the interaction between treatment and month fixed effects. The confidence interval is at the 95% level. Standard errors are clustered by city.

Figure 10: City treatment and HHI

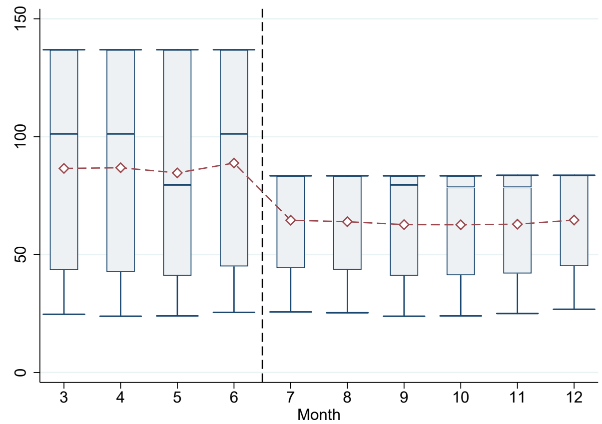


Note: This figure plots the relationship between treatment and HHI across cities. Treatment is the standardized decline in annualized interest payments necessary to satisfy the regulation between March and June 2021.

Figure 11: Distribution of Interest Rates by Firm Ex-ante Risk



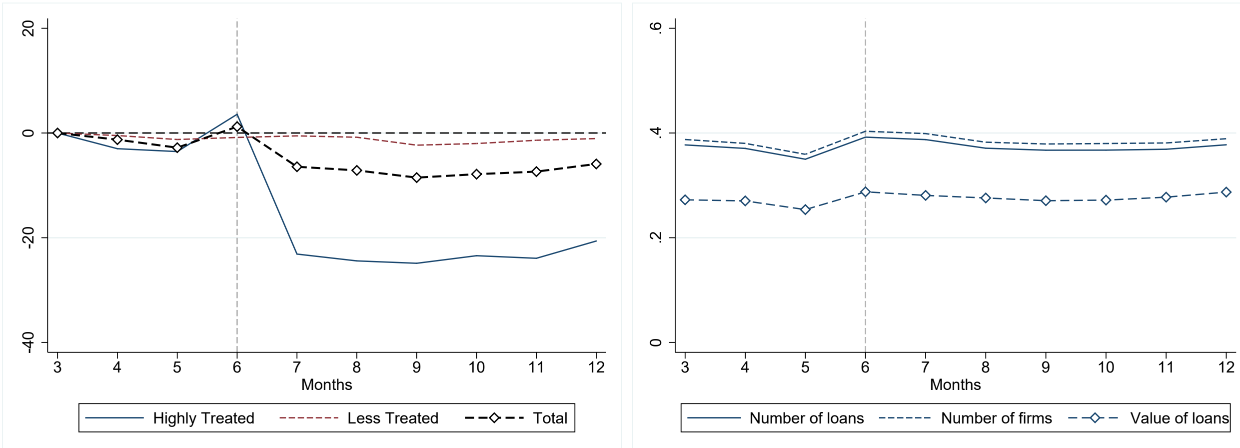
(a) Safe



(b) Risky

Note: This figure shows the distribution of annualized interest rates in 2021 for ex-ante safe and risky borrowers. Ex-ante safe firms have not experienced more than 30 days of repayment delay in 2020, while the ex-ante risky firms did. Each box plots the percentiles 10th, 25th, 50th, 75th, and 90th of the distribution of interest rates corresponding to each month from March to December 2021. The connected red diamonds show the simple average interest rate.

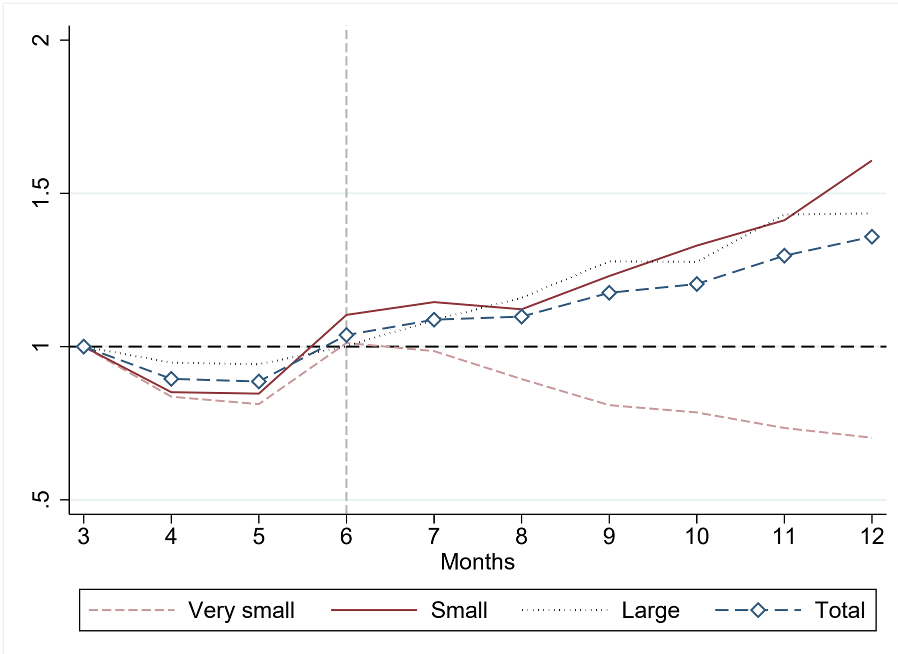
Figure 12: Interest Rates and Treated Banks' Market Share



