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 reduces interest rates and small-size credit supply. However, in equilibrium, highly exposed banks expand bigger loans, keeping their market share constant despite a 23 percent decline in interest rates. In concentrated markets, highly treated banks can replace risky borrowers with safe and new firms, which leads to a net positive effect on credit and real outcomes. In contrast, the effect is negative in competitive locations as banks cannot replace risky firms. Finally, we document that small entrepreneurs with higher returns to capital accumulate more of this input and grow faster after the policy, while small businesses with low returns to capital shrink, providing novel evidence that lending rate caps can reduce capital misallocation in concentrated credit 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 dominateas is common in developing economiescaps may exclude opaque but potentially productive 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 efficient. 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 micro and 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 micro and 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 micro and small firm credit 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, low credit access, 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 stronger informational frictions. Third, Peru's long period of macroeconomic stability,

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

characterized by low inflation and delinquency rates provides a unique opportunity to isolate the effects of interest rate regulations.

We estimate the effects of lending rate caps using 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 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 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 2018 to 2022. Putting them together, our data allow us to trace the effects of lending rate caps on small firms' financial and real outcomes, disentangling the role of credit access and capital allocation among different borrowers.

We start developing a simple static model to guide our empirical analysis. In our setting, a fixed number of banks compete a la Cournot over a continuum of small firms. Each firm has one investment project with an exogenous, firm-specific probability of failure. The model yields three key equilibrium results that we will then test in the data. First, equilibrium interest rates depend positively on banks' cost of providing credit. Thus, the implementation of a cap leads to a stronger reduction of the supply of loans that are more costly to originate. Second, risky firms defined as those with high probability of failure, borrow at high interest rates and are more likely to be excluded from credit markets after the lending rate cap implementation. Third, if banks face frictions to raise capital that lead to an increasing marginal cost curve, the cap will generate a reallocation of credit from those with high marginal costs towards those with low marginal costs to be originated, and from risky firms towards safer clients. These reallocation effects are stronger in concentrated markets.

Guided by our theoretical framework, we organize our empirical findings in three main sections.

First, we estimate the loan-level effects of lending rate caps. Second, we examine the broader implications for local credit markets. Finally, we assess the real economy impact of the policy. To estimate the loan-level effects, we rely on the strong negative relationship between loan size and interest rates–even after accounting for city and industry fixed effects. This pattern is consistent with our model, where the marginal cost of originating loans predict interest rates. Since loan origination implies fixed costs, e.g., costs associated with processing loan applications, originating small-size loans are likely to be more expensive than originating big loans. This relationship between interest rate and loan-size is also consistent with market concentration: while three banks dominate the supply of small-size loans, representing over 80 percent of the market, the top 3 banks in the segment of large loans represent only 40 percent.[2] Thus, smaller loans are highly affected by the regulation, while larger loans are not.

Leveraging this variation in interest rates across size bins, we split loans in terciles, based on the pre-reform loan-size distribution. We define micro loans as those in the first tercile, small loans are those in the second tercile, and large loans are in the third tercile. We define treated loans as those in the bottom two terciles, whose value is below USD 1,061. For our empirical estimation, we aggregate our data to the loan-size-bin $\times$ industry $\times$ city level.[3] Then, we employ a difference-in-differences approach to estimate the policy's loan-level effect by comparing the evolution of treated (micro and small) versus control (large) loans, before and after the introduction of the lending rate cap. Our identifying assumption is that, absent the policy, small and large loans would have evolved in similar trends. We provide evidence supporting our identifying assumption in two ways. First, we plot event-study graphs showing that small and large loans were in parallel trends before the policy. Second, we include high-dimensionality fixed effects to account for any time-varying shock taking place at the city and industry levels. Our benchmark results show that treated loans experienced a 6-percentage-point decline in interest rates, alongside reductions of 9 percent in loan value and 8 percent in loan volume. Riskier borrowers saw steeper declines, consistent with the policy constraining risk-based pricing.

[2]Even though understanding the drivers of market segmentation is out of the scope of our paper, it aligns with the strong presence of microfinance institutions (MFIs), which account for more than 70 percent of small borrowers in Peru.

[3]As we discuss below, we further split each tercile in 6 bins, which gives us 18 loan-size-bins, 200 industries, and 190 cities.

While these loan-level results provide a partial equilibrium perspective, the aggregate impact of lending rate caps hinges on how banks and small firms adjust in equilibrium. To explore these general equilibrium forces, we aggregate our data to the bank level, constructing a treatment measure based on the hypothetical reduction in interest revenues banks would have incurred had the policy been implemented pre-reform.[4] Given the concentrated supply of small-size loans, only five banks exhibit treatment exposures exceeding 1 percent; we classify these as highly treated. Comparing their outcomes to less-treated banks, we find that despite a 20-percentage-point larger decline in aggregate interest rates, highly treated banks maintain stable market shares at around 40 percent of clients and 27 percent of loan value. However, their lending composition shifts sharply: small-size credit contracts by 30 percent, while medium and large loans expand by 50 percent, leading to a null response of total credit. These results underscore the critical role of general equilibrium adjustments–particularly credit reallocation within banks' portfolios–in shaping the policys impact on credit supply.

In the second part of the paper, we investigate the mechanisms that facilitate credit reallocation and assess their implications for the aggregate effects of lending rate caps on local credit markets. Specifically, we test the predictions of our stylized model by examining credit flows to risky versus safe firms across markets with varying bank concentration. To do so, we define credit markets at the city level, which relies on the assumption that small entrepreneurs depend on local lenders. We then aggregate our data up to this level and construct a measure of treatment equal to the hypothetical decline in interest payments small businesses would have faced had the policy been implemented pre-reform. This measure captures the degree to which the rate cap constrained lending in each market. 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 small-size credit that was completely counterbalanced by a 6 percent expansion in larger loans. Thus, banks also rebalanced their portfolios locally in response to the policy. This pattern is consistent with financial intermediaries facing constrains to raise

[4]This treatment measure equals the percentage decline in annualized interest payments necessary to bring interest rates on all loans originated before the regulation down to the cap value, and it follows the minimum wage literature (see, for example, Card and Krueger (2000), Dustmann et al. (2021), and references therein.).

capital. In our model, such constrains lead to an increasing marginal cost curve that depends on the total value of loans, which generates that a shock to one market segment such as small-size loans could affect the supply in a different market segment such as big-size credit.

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 that reveal no systematic differences in interest rates or loan values 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 industry-specific characteristics. Third, we incorporate high-dimensionality fixed effects to absorb shocks at the industry, region, and city-size-bin levels. Finally, we perform placebo tests by estimating the response of low-treated banks' outcomes across locations. We find null effects: neither interest rates nor credit reallocation evolve differently across low versus high treated locations. Taken together, these results confirm that the policy successfully reduced interest rates while inducing highly treated banks to reallocate credit within local markets–without spillovers to unaffected lenders.

We now examine how bank competition shapes the impact of lending rate caps, testing two competing hypothesis. First, a standard industrial organization view formalized in our model, where rate caps improve efficiency by constraining bank monopoly power. Second, an alternative perspective emphasizing informational frictions and repeated interactions with borrowers (Stiglitz (1993), Petersen and Rajan (1995), Crawford et al. (2018)) where caps may reduce credit access by disrupting relationship lending a mechanism we acknowledge but do not formally model. We use the Herfindahl-Hirschman index (HHI) to proxy for bank market power, after documenting that interest rates are higher in concentrated markets even when controlling for loan-level observables. Since highly treated banks' geographical footprints are orthogonal to city level concentration, we find substantial variation in treatment across cities with different levels of HHI. It allows us to uncover significant heterogeneity in city-level responses to the lending rate cap.

While in average-competition markets, the policy had null effects on aggregate credit, three key patterns emerge in the corss-section of cities 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 small loans (with steeper rate declines) 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, as suggested by our model. On the other hand, the cap reduces total credit in competitive locations where banks cannot reallocate credit.

We next examine how informational frictions, specifically firm risk, shape the distributional effects of lending rate caps. A central policy concern is that by preventing risk-based pricing, these caps may disproportionately exclude opaque borrowers–particularly young and informal firms that pay higher interest rates to compensate lenders for their greater default risk. To investigate this, we classify firms based on pre-regulation repayment behavior: those with any history of more than 30 day delays (our ex-ante risky group) faced median interest rates of 100 percent, compared to just 50 percent for firms without such delays (our ex-ante safe group). This interest rate premium for riskier borrowers confirms that pre-regulation interest rates effectively priced firm risk, supporting our use of payment delays as a risk proxy.

Our analysis reveals a fundamental trade-off created by the policy. While bank concentration mediates aggregate effects (total number of borrowers increase in concentrated markets but decline in competitive ones), risky borrowers are excluded regardless of market structure. This suggests rate caps create an efficiency-equity trade-off: they improve aggregate credit access in concentrated markets while systematically harming the riskiest borrowers everywhere. The expansion of credit in concentrated markets occurs through compositional shifts–treated banks reallocate credit by replacing risky clients with safer incumbent 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 the highest-risk firms. They also highlight the frictions faced by banks when raising capital, which makes them to search for new and safe borrowers only when it becomes not profitable to attend risky clients.

Having established how lending rate caps affect credit markets, we now estimate their real economy consequences, with particular focus on capital allocation and productivity. Notice that despite the decline in credit for risky borrowers relying on small-size loans, the real impact is apriori unclear. Fro example, firms could substitute formal credit with informal financing, attenuating the real effects of a contraction in bank lending.[5] To test this, we analyze tax records for firms borrowing between December 2019 and June 2021. Aggregating sales and capital to the local market level reveals parallels with credit responses: economic activity increased in concentrated high-treatment markets (a 7 percent increase in sales and 8 percent in capital per SD treatment) but declined in competitive areas. This mirroring of credit effects demonstrates that informal loans can not substitute for lower bank credit, and crucially, confirms the role of market power in shaping real outcomes.

Finally, we explore the impact of lending rate caps on capital misallocation, which is a key driver of economic development (Hsieh and Klenow (2009), Restuccia and Rogerson (2008)). If excluded risky firms are highly productive while safe firms are not, the cap might worsen off the allocation of capital in the economy. We extend our conceptual framework to address this, deriving a sufficient statistic from the joint distribution of productivity and risk. Allocative efficiency declines if excluded riskier firms are disproportionately productive, and improves if benefited safer firms are more productive. This framework shifts our focus beyond credit markets to the pivotal question of whether these regulations enhance or impede capital deployment to its most productive uses (Banerjee and Moll (2010), Moll (2014), Bau and Matray (2020)).

To evaluate these distributional effects, we track firms borrowing in the pre-reform period, between March and April 2021, and match them to annual tax records reported from 2019 to 2022. We rank firms by pre-reform marginal revenue product of capital (MRPK) within industries[6] and split them into high and low MRPK depending on whether they are above or below the industry median. 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

[5]It is worth mentioning that informal credit is more prevalent among smaller and opaque firms. Despite this type of credit not being recorded, exploring the real effects of lending rate caps can shed light on the actual relevance of this margin.

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

aligns with financial friction models suggesting high-productivity firms face credit constraints that generate misallocation (Moll (2014), Midrigan and Xu (2014), Buera and Shin (2013)).

By comparing firms borrowing just above and just below the cap, before and after the reform, we find statistically insignificant responses of capital and sales. However, these findings hide key heterogeneity. High-MRPK firms that borrow above the cap accumulated 19 percent more capital after the introduction of lending rate caps, while low-MRPK firms contracted sharply by 19 percent in terms of capital and 38 percent in sales. We find null effects on sales among high-productivity firms, suggesting capital investments precede output gains. These results indicate that rate caps improved capital allocation among incumbents by redirecting resources toward highly productive firms–a mechanism that may yield long-term aggregate productivity gains.

Our paper analyzes how lending rate caps reshape credit markets and economic outcomes. Combining loan-level, bank-level, and market-level evidence, we show that these policies create sharp trade-offs: while lowering rates for small borrowers, they exclude risky entrepreneurs everywhere, and expand credit to safer firms only in concentrated markets. We provide evidence that caps can improve capital allocation by redirecting resources to high-productivity firms.

Literature Review. Our paper contributes to three main strands of research. First, we contribute to the literature studying the effects of price regulations in bank credit markets (Benmelech and Moskowitz (2010), Rigbi (2013), Agarwal et al. (2014), Madeira (2019), Cuesta and Sepúlveda (2021), Nelson (2022), Kuroishi et al. (2025)). Our contribution is threefold. First, while most of the literature has focused on consumer credit, we estimate the impact on small business loans. Thus, we can link the direct impact of lending rate caps on the real economy through a financial channel. Second, this literature highlights that the impact of interest rate regulations depends on the degree of competition and informational frictions in credit markets (Stiglitz and Weiss (1981), Stiglitz (1993), Petersen and Rajan (1995) Crawford et al. (2018), Galenianos and Gavazza (2022)). By conducting our analysis at multiple layers of aggregation, we can empirically test the role of these mechanisms, showing that bank concentration allows lenders to reallocate credit away from risky borrowers, insulating aggregate loan supply. Third, we contribute by studying the impact of lending rate caps in emerging markets, where small firms exhibit low credit access, paying very high interest rates when obtaining a loan, and where banking sectors tend to be concentrated, and information frictions are particularly strong given the high levels of informality. We document that these two characteristics of banking sectors determine the aggregate impact of lending rate caps on local credit markets.

Second, we contribute to the literature that studies the role of financial frictions in shaping low credit access and misallocation in emerging markets and, through this channel, underdevelopment (Hsieh and Klenow (2009), Restuccia and Rogerson (2008), Buera and Shin (2013), Moll (2014), Midrigan and Xu (2014), Bau and Matray (2020)). We contribute in three ways. First, most of this literature models financial frictions as collateral constraints (Banerjee and Moll (2010), Moll (2014), Itskhoki and Moll (2019)). Such constraints are motivated by informational frictions in bank credit markets and are silent about price regulations despite growing evidence that bank concentration might reduce credit access and economic development in emerging markets (Joaquim et al. (2020), Burga and Céspedes (2021)). We show that lending rate caps can expand credit supply in highly concentrated markets, suggesting that bank market power can partially explain financial frictions in developing economies. Our second contribution is to study how firm risk and marginal returns interact to determine the impact of lending rate caps (Joaquim and Sandri (2020) provide a theoretical framework). We document that lending rate caps can reduce capital misallocation in the economy by excluding firms with low returns to capital and allowing firms with high returns to expand. Lastly, we contribute by providing novel evidence on the distribution of firms over risk, productivity, and interest rates, which is critical to understanding economic development (e.g., Banerjee (2003), Banerjee and Moll (2010)). To the best of our knowledge, ours is the first paper documenting this distribution with administrative data.

Finally, we contribute to the empirical literature that studies the impact of financial policy on economic development (Burgess and Pande (2005), Banerjee and Duflo (2014), Bruhn and Love (2014), Ponticelli and Alencar (2016), Garber et al. (2021), Bau and Matray (2020), Fonseca and Van Doornik (2022), Fonseca and Matray (2022)). Our contribution is threefold. First, we study the effects of lending rate caps, a policy widely used in emerging markets, but whose effect on small firm dynamism remains an open question. Second, we use administrative data to explore how two critical characteristics of emerging markets' financial sectors, firm risk and bank market power, interact shaping the aggregate impact of these policies. Third, we document that improving capital allocation across heterogeneous firms is a novel channel through which lending rate caps can impact long-term economic development.

Our paper has multiple policy implications. First, the evidence we present in our paper suggests that place-based policies can improve credit access. In particular, lending rate caps can be more effective if they target highly concentrated markets. Second, these regulations can have significant distributional effects when the credit market's structure interacts with firm risk and marginal returns to capital. Finally, the degree of competition in the banking sector can generate misallocation. In this line, lending rate caps can improve the allocation of resources in the economy by expanding credit supply to highly productive firms in concentrated markets at the expense of less productive, risky firms in competitive locations.

The rest of the paper is organized as follows. Section 2 provides a description of the data, and section 3 presents our empirical approach. Section 4 and 5 report our loan-level and local credit market results. Section 6 present the real effects and section 7 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 micro and small businesses.

1. Interest rate report. We use loan-level data from the *Reporte de Tasas de Interés*, which includes information on new originated loans at the bank-firm level. We observe the value, duration, and annualized interest rate on every micro and small firm loan 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 the origination of loans and the number of borrowers.

2. Credit registry data. We use loan-level data from the *Reporte Crediticio de Deudores*, which includes information on the balance of loans 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 2018 and 2022. 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 combine this dataset with our financial outcomes described above. We use this data to estimate the real effects of lending rate caps on micro and small firms, as well as quantifying the role of credit reallocation across firms.

We complement our analysis using survey data provided by the Peruvian statistics office, *Instituto Nacional de Estadística e Informática* (INEI). This is a repeated cross-sectional data that includes an indicator variable equal to one for individuals reporting lending relationships outside the formal banking sector. We use this survey to estimate the response of informal credit at the local level.

2.2 The market of micro and small firm loans

Lending rate caps were implemented for all micro and small firm loans. Before discussing the policy implementation, we briefly describe this segment of the market. Micro-credit includes loans granted to firms whose total bank debt is not higher than USD 6 thousand, while small firm credit includes loans granted to businesses whose total bank debt is above USD 6 thousand

and below USD 80 thousand[7]. From now on, we will refer to both types of credit as small firm loans. Table 1 reports summary statistics of the value, duration, and annualized interest rate of small firm 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.[8] 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 loans, including traditional banks and micro-finance institutions (MFIs).[9] 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. It is worth noticing the role of MFIs in this market, with 4 of them ranked at the top 5.[10] 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 this segment 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 Implementation of a lending rate cap

The Central Reserve Bank of Peru established a lending rate cap for small business loans in 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. Moreover, 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 supply of small firm lending.

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

[8]It is worth noticing that duration refers to the length of the loan repayment period, and this period starts one month after origination.

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

[10]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.

Figure 1 plots monthly statistics of the distribution of interest rates for the universe of small firm 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 95 percent in the pre-reform period, it dropped to the cap after the reform. Such bunching of 25 percent of loans originated at the cap value is suggestive evidence of market power. On the other hand, the median and percentiles 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 C1. The average and median loan-size increased by 9 and 7 percent after the reform, respectively, while the average and median duration remained constant.

2.4 Interest rates in the cross-section

We conclude this section providing evidence on the drivers of interest rates in Peru. 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 firm 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 shed light on the drivers of interest rates in the cross-section of loans. We test the role of loan size, bank market power, and firm risk by estimating the following regression:

$$i_{\ell f b t} = \alpha \times \text{Small}_\ell + \beta \times \text{Small}_\ell \times \text{HHI}_{c,\text{small}} + \gamma \times \text{Small}_\ell \times \text{Risk}_f + \Omega X_{\ell f b t} + u_{\ell f b t} \qquad (1)$$

Where $i_{\ell f b t}$ denotes the interest rate on loan ℓ granted by bank b to firm f in month t. We define small-size loans Small_ℓ as an indicator variable equal to one if the value of loan ℓ is below, approximately, USD 1 061 thousand, which is the second tercile of the loan-size distribution.[11] $\text{HHI}_{c,\text{small}}$ represents the Herfindahl-Hirschman index (HHI) of city c considering small-size loans only, and is our proxy to test the role of bank market power in shaping interest rates. We define

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

Risk_f as an indicator variable equal to one if firm f exhibited 30 or more days of repayment delay at least once in 2020. This is our proxy for firm risk. Finally, $X_{\ell fbt}$ contains control variables, including firm risk and city HHI, and fixed effects by loan currency, firm industry, bank city, and time.

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 dig deeper into 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 5 percentage points in interest rates. Moreover, if small-size loans are granted to ex-ante risky firms, interest rates increase by 9 additional percentage points. 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 loan size is a key determinant of interest rates in the cross-section. Moreover, our results indicate that the interaction of loan-size with market power and firm risk is crucial to understand the high interest rates observed in Peru.

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 which succeed with probability $(1 - \sigma)$. Entrepreneurs are heterogeneous in σ.

When the project succeed, entrepreneurs use their stock of capital to produce according to the following technology:

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

where $\alpha \in (0,1)$ captures decreasing marginal returns. If the project fails, entrepreneurs exit the market. Entrepreneurs take the cost of capital r^{ℓ} as given and maximize expected profits as follows:

$$\pi(z,\sigma) = \max_{k} \ (1-\sigma) \times \left\{ zk^{\alpha} - r^{\ell}k \right\} \tag{2}$$

Thus, for a given interest rate and firm risk, we have the following credit demand:

$$Q(r^{\ell}) = (\alpha z)^{\frac{1}{1-\alpha}} \, r^{\ell^{-\frac{1}{1-\alpha}}} \tag{3}$$

where a higher cost of capital r^{ℓ} reduces the demand for credit. Notice that our measure of decreasing returns α shapes the elasticity of our demand curve. When marginal returns to capital decline more slowly (α is closer to one), the demand curve is more elastic, and an increase in interest rates has a stronger impact on credit demand.

3.2 Banks

The financial sector includes N banks in Cournot competition who take the demand function $Q(r^{\ell})$ as given. Banks are heterogeneous in their marginal cost of raising funds c_b. We assume that firm risk is observed by lenders. Thus, for a given level of firm risk, bank b chooses the amount of credit $Q_b(\sigma)$ that maximizes expected profits as follows:

$$\max_{Q_b(\sigma)} \left\{ (1-\sigma)\, r^{\ell}(Q(\sigma)) - c_b \right\} Q_b(\sigma) \tag{4}$$

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 (3). Assuming a symmetric Cournot equilibrium, interest rates are given by:

$$r^{\ell}(\sigma) = \frac{c}{(1-\sigma)\,(1-(1-\alpha)\times \text{HHI})} \tag{5}$$

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, then interest rates are more sensitive to HHI when α is small. 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 (3), 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 (5).

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 (5) will be below the cap. We define the function $\sigma^B(\text{HHI})$ representing the maximum level of risk for a given level of credit market concentration such that interest rates in the market equilibrium are below the cap.

$$\sigma^B(\text{HHI}) = 1 - \frac{c}{\overline{r} \times (1 - (1-\alpha) \times \text{HHI})} \tag{6}$$

Thus, the cap affects pricing among firms with risk above σ^B. This value is positively related to the cap, since a greater cap affects pricing on a smaller set firms. Moreover, a banking sector with lower cost of financing c is also less affected by the cap, as such institutions already operate with lower interest rates. Finally, the set of borrowers above σ^B is bigger in highly concentrated markets, as these markets have higher interest rates.

Banks will charge the maximum interest rate allowed $\overline{r}$ on firms with risk above σ^B only if it is profitable for them to do so. The maximum level of risk σ^E such that this condition holds, i.e., if banks set interest rates at the cap value, total profits are still positive, is defined as follows:

$$\sigma^E = \frac{\overline{r} - c}{\overline{r}} \tag{7}$$

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

$$\overline{r}^{\ell}(\sigma) = \begin{cases} \emptyset & \text{for } \sigma \geq \sigma^E \\ \overline{r} & \text{for } \sigma \in (\sigma^B, \sigma^E) \\ \dfrac{c}{(1-\sigma)\,(1-(1-\alpha)\times \text{HHI})} & \text{for } \sigma \leq r^B \end{cases} \tag{8}$$

This new equilibrium indicates that lending rate caps affect total credit through two main channels. First, they exclude risky borrowers, i.e., those with $\sigma > \sigma^E$. Then, if the lending rate cap is too high, or if the distribution of firms is concentrated among risky clients, this negative impact on total credit would be stronger. Second, the lending rate cap reduces interest rates and expand credit supply for firms with moderate risk, i.e., those with $\sigma \in (\sigma^B, \sigma^E)$. If markets are more competitive or the distribution of firms is concentrated among firms with moderate risk, this positive impact on total credit would be stronger. Thus, whether lending rate caps can expand or reduce total credit in local markets is an empirical question. Additionally, both mechanisms are expected to play a significant role in emerging markets, which are often characterized by substantial informational frictions that can skew the distribution of firms toward higher risk levels, as well as high market concentration that may amplify the benefits of lowering interest rates.