(a) Interest Rate (b) Market Share

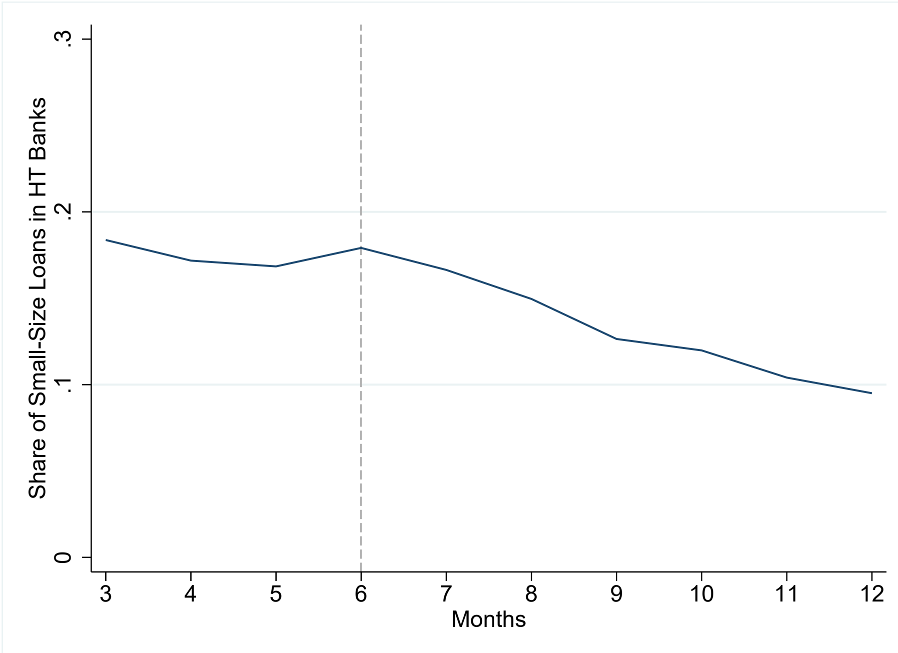
Note: This figure plots interest rates and market share of highly treated banks, defined as those with exposure higher that 1 percent, and less treated ones. Exposure is defined by equation (**??**). Panel (a) plots the weighted average interest rate, and panel (b) plots highly treated banks' market share in terms of value, number of clients, and number of loans. The dashed line indicates the month prior to the implementation of the lending rate cap.

Figure 13: Highly Treated Banks' Lending by Loan-Size



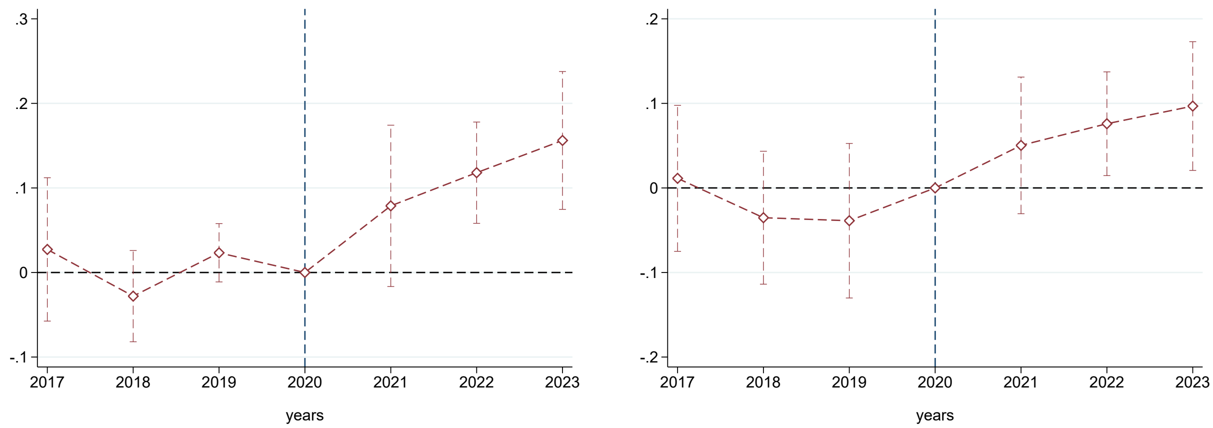
Note: This figure plots the growth rate of loans in different size-bins relative to their values in March 2021, the first month of our data. The light red dashed line denotes micro-size loans in the bottom tercile (i.e., below approximately USD 575). The solid red line represents small-size loans in the middle tercile (i.e., between approximately USD 575 and 1061). The gray dotted line denotes large loans in the top tercile. The connected blue line plots the evolution of the total value of loans. The dashed gray vertical line indicates the month prior to the implementation of the cap.

Figure 14: Small-Size Loans in Highly Treated Banks Portfolios



Note: This figure plots the share of micro-size loans in highly treated banks portfolios over time. Micro-size loans are those whose value is below the bottom tercile of the pre-reform loan-size distribution (below USD 575). Highly treated banks are those whose exposure is above 1 percent.

Figure 15: Event Study Graphs for the Average Effect of Lending Rate Caps on Real Outcomes in Concentrated Markets



(b) Ln Capital (c) Ln Sales

Notes. This figure reports the event study graph for the average city-level effects of lending rate caps on interest rates in concentrated markets, using equation (9). Treatment$_c$ is the standardized decline in annualized interest payments necessary to satisfy the regulation between March and June 2021. We consider all natural person with business and then aggregate outcomes up to the city level. The policy was implemented in June 2021. Each dot is the coefficient on the interaction between treatment and month fixed effects. The confidence interval is at the 95% level. Standard errors are clustered by city.