4 Empirical approach

Guided by our theoretical framework, we conduct our empirical analysis at multiple levels of aggregation, which allows us to estimate the role of general equilibrium effects that might occur at different layers. First, we estimate the loan-level impact of lending rate caps by comparing the evolution of small and medium size versus bigger loans' outcomes using a difference-in-differences approach. Then, we aggregate our data up to the bank level and estimate to what extent lenders can rebalance their loan portfolios after the reform. Finally, we quantify the local credit market effects of lending rate caps by exploiting the geographical footprint of highly exposed banks.

4.1 Loan-level analysis

We build our measure of loan-level treatment leveraging variation in interest rates across the loan size distribution. As we documented in section 2, interest rates are higher for smaller loans, even after controlling for industry and city fixed effects. Furthermore, we show in Figure 2, that interest rates are significantly higher for small and medium size loans. Thus, we define a loan-level measure of treatment or exposure to the policy as a dummy variable that equals one for loans whose value is below the second tercile of the pre-reform loan-size distribution (approximately USD 1061). To be more specific, we split loans in 18 bins and then aggregate our data up to the size-bin $\times$ industry (ISIC 2 digits) $\times$ city level.[12] We define treated bins as those at the bottom 12 bins, i.e., the bottom two terciles, or small and medium size loans.

We estimate the loan-level effects of lending rate caps by comparing different outcomes in treated bins relative to control ones, before and after the policy, using the following difference-in-differences specification:

$$Y_{kjct} = \gamma_t \times \text{Treatment}_k + \delta_{kjc} + \delta_t + u_{kjct} \tag{9}$$

Where Y_{kjct} is an outcome variable, such as loan value or weighted average interest rate, of size-bin k, industry j, city c, and time t. Treatment_k equals one for the bottom 12 bins, δ_{kjc} denotes time invariant size-bin by industry and city fixed effects, and δ_t includes time fixed effects. Standard errors are clustered at the size-bin level.

Our coefficient of interest γ_t measures the monthly treatment effect of the policy on small and medium size credit for a variety of outcomes such as interest rates, value, and number of loans. Our identifying assumption is that, absent the regulation, small and medium size loans would

[12]Notice that we excluded the top decile of the original distribution of small business loans as they are granted at very low interest rates. In the remaining 90 percent of loans, we keep those originated between March and June 2020, rank them by size, and split them in 18 bins. Each bin accounts for (approximately) the same number of observations. These bins provide the cutoffs that we will use to aggregate our data.

have evolved in similar, parallel trends as bigger loans. We provide evidence supporting our identifying assumption in two ways. First, we provide clean event-study graphs showing that small and medium size loans evolved on similar trends with bigger loans before the regulation. Second, we include high dimensionality fixed effects to control for various unobserved time-varying shocks taking place at the industry and city level.

4.2 Bank-level analysis

We then aggregate our data to the bank level and explore how financial intermediaries adjust their portfolios to the regulation of interest rates. On the one hand, we might expect that banks whose portfolios were more oriented towards small and medium size, high-interest-rate loans, will shrink as they will find it more difficult to provide small and medium size loans after the policy. On the other hand, if banks could rebalance their portfolio by expanding the supply of bigger loans, we might expect null effects in aggregate bank lending. To explore the role of credit reallocation within bank portfolios, we build a measure of bank exposure to the policy that is equal to the decline in annualized interest payments necessary for a given bank b to satisfy the lending rate cap on loans originated before the policy. Specifically, we compute the following measure:

$$\text{Exposure}_b = \frac{\sum_{i \in b} \ell_i \times \max\{r_i - \overline{r}, 0\} \times 100\%}{\sum_{i \in b} \ell_i \times r_i} \tag{10}$$

Where the summation considers all loans i originated by bank b in the pre-reform period. ℓ_i and r_i denotes the value and annualized interest rate of loan i, and $\overline{r}$ represents the lending rate cap. The distribution of bank exposure is highly skewed to the right, with only five lenders exhibiting exposures greater than 1 percent. These institutions serve around 40 percent of clients in the market of small business loans. We call them highly treated banks.

By aggregating our data up to the bank level, we can explore how financial intermediaries adjust their portfolios to the regulation of interest rates. We study whether highly treated banks lose market share or are able to rebalance their portfolios originating bigger loans at lower interest rates. Thus, our bank-level analysis allows us to explore the role of this first layer of general equilibrium effects taking place within bank portfolios.

4.3 Local credit market analysis

In the last part of our paper, we estimate the impact of lending rate caps on local credit markets, which are defined at the city level.[13] This layer of aggregation allows us to explore additional margins of adjustment such as credit reallocation across industries and cities, as well as credit reallocation across firms within industry-city bins. By doing so, we can test the role of two key features of developing economies, credit market concentration and firm risk, in shaping the impact of lending rate caps. Moreover, this setting allows us to estimate the response of aggregate outcomes such as credit access and small firm performance.

We define our city-level treatment as the 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:

$$\text{Treatment}_c = \frac{\sum_{i \in c} \ell_{it} \times \max\{r_{it} - \overline{r}, 0\}}{\sum_{i \in c} \ell_{it} \times r_{it}} \times 100 \tag{11}$$

Where ℓ_{it} denotes the value of 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 3 plots the distribution of treatment, and shows that it is highly skewed to the right. 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:

$$Y_{ct} = \beta_t \times \text{Treatment}_c + \delta_c + \delta_t + u_{ct} \tag{12}$$

Where Y_{ct} denotes an outcome variable in city c and time t. We include city fixed effects δ_c to

[13] We define cities at the province level. Peru has 196 provinces in total, and 157 of them have branches, either from traditional banks or micro-finance institutions.

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

control for pre-determined time-invariant characteristics 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 explore the drivers of our treatment measure and show that it is fully driven by highly treated banks' geographical footprint. For example, Figure 4 plots our city-level treatment against the city-level share of highly treated banks, showing that bank geographical footprint determines the exposure of cities. Thus, it is plausible to assume that bank geographical footprint depends on long-term considerations and is exogenous to the sudden regulation of interest rates.

Third, we include time-varying fixed effects at the region and city-size level. This allows us to control for any region-specific shock as well as accounting for city size specific trends. Furthermore, we use our detailed data to estimate a city × 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:

$$Y_{jcrt} = \beta_t \times \text{Treatment}_c + \delta_{jc} + \delta_{jt} + \delta_{q(c),t} + \delta_{rt} + u_{jcrt} \tag{13}$$

Where Y_{jcrt} denotes an outcome variable in industry j, city c, region r, 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 × city-size × region bins, which allows us to control for multiple shocks that may correlate with our city-level measure of treatment. Thus, we deal with multiple potential concerns including the possibility that highly treated banks could be specialized in industries that may be differently affected during the last recession, or the possibility that highly treated banks enter smaller locations that evolve in different trends relative to bigger cities. Finally, we conduct a placebo test by considering only low-treated banks in our estimation, i.e., banks with exposure below 1 percent. 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

5.1 Loan-Level Effects

We start by discussing the loan-level effects of the policy. We estimate equation (9), where treatment is a dummy variable that equals one for small and medium size loans, at the bottom 12 bins, and zero for bigger loans, at the top 6 bins.[15] Table 4 reports the average loan-level effect of the reform. Column (2) shows the response of the weighted average interest rate in our benchmark specification. We find that small and medium size loans are originated at 6 percentage points lower interest rates than bigger loans after the policy, suggesting that lending rate caps were effective in reducing interest rates. We then estimate the impact of the policy on credit supply. Column (4) shows that the value of small and medium size loans declined by 9 percent relative to bigger loans after the policy, and this is mainly driven by a reduction in the number of loans that declined by 8 percent, as reported in column (6). Notice that, our benchmark specification includes a set of city and industry time-varying fixed effects, indicating that the decline in interest rates and loan origination is not driven by any city nor industry level shock. We interpret our results as evidence that the policy was effective in reducing interest rates of small and medium size loans, but at the cost of reducing the supply of such loans.

Figure 5 plots event-study graphs associated with our average effects. Panel (a) shows a sharp and persistent decline of interest rates on small and medium size loans relative to bigger credit. Furthermore, this decline starts immediately after the policy was implemented, while before the reform, treatment had null effects on interest rates, consistent with our identifying assumption. Panel (b) shows a significant reduction on the value of loans. Similarly, this decline takes place immediately after the policy implementation, and there is no evidence of pre-trends. Panel (c)

[15] Small and medium size loans are below approximately USD 1 061, and represent around 29 percent of the value of small business loans in the pre-reform period.

plots the corresponding event-study graph for the number of firms, showing a similar pattern. Our results are not driven by the high-dimensionality fixed effects included in our benchmark specification. Columns (1), (3), and (5) in Table 4 show a similar decline in interest rates, value, and number of loans in a *naive* specification where we exclude city and industry time-varying fixed effects. We plot corresponding event-study graphs in Figure C2, and all figures exhibit similar patters as our benchmark estimation.

Overall, our estimated loan-level effects indicate that lending rate caps reduced the cost of credit of small and medium size loans. However, the regulation also reduced bank incentives to offer this type of credit. It is worth noticing that this is a very partial equilibrium result and is not conclusive about the aggregate impact of lending rate caps. In the next sections, we aggregate our data up to the bank and city level to estimate the role of general equilibrium effects, and test to what extent bank market power and firm risk shape the impact of lending rate caps.

5.2 Bank-level portfolios

In this section, we explore whether banks rebalance their portfolios or not, and discuss what are the aggregate implications of this behaviour. We leverage key heterogeneity on the supply side, which leads to significant variation in bank exposure to the regulation of lending rates.

Before presenting our bank-level results, it is important to notice that the market of small business loans is highly segmented based on loan-size. To illustrate this point, Figure 6 plots the weighted average interest rate, against two proxies of bank competition, for each decile of the loan-size distribution. The circle size denotes how big is each decile in terms of loan value, and the dashed line separates small and medium size (right) from bigger loans (left). Panel (a) shows that the segment of smaller size loans is more concentrated, as measured by the share of the three largest banks in each decile.[16] Around 85 percent of smaller loans, at the bottom four deciles, are offered by only three financial institutions. Interestingly, this measure of concentration strongly correlates with interest rates. In contrast, only 45 percent of bigger loans are provided by the three largest financial institutions competing in those bins.

[16]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.

Panel (b) uses the HHI as the measure of concentration for each decile and shows a similar pattern. Thus, competition varies substantially across the loan-size distribution, and there are few institutions providing smaller size loans at high interest rates. As we discussed in section 3, we measure the decline in annualized interest payments necessary to satisfy the regulation in the pre-reform period using equation (10). We find that 5 banks are highly exposed to the policy, with exposures above 1 percent.[17] These highly treated banks represent around 40 percent of the total value of small business loans and are specialized in smaller size credit. For example, while small and medium size loans represent 19 percent of low treated banks' portfolios, the share is more than 50 percent for highly treated banks.

Figure 7 plots the weighted average interest rate relative to March 2021, the first month of our data, and market shares of differently treated banks. Panel (a) displays the evolution of interest rates. The dark connected line shows that small business loans were originated at 13 percentage points lower interest rates after the policy. This contraction is fully driven by highly treated banks, as we can observe in the solid blue line. Finally, the red dashed line shows that interest rates of less treated institutions did not change in our sample period. Thus, the policy reduced interest rates on highly treated banks that were specialized in smaller loans, with negligible effects on the remaining institutions. Panel (b) shows the market share of highly treated banks. We can see that, despite the large decline in interest rates, highly treated banks did not lose market share. Instead, their presence in the market of small business loans remained constant at 38 percent in terms of number of borrowers, and 27 percent in terms of total value. Thus, banks totally offset the contraction of small and medium size loans with alternative credit.

We further study this rebalancing of banks' portfolios by splitting small business loans in terciles, based on the pre-reform loan-size distribution. Thus, we explore the evolution of small and medium size loans separately. For each group, we compute the growth rate of loan value relative to the first month of our data, and plot them in Figure 8. Consistent with our loan-level evidence, we observe a reduction of around 30 percent in small-size loans. However, this reduction is offset by an expansion of around 50 percent in medium-size and bigger loans. Overall, total loans provided by highly treated banks increase by around 35 percent. Figure 9

[17] 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.

complements our analysis by showing that the share of small-size loans within highly treated banks' portfolios declines sharply from 18 to below 10 percent.

Our bank-level analysis provides two main insights related to the impact of lending rate caps in our setting. First, the market of small firm lending is highly segmented. Few institutions provide very small-size loans, which is strongly associated with the observed high interest rates. Second, even though banks specialized in small-size loans have to reduce significantly the supply of this type of credit to meet the regulation of interest rates, they can rebalance their portfolios and expand the supply of bigger loans. In the next sections, we study the drivers and implications of bank credit reallocation.

5.3 Local Credit Market Effects

We have documented that lending rate caps were effective in reducing interest rates at the cost of reducing the supply of small-size loans. However, banks that are specialized in this type of credit can rebalance their portfolios by expanding the supply of bigger loans, which leads to negligible effects on bank total credit. In this section, we study the drivers and aggregate consequences of such credit reallocation. To do so, we define credit markets at the city level, relying on the assumption that small firms rely on local lenders. Then, we compute a measure of treatment following equation (11). As we discussed in previous sections, this measure strongly correlates with the presence of highly treated banks specialized in small-size loans. Finally, we estimate the local credit market effects of lending rate caps by comparing the evolution of multiple outcomes in high and low treated cities, before and after the policy, following the difference-in-differences approach described by equation (12).

We start by estimating the response of interest rates. Our results are reported in Table 5. Column (1) shows that one standard deviation (SD) higher treatment led to a 5 percentage points reduction in interest rates, using our baseline specification (12) which includes city and time fixed effects. A potential threat to our identification is that bank specialization in small-size loans might not be random. Instead, it could be driven by industry, region, or city specific characteristics. Then, the observed response of highly exposed banks in highly treated locations might reflect shocks occurring at these levels. To deal with this concern, we disaggregate our data and estimate equation (13), which includes time-varying fixed effects at the industry, region, and city-size levels. Our result is reported in columns (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 10 plots the monthly treatment effect of lending rate caps on interest rates. Panel (a) shows that cities with one SD higher treatment experience a rapid and persistent contraction in interest rates of around 6 percentage points 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. We deal with such concern by splitting city-level interest rates into the contribution of highly treated banks and low treated ones, as follows:

$$\sum_{i\in c}\left(\frac{\ell_{it}}{\sum\limits_{j\in c}\ell_{jt}}\right)\times r_{it}=\sum_{i\in HTB\cap c}\left(\frac{\ell_{it}}{\sum\limits_{j\in c}\ell_{jt}}\right)\times r_{it}+\sum_{i\in LTB\cap c}\left(\frac{\ell_{it}}{\sum\limits_{j\in c}\ell_{jt}}\right)\times r_{it}$$

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 5. 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). We find 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 10 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 lending rate caps. Both figures show no evidence of pre-trends, which is consistent with our identifying assumption.

We then estimate the response of loan origination. We use the mid-point growth rate of loan value, relative to the city $\times$ industry average, as our dependent variable in equation (13).[18] Column (4) of Table 6 shows that, despite the large decline in interest rates presented above, one SD higher treatment is associated with a statistically insignificant response of loan value. We then split loans into two groups, as we did in our bank-level analysis, and study whether banks reallocate credit within local credit markets. Specifically, we decompose our mid-point growth rate into the contribution of small-size and bigger loans as follows:

$$\frac{\ell_{jct} - \overline{\ell}_{jc}}{(\ell_{jct} + \overline{\ell}_{jc})/2} = \frac{\ell_{jct}^{T1} - \overline{\ell}_{jc}^{T1}}{(\ell_{jct} + \overline{\ell}_{jc})/2} + \frac{\ell_{jct}^{T2\&T3} - \overline{\ell}_{jc}^{T2\&T3}}{(\ell_{jct} + \overline{\ell}_{jc})/2}$$

Where the super-index $T1$ indicates small-size loans, i.e., those at the bottom tercile of the loan-size distribution. Then, the first component represents the contribution of small-size loans 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 small-size towards bigger loans within local credit markets. While the contribution of small-size loans decline my 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 (12) 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 small-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 small-size and bigger loans, separately. If our identifying assumption is valid, the response of credit should be driven by highly treated banks. By doing so, we are actually performing a placebo test, as low treated banks might not respond to the policy. We report our results in Table 7. Column (1) shows that one SD higher treatment leads to a 5.4 percent decline in small-size loans, and column (2) indicates that highly treated banks explain 4.1 percentage points of this reduction. Column (4)

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

shows that bigger 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 expansion and reallocation of credit are 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 11. 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.

5.3.1 The role of 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 then we estimate the following equation where HHI is demeaned and standardized:

$$Y_{ct} = (\beta + \gamma \times \text{HHI}_c) \times \text{Treatment}_c \times \text{Post}_t + \lambda \times \text{HHI}_c \times \text{Post}_t + \delta_c + \delta_t + u_{ct} \tag{14}$$

We report our results in Table 8. Column (1) shows that one SD higher treatment leads to 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 the average response of credit is statistically insignificant. We further document that credit grows in highly concentrated cities. One SD 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 the aggregate supply. We explore the role of bank market power in shaping credit reallocation. Columns (3) and (4) of Table 8 report the response of the contribution of small and bigger loans, respectively. We can see that, while small-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 small-size loans in highly concentrated markets, which is consistent with the stronger response of interest rates presented in column (1).

Our results indicate that market power is key to explain the impact of lending rate caps. In highly concentrated markets, lending rate caps can reduce interest rates and expand credit supply because banks can rebalance their portfolios away from small-size loans towards bigger 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 small-size loans that cannot be reallocated.

5.3.2 The role of firm risk

We now study the role of firm risk. In principle, if markets are competitive, interest rates might reflect bank cost and firm risk (e.g., default probability). 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 noticing that this measure is defined for firms with active lending relationships in 2020. Figure 12 in the Appendix 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 firms is 50 percent, while loans offered to ex-ante risky borrowers exhibit a median interest rate of 100 percent.

We test the role of firm risk by estimating equation (12) using the number of firms and the share of risky borrowers as our dependent variables. We report our results in Table 9. 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. We report the impact on the share of risky firms in column (3) and (4). We find that the share of risky borrowers declines significantly in treated locations after the reform, independently on the degree of bank concentration. Thus, our results indicate that lending rate caps harm risky borrowers by reducing their participation in credit markets, while bank market power allows lenders to find safe borrowers leading to null effects on aggregate credit access.

Finally, we study the implications of lending rate caps for aggregate firm performance in bank credit markets. It is worth noticing that reallocating credit towards bigger loans might be inefficient for multiple reasons. First, it might increase firm leverage, increasing incentives to take riskier investment projects. Second, bank expertise in providing small-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, which increases bank risk-taking incentives.

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 micro and small firm credit is paid on a monthly basis, and loan repayment starts immediately the month after loan origination, the share of NPL is highly sensitive to financial conditions. Our results are reported in columns (5) and (6) of Table 9. We find that one SD 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 banks do not loose in terms of market expertise when reallocating credit. Overall, our results show that 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. In the next section, we further explore the response of firm performance by estimating the real effects of the policy. This allows us to test additional margins through which lending rate caps affect the economy.

5.4 Real Effects

In the previous sections, we documented that lending rate caps generate winners and losers in financial markets. For example, risky firms are excluded from bank credit markets, while ex-ante safe and new borrowers obtain more credit in highly concentrated locations. In this section, we estimate the real effects of this policy. It is worth noticing that the observed decline in delinquent debt does not imply higher growth rates. Indeed, excluding ex-ante risky borrowers could lead to lower economic growth if, for example, such risk correlates positively with productivity.

5.4.1 Conceptual framework

Entrepreneur are now heterogeneous not only in terms of risk but also in productivity z. Our aggregate credit demand becomes:

$$Q(r^{\ell}) = \xi r^{\ell^{-\frac{1}{1-\alpha}}} \tag{15}$$

where $\xi = \alpha^{\frac{1}{1-\alpha}} \int\limits_{z} z^{\frac{1}{1-\alpha}} dF(z)$.

The banking sector is similar as before, banks take the demand as given and compete a la Cournot. Thus, interest rates without and with the cap are similar to those in equations (5) and (8), respectively. Then, aggregate output without the cap is given by:

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

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. Thus, market concentration distorts the allocation of capital in the economy.

As we showed before, the interest rate cap will harm some borrowers kicking them out of credit markets and will benefit other firms from lower interest payments. In this new setting, firms are heterogeneous in productivity. Then, benefited and harmed firms may have different productivity levels. Thus, aggregate output with the cap is given by:

$$Y_R = \Lambda \times \int\limits_{z} \int\limits_{0}^{\sigma^B} ((1-\sigma)z)^{\frac{1}{1-\alpha}} \, dF_{(z,\sigma)} + \int\limits_{z} \int\limits_{\sigma^B}^{\sigma^E} (1-\sigma) z^{\frac{1}{1-\alpha}} \left[\frac{\alpha}{\overline{r}}\right]^{\frac{\alpha}{1-\alpha}} dF_{(z,\sigma)} \tag{16}$$

Thus, the impact of the lending rate cap on aggregate output, $\Delta = Y_R - Y$, is given by:

$$\begin{aligned} \Delta = \int\limits_{z} \int\limits_{\sigma^B}^{\sigma^E} \left\{ (1-\sigma) z^{\frac{1}{1-\alpha}} \left[\frac{\alpha}{\overline{r}}\right]^{\frac{\alpha}{1-\alpha}} - \Lambda\left((1-\sigma)z\right)^{\frac{1}{1-\alpha}} \right\} dF_{(z,\sigma)} \\ - \Lambda \times \int\limits_{z} \int\limits_{\sigma^E}^{1} ((1-\sigma)z)^{\frac{1}{1-\alpha}} \, dF_{(z,\sigma)} \end{aligned} \tag{17}$$

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. Notice that the correlation between risk and productivity is crucial to understand the real effects of the lending rate cap. If highly productive firms are more concentrated over medium-risk values (i.e., stayers benefited from lower rates), then the first term will dominate. In this context, the cap will improve the allocation of capital in the economy. On the other hand, if highly productive firms are actually the riskiest ones (i.e., firms excluded from credit market), then the second term might dominate. In that case, the interest rate cap will increase capital misallocation.

5.4.2 Empirical results

To empirically study the real impact of the policy, we start by aggregating our data up to the local credit market level and measuring the response of sales and capital.

A first challenge when using tax reports is that we have a different definition of small business than we did in our credit registry data. We overcome this challenge by keeping all firms that obtained a small business loan at least once from 2019, the first year of our credit registry, to 2021, the year of the regulation. Then, we aggregate our annual tax reports to the province level and estimate equation (14) using sales and capital as our dependent variables.

Table 10 shows our results. We can observe that bank concentration also shapes the response of real outcomes. Columns (1) and (3) show the average response of sales and capital, respectively. These effects are small and statistically insignificant. On the other hand, columns (2) and (4) show the treatment effect on the average location, and interacts treatment with a demeaned and standardized measure of HHI. We can see that the degree of competition determines the real impact of lending rate caps in local credit markets. While the responses of sales and capital are insignificant in locations with the average HHI, one SD higher treatment leads to a 7 percent increase in sales in cities with one SD higher concentration relative to the mean. Capital accumulation explains this effect, increasing by 8 percent in concentrated locations. Our results are consistent with the expansion in credit documented in the previous section. Figure 14 shows event-study graphs associated to our average effects. We can see that the expansion of capital and sales in concentrated locations occurs after the regulation of lending rate caps, while the interaction of treatment and HHI did not play any role in the evolution of these outcomes before the reform.

5.4.3 Distributional effects in the real economy

We showed in our conceptual framework that the policy can improve the allocation of resources in the economy by reducing financial costs for high-return firms, allowing them to grow faster. However, if risky firms are those with high returns, we showed that the implementation of an interest rate cap can actually worsen off the allocation of capital. We look at the response of firm-level outcomes to shed light on the distributional impact of lending rate caps in the real economy.

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 define marginal revenue productivity of capital for firm i operating in industry j as follows:[19]

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

This definition of marginal revenue productivity assumes that small firms belonging to the same industry operate the same Cobb-Douglas technology. Thus, we can rank firms operating in the same industry according to their sales over capital ratios, as this is proportional to MRPK. Then, we split firms in terciles within industries: low MRPK, middle MRPK and high MRPK (Bau and Matray (2020)).

Table 11 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

[19] 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.

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, we estimate the following equation:

$$\ln Y_{ijct} = \beta \times \text{Above}_i \times \text{Post}_t + \delta_i + \delta_{x(i)t} + \delta_{jt} + \delta_{ct} + u_{ijct} \tag{18}$$

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 represent time-invariant firm fixed effects and time-varying industry j, city c, and firm size tercile $x(i)$ fixed effects.

We report our results in Table 12. 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 distirbutional 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 small and statistically insignificant, suggesting that the impact of capital accumulation on sales might be slow for the average borrower. Finally, low MPRK firms shrink, deaccumulating capital by 19 percent and reducing sales by 38 percent.

Our results indicate that lending rate caps can improve the allocation of capital in developing countries. Small firms with high MRPK can borrow more and accumulate more capital, while firms with low MRPK are excluded from credit markets and shrink after the reform.

6 Conclusions

Small firms in developing countries usually pay 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 in emerging markets. In this paper, we study the effects of a lending rate cap in Peru that affected 26 percent of small firm 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. Banks reallocate credit away from small-size loans towards bigger loans, and by doing so, they keep their market share constant despite a 23 percentage point decline in interest rates. Banks replace risky borrowers with safe and new clients in concentrated markets, leading to an expansion of credit supply and real outcomes after the policy, contrasting with the negative effects in more competitive cities. Finally, we find that small entrepreneurs with high returns to capital accumulated more of this input and grew faster after the policy, while small businesses with low returns to capital shrink. Our results reveal that the aggregate effects of interest rate caps depend critically on the degree of local bank competition and the allocation of capital across firms with different risk-productivity profiles.

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Appendix A. Tables

Table 1: Characteristics of Small Firm Loans

	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 Lending

	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 loans. 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)
Small & Med	44.23***	38.70***	36.61***	21.55***	
	(0.06)	(0.06)	(0.05)	(0.15)	
$\text{HHI}_{\text{Small \& Med}}$			7.95***	4.46***	
			(0.03)	(0.04)	
Risky			15.38***	9.25***	
			(0.08)	(0.14)	
(Small & Med) $\times$ $\text{HHI}_{\text{Small \& Med}}$				5.51***	3.83***
				(0.05)	(0.05)
(Small & Med) $\times$ Risky				8.78***	6.13***
				(0.17)	(0.16)
Fixed Effects					
Time and currency	✓	✓	✓	✓	✓
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 and currency fixed effects. Columns (2)-(4) include industry fixed effects, and column (5) includes size, risk, and city fixed effects. Small & Med is a dummy variable equal to one for small and medium size loans, whose value is below USD 1061, which is the 66th percentile of the pre-reform loan size distribution. $\text{HHI}_{\text{Small}}$ is the Herfindahl-Hirschman index of small and medium 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 Small-Size Loans

	Interest rate		Loan value		Number of loans	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treatment}_k \times \text{Post}_t$	-6.17***	-5.75***	-0.08**	-0.09**	-0.07**	-0.08**
	(1.60)	(1.44)	(0.03)	(0.03)	(0.03)	(0.03)
Fixed Effects						
Size-bin×Industry×City	✓	✓	✓	✓	✓	✓
Month	✓	✗	✓	✗	✓	✗
Industry×City×month	✗	✓	✗	✓	✗	✓
Observations	471,432	449,920	471,432	449,920	471,432	449,920

Notes. This table reports our results from estimating equation (9). We define 18 loan-size bins with equal number of observations based on the pre-reform distribution of loans. Interest rates are weighted by loan-size. Treatment_k is an indicator variable equal to one for small and medium size loans ($k \leq 12$, or bottom and middle terciles) and Post_t equals one after June 2021. We include a vector of time-invariant fixed effects at the size-bin×industry×city level and a vector of time-varying fixed effects at the industry and city level. Standard errors are clustered by size-bin. *, **, and *** denote 10, 5, and 1 percent statistical significance, respectively.

Table 5: 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	✓	✓	✓	✗	✗	✗
Month	✓	✓	✓	✗	✗	✗
Province × Industry	✗	✗	✗	✓	✓	✓
Industry × Month	✗	✗	✗	✓	✓	✓
Region × Month	✗	✗	✗	✓	✓	✓
City-size × Month	✗	✗	✗	✓	✓	✓
Observations	1,548	1,548	1,548	120,828	120,828	120,828

Notes. This table reports our results from estimating equation (12). 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 (12) incorporating city and time fixed effects, and columns (4) to (6) estimate equation (13) 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 6: Average Effect of Lending Rate Caps on Total Loans

	Province-level			Province × Industry-level		
	MPGR	Contr. small	Contr. big	MPGR	Contr. small	Contr. big
	(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	✓	✓	✓	✗	✗	✗
Month	✓	✓	✓	✗	✗	✗
Province × Industry	✗	✗	✗	✓	✓	✓
Industry × Month	✗	✗	✗	✓	✓	✓
Region × Month	✗	✗	✗	✓	✓	✓
City-size × Month	✗	✗	✗	✓	✓	✓
Observations	1,570	1,570	1,570	182,080	182,080	182,080

Notes. This table reports our results from estimating equation (12). 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 (12) incorporating city and time fixed effects, and columns (4) to (6) estimate equation (13) including industry, region, and city-size fixed effects. All specifications include standardized HHI interacted with Post_t. Contr. small refers to the contribution of small-size loans to city-level loan growth, and Contr. big denotes the contribution of bigger loans, i.e., medium and large loans. Small-size loans are those whose value is below 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 7: Average Effect of Lending Rate Caps on Total Loans

	Small-size loans			Bigger 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	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓
Observations	1,550	1,550	1,550	1,570	1,570	1,570

Notes. This table reports our results from estimating equation (12). 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 small-size loans and columns (4) to (6) estimate the response of bigger loans, i.e., medium and large loans. Small-size loans are those whose value is below 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 8: Lending Rate Caps and Bank Market Power

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

Notes. This table reports our results from estimating equation (14). 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. small refers to the contribution of small-size loans to city-level loan growth, and Contr. big denotes the contribution of bigger loans, i.e., medium and large loans. Small-size loans are those whose value is below 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 9: Lending Rate Caps and Firm Risk

	Num. of firms		Share of risky firms		Share of NPL	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment$_c$× 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$_c$× HHI$_c$× Post$_t$		0.018*		-0.001		-0.001
		(0.010)		(0.001)		(0.001)
Fixed Effects						
Province	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓
Observations	1,570	1,570	1,548	1,548	2,826	2,826

Notes. This table reports our results from estimating equation (14). 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 10: Real Effects of Lending Rate Caps

	Sales		Capital	
	(1)	(2)	(3)	(4)
Treatment$_c$× Post$_t$	-0.019	0.010	-0.027	0.006
	(0.017)	(0.021)	(0.018)	(0.016)
Treatment$_c$× HHI$_c$× Post$_t$		0.067*		0.080***
		(0.035)		(0.028)
Fixed Effects				
Province	✓	✓	✓	✓
Year	✓	✓	✓	✓
Observations	785	785	785	785

Notes. This table reports our results from estimating equation (14). We consider firms obtaining a small business loan at least once between 2019 and 2021, and then 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 11: 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 only firms obtaining a small business loan between March and June 2021, and reporting taxes in 2020.

Table 12: Distributional Effects of Lending Rate Caps

	All Small Firms		High-MRPK		Low-MRPK	
	Capital (1)	Sales (2)	Capital (3)	Sales (4)	Capital (5)	Sales (6)
$\text{Above}_i \times \text{Post}_t$	0.070 (0.079)	-0.118 (0.103)	0.193* (0.113)	0.025 (0.133)	-0.186* (0.105)	-0.379** (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 (18). 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.

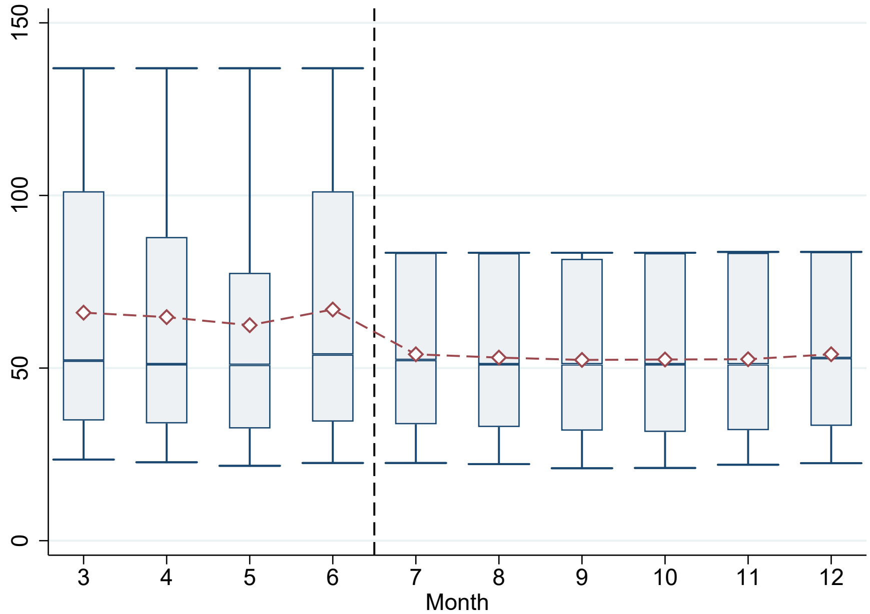
Table 13: Distributional Effects of Lending Rate Caps

	All Small Firms		High-MRPK		Middle-MRPK		Low-MRPK	
	Capital (1)	Sales (2)	Capital (3)	Sales (4)	Capital (5)	Sales (6)	Capital (7)	Sales (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 (18). 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.

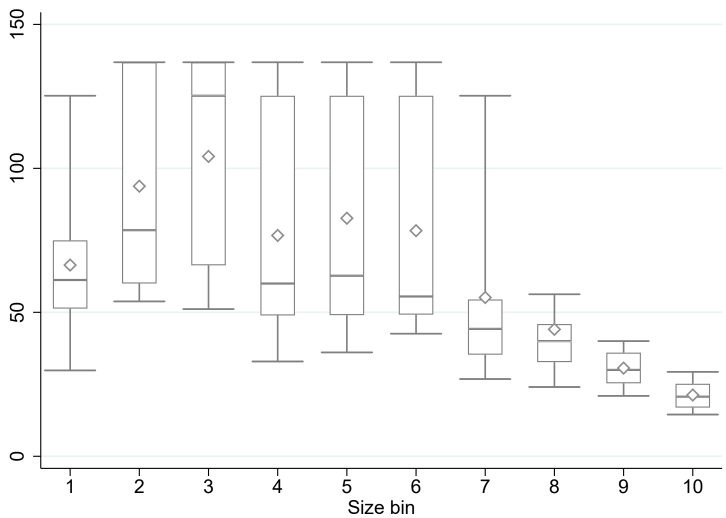
Appendix B. Figures

Figure 1: Distribution of Interest Rates



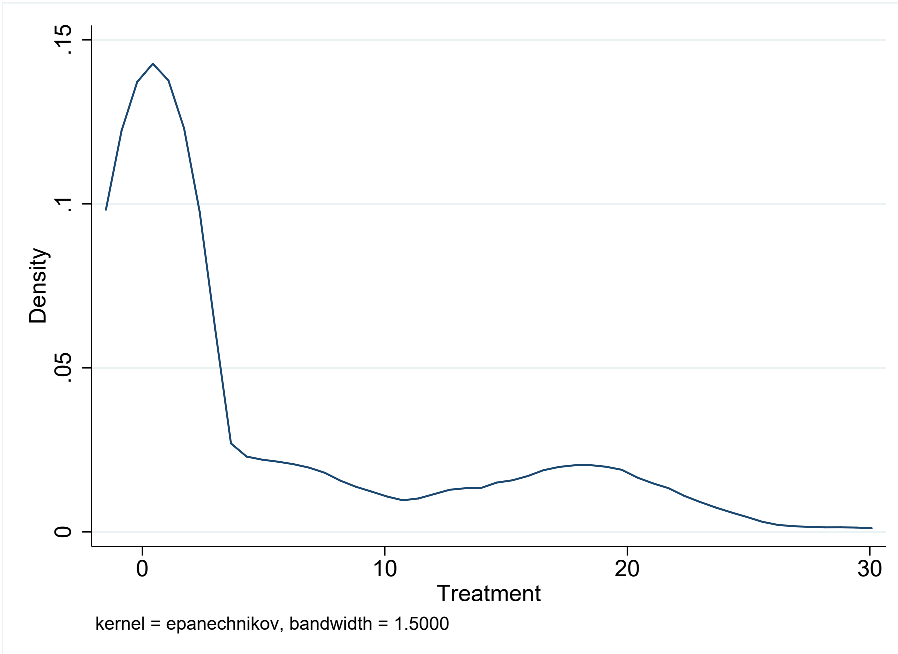
Note: This figure shows the distribution of annualized interest rates in 2021. Each box plots the percentiles 10th, 25th, 50th, 75th, and 90th of the distribution of interest rates corresponding to each month from March to December 2021. The connected red diamonds show the simple average interest rate.

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



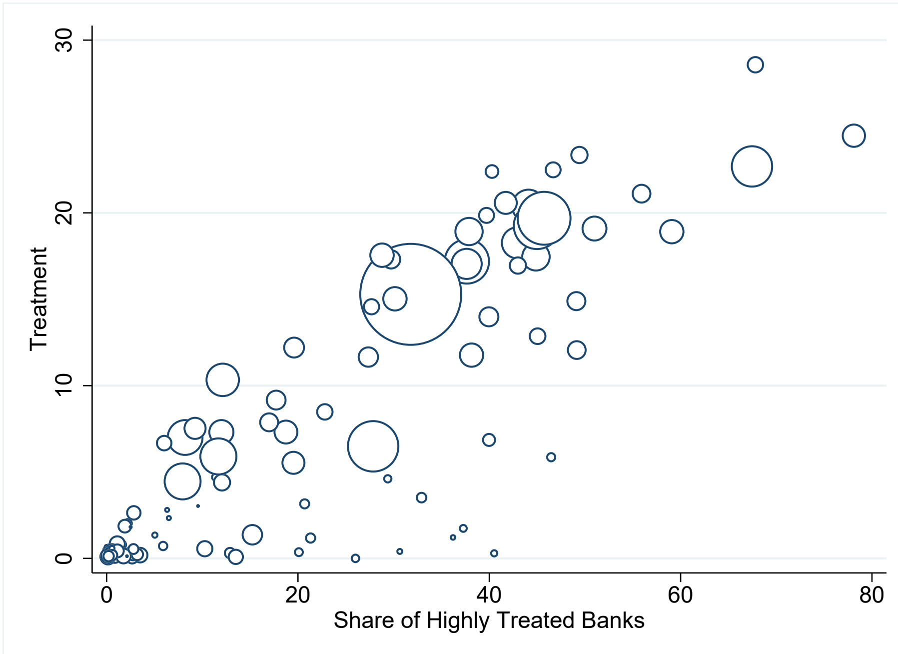
Note: This figure plots the distribution of annualized interest rates for each decile of the loan-size distribution. Boxplots show the percentiles 10th, 25th, 50th, 75th, and 90th, while the diamonds represent the average interest rate.

Figure 3: Density of City Exposure to Lending Rate Caps



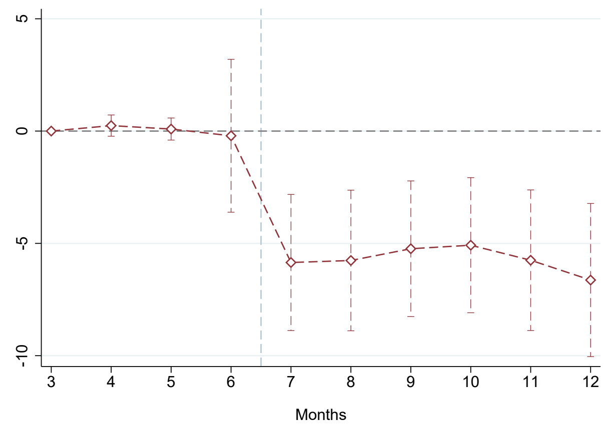
Note: This figure shows the distribution of treatment defined as the percentage decline in annualized interest payments of small business loans required to satisfy the regulation of lending rates between March and June 2021, as defined in equation (11).

Figure 4: City treatment and presence of highly treated banks

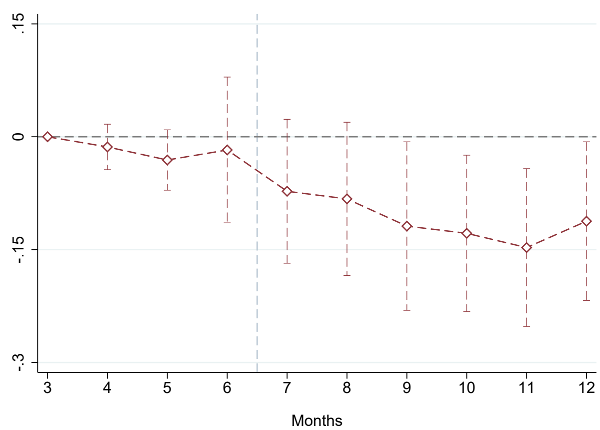


Note: This figure plots the relationship between treatment and highly treated banks' market share across cities. Treatment is the standardized decline in annualized interest payments necessary to satisfy the regulation between March and June 2021. Highly treated banks are those whose exposure is above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

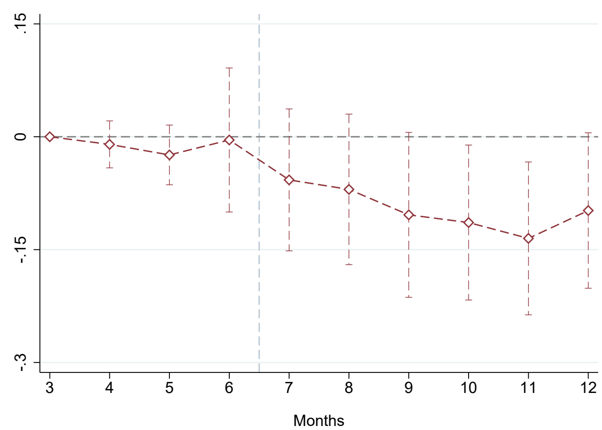
Figure 5: Event Study Graphs for the Loan-Level Effects of Lending Rate Caps



(a) Interest rates



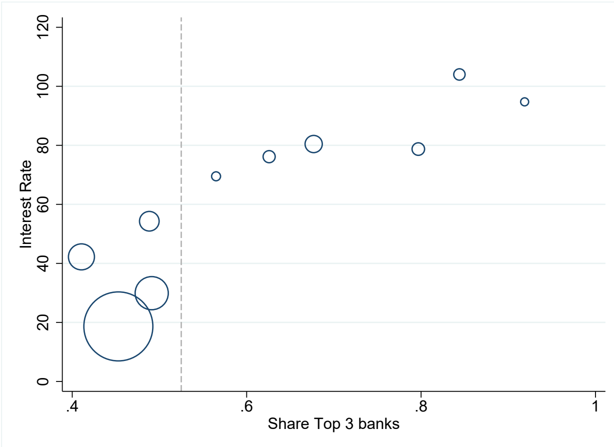
(b) Loan value



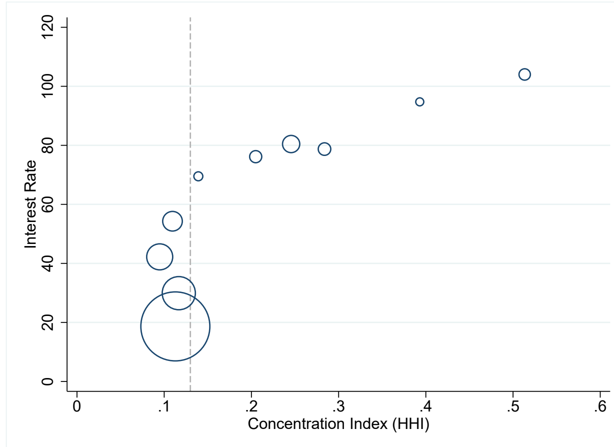
(c) Num. of loans

Notes. This figure reports the event study graph for the average loan-level effects of lending rate caps on interest rates, total loan value, and number of loans, using equation (9) with size-bin×region×industry and region×industry×time fixed effects. The policy was implemented in June 2021. We define 18 loan-size bins with equal number of observations based on the pre-reform distribution of loans. Treatment$_k$ is an indicator variable equal to one for small and medium size loans ($k \leq 12$, or bottom and middle terciles). Each dot is the coefficient on the interaction between being treated and month fixed effects. The confidence interval is at the 95% level. Standard errors are clustered by size-bin.

Figure 6: Interest rates and size-bin specific characteristics



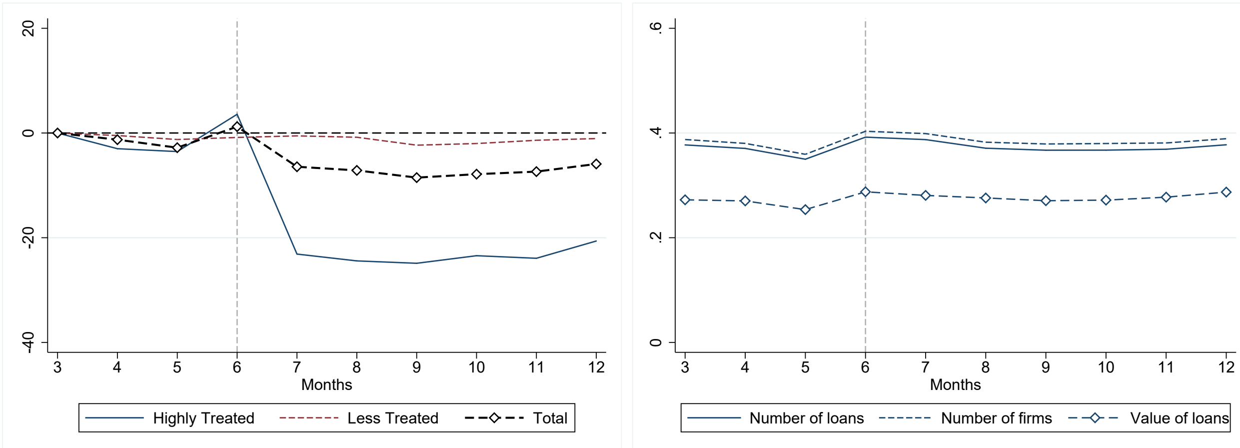
(a) Share top 3 banks



(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).

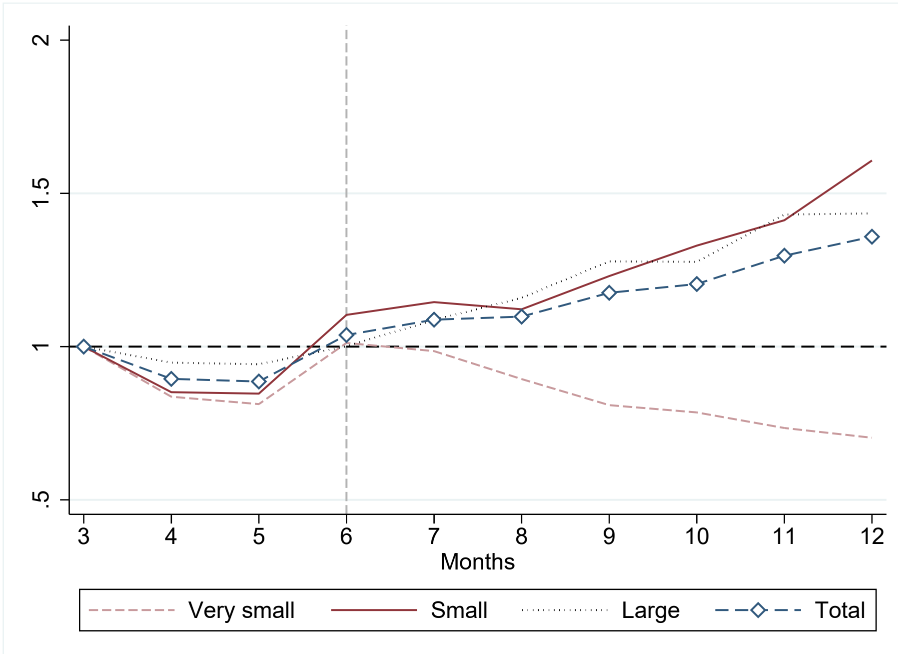
Figure 7: Interest Rates and Treated Banks' Market Share



(a) Interest Rate (b) Market Share

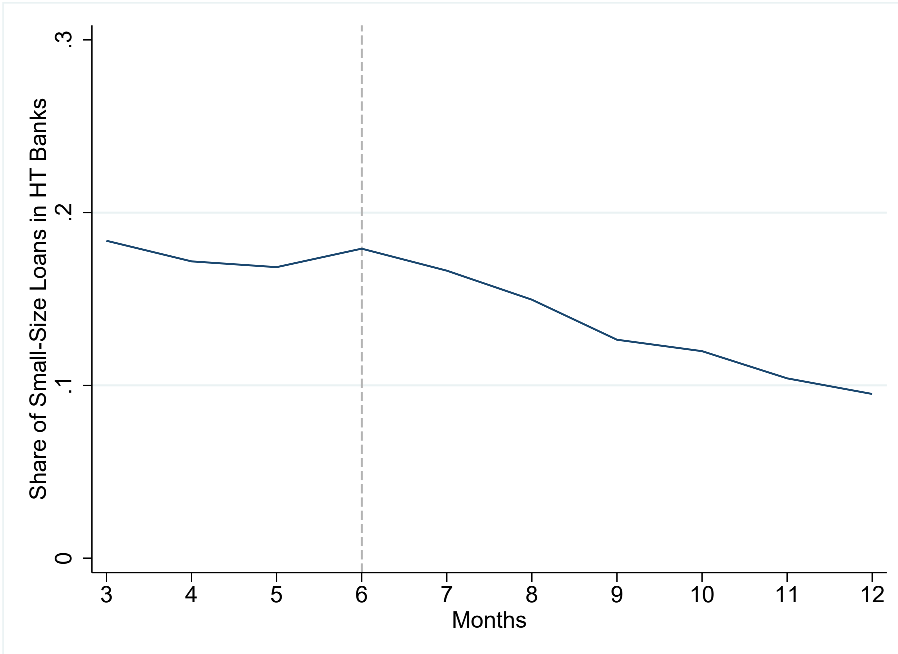
Note: This figure plots interest rates and market share of highly treated banks, defined as those with exposure higher that 1 percent, and less treated ones. Exposure is defined by equation (10). Panel (a) plots the weighted average interest rate, and panel (b) plots highly treated banks' market share 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 8: Highly Treated Banks' Lending by Loan-Size



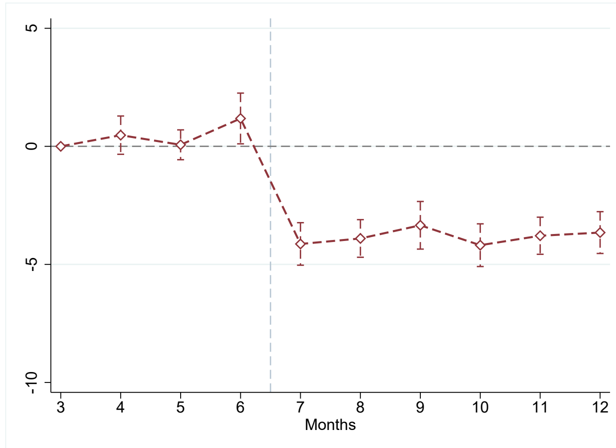
Note: This figure plots the growth rate of loans in different size-bins relative to their values in March 2021, the first month of our data. The light red dashed line denotes small-size loans in the bottom tercile (i.e., below approximately USD 575). The solid red line represents medium-size loans in 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 9: Small-Size Loans in Highly Treated Banks Portfolios

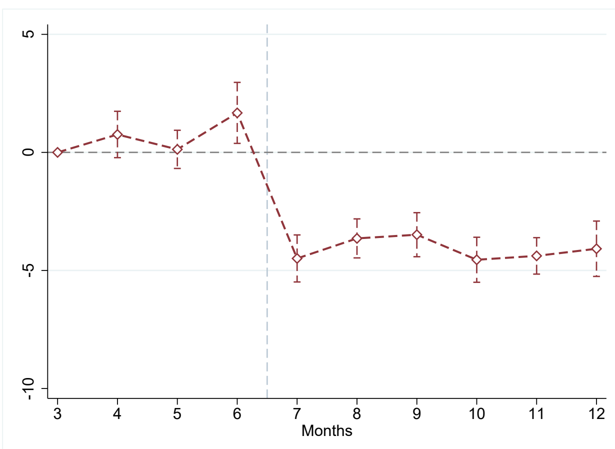


Note: This figure plots the share of small-size loans in highly treated banks portfolios over time. Small-size loans are those whose value is below the bottom tercile of the pre-reform loan-size distribution (below USD 575). Highly treated banks are those whose exposure is above 1 percent.

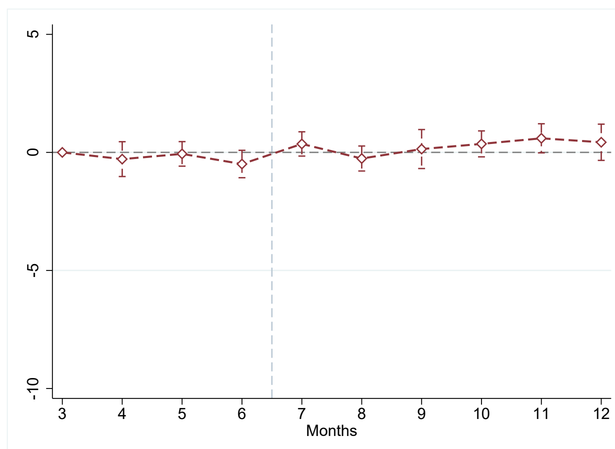
Figure 10: Event Study Graphs for the Average Effect of Lending Rate Caps on Interest Rates



(a) Interest rates



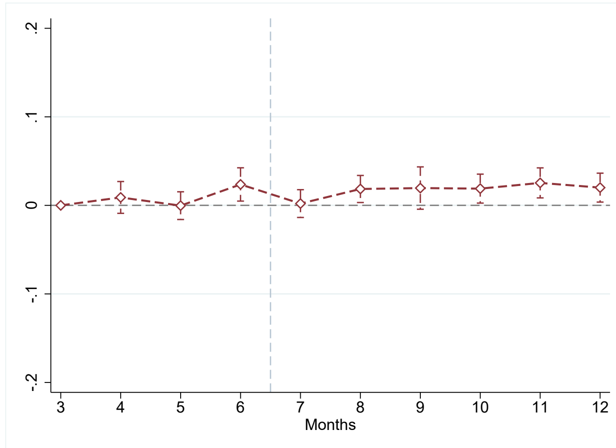
(b) Highly Treated Banks



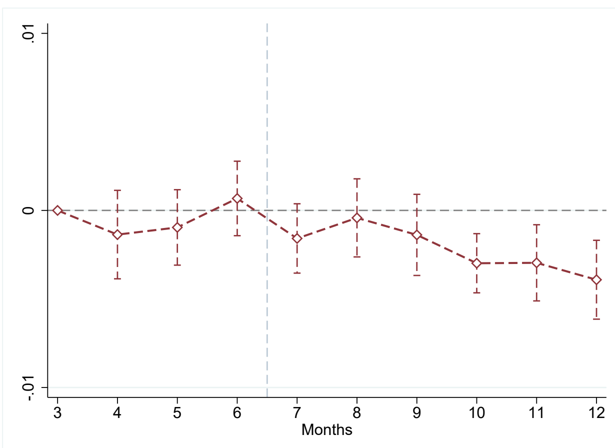
(c) Low Treated Banks

Notes. This figure reports the event study graph for the average city-level effects of lending rate caps on interest rates, using equation (13). 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.

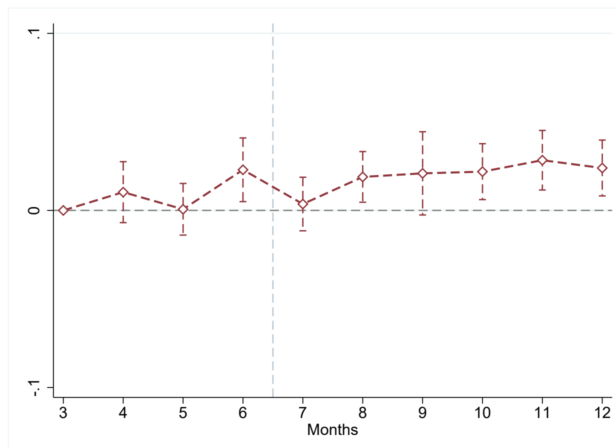
Figure 11: Event Study Graphs for the Average Effect of Lending Rate Caps on Loan Value



(a) Loan Value



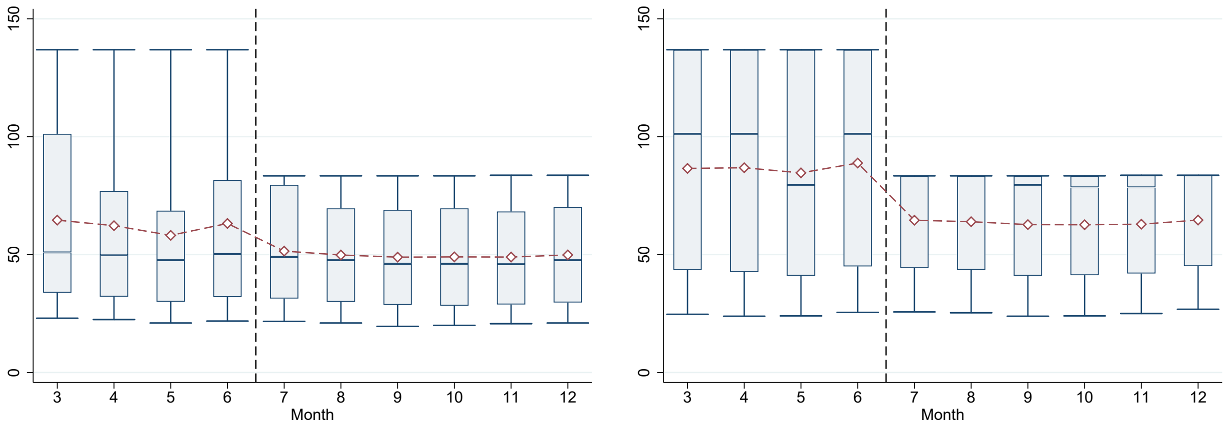
(b) Small-size loans



(c) Bigger loans

Notes. This figure reports the event study graph for the average city-level effects of lending rate caps on interest rates, using equation (13). Treatment$_c$ is the standardized decline in annualized interest payments necessary to satisfy the regulation between March and June 2021. Small-size loans are those whose value is below 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 12: 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 13: Interest rate schedule

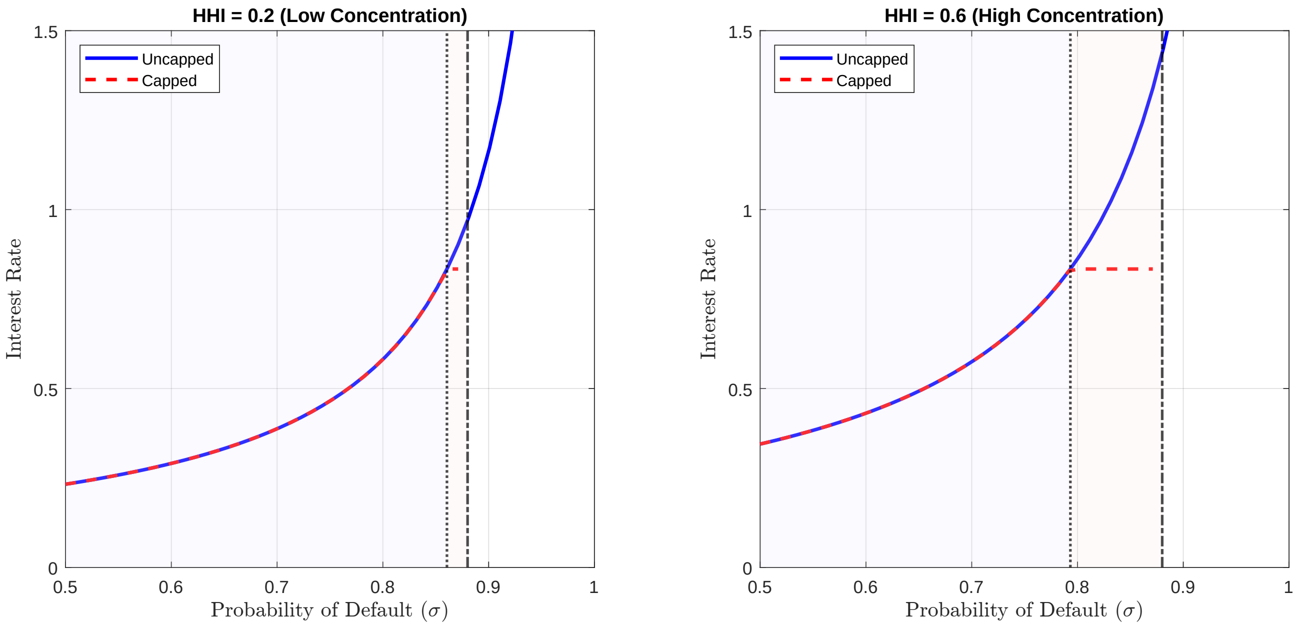
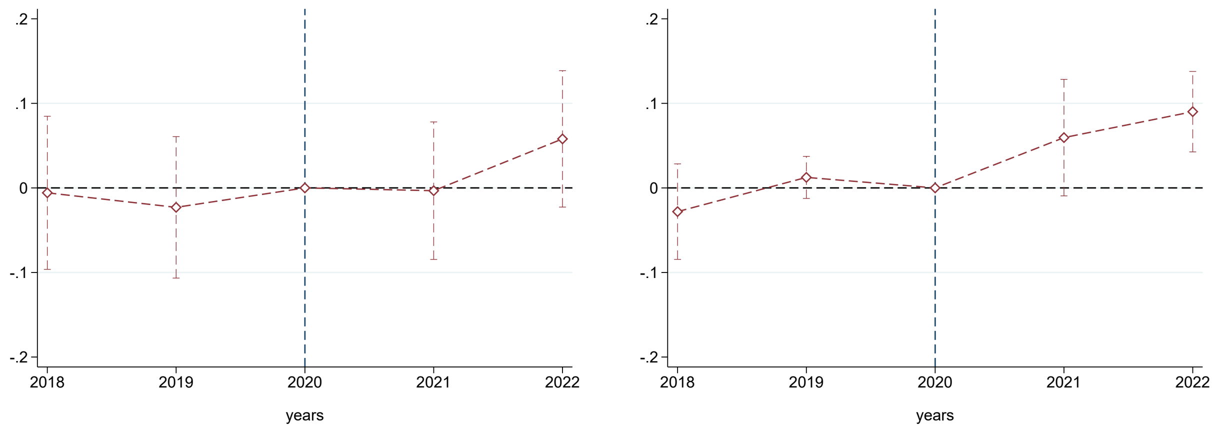


Figure 14: Event Study Graphs for the Average Effect of Lending Rate Caps on Real Outcomes



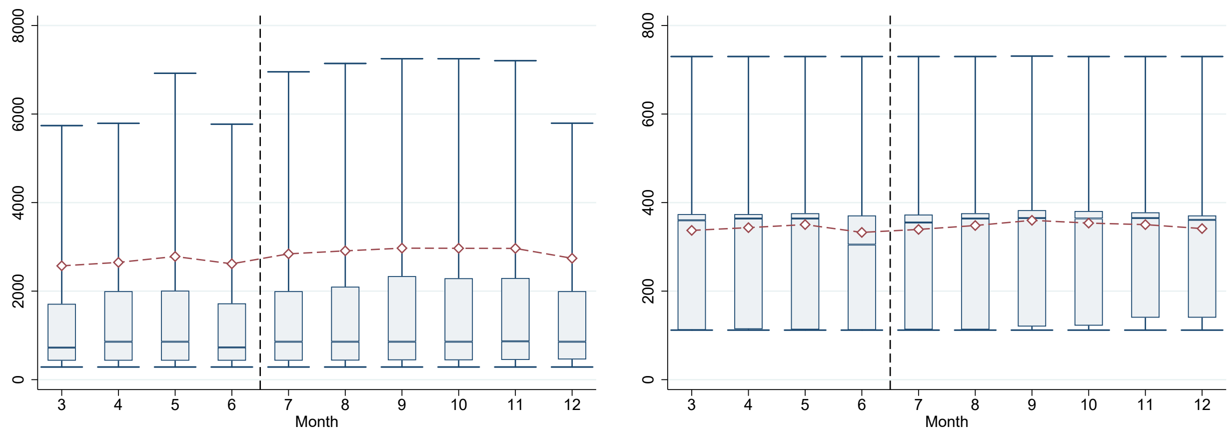
(a) Sales

(b) Capital

Notes. This figure reports the event study graphs for the real effects of lending rate caps using equation (14). The policy was implemented in 2021. Each dot is the coefficient on the interaction between treatment, HHI, and year fixed effects. We consider firms obtaining a small business loan at least once between 2019 and 2021, and then aggregate outcomes up to the city level. HHI is expressed in standard deviations from the mean. Standard errors are clustered at the city level. The confidence interval is at the 95% level.

Appendix C. Additional Figures and Tables

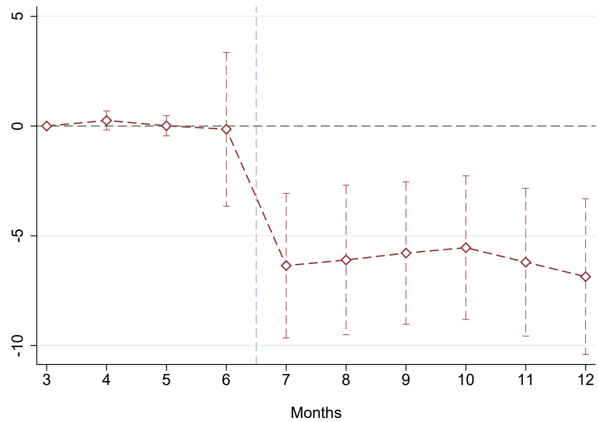
Figure C1: Distribution of Loan Size and Duration



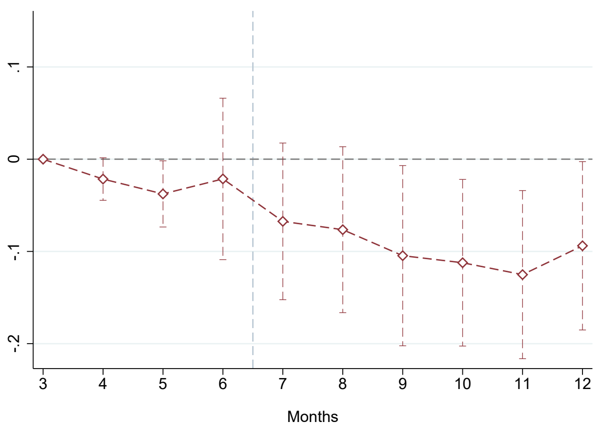
(a) Loan Size (b) Loan Duration

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.

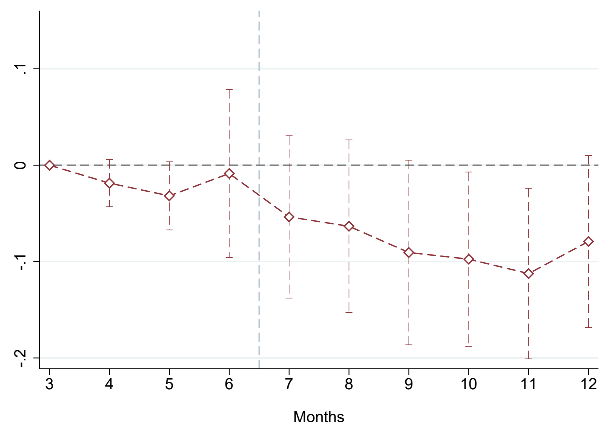
Figure C2: Event Study Graphs for the Average Effect of Lending Rate Caps on Loan-level Outcomes



(a) Interest rates



(b) Loan value



(c) Num. of loans

Notes. This figure reports the event study graph for the average loan-level effects of lending rate caps on interest rates, total loan value, and number of loans, using equation (9) with size-bin×region×industry and time fixed effects. The policy was implemented in June 2021. We define 18 loan-size bins with equal number of observations based on the pre-reform distribution of loans. Treatment$_k$ is an indicator variable equal to one for small and medium size loans ($k \leq 12$, or bottom and middle terciles). Each dot is the coefficient on the interaction between being treated and month fixed effects. The confidence interval is at the 95% level. Standard errors are clustered by size-bin.