Risk-shifting Incentives Under Government Credit Guarantees

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February 25, 2025

Abstract

This paper studies the risk-shifting behavior of banks under the FOGAPE COVID credit guarantee program in Chile, a large-scale program implemented during the pandemic. Exploiting the program's design, which features varying guarantee rates based on firm size, and using detailed tax and credit data, we investigate whether banks reclassify firms to obtain higher guarantee rates.

Our findings indicate significant reclassification of firms into the small-size category, which benefits from higher guarantee rates. This reclassification is more likely among firms with an existing credit history with the bank.

We develop a structural model to understand how these incentives vary by firm characteristics and to improve the program's design. Our results have important policy implications, suggesting that credit guarantee programs should carefully balance improving credit access with the potential for bank's moral hazard.

1 Introduction

There is strong evidence that small and medium-sized enterprises (SMEs) are disproportionally affected by abrupt changes in the macroeconomic environment (Gertler and Gilchrist (1994); Deyoung et al. (2015)). In response, a widely used tool by governments during crisis times is the enhancement of their partial credit guarantees (PCG) programs (OECD (2013); Cao et al. (2024)), which foster credit access by partially insuring the lender in case of default (Mullins and Toro (2018)). Because most PCG programs involve the private allocation of guarantees, during times of distress, governments face a trade-off between a fast and broad implementation of these programs and increasing distortions of private incentives that can cause inefficient risk-shifting to taxpayers. Although previous studies have assessed the appropriateness of these interventions from the perspective of this trade-off (Joaquim and Netto (2021); Griffin et al. (2023); Huneeus et al. (2022)), the determinants of the costs and benefits that lenders face in shifting risk to taxpayers, which largely depend on the design of these programs and critically affect their performance, has been so far neglected.

In this paper, we study banks' incentives, in the form of benefits and costs to shift risk by allocating loans and government guarantees under the Fogape COVID program in Chile during COVID-19, a large intervention equivalent to 9.7% of GDP. The unique design of the program, which at its start featured a fixed interest rate along with deductible fees that varied with firm size, and a rich dataset that combines borrowers' financial and tax information with loan applications, credit conditions and default before and after the intervention, allows us to estimate these costs and benefits.

In particular, we focus on banks' decisions to reclassify firms as small- or medium-sized in opposition to the program's administrator own classification, where small firms carry higher government guarantees and therefore larger credit risk for the government. However, reclassification is costly as it has to be justified in case of default, and there is a probability that the administrator will deny the payment. We develop a structural model of debt repayment, loan size and reclassification costs to estimate the implied costs of bypassing the program's rules. Then, we analyze how these costs vary along different dimensions, such as public and private information on the firm, and the program's features, such as deductible fees. Finally, we analyze counterfactual program designs that could potentially increase coverage while reducing risk shifting.

We start by documenting banks' reclassification behavior. We show that in most cases banks comply with the program administrators' firm classification and that when they are allowed to exercise discretion, they do it. This result suggests that, even in the case of relatively small loans and a lending operation that involves the processing of a massive number of loans in a short period of time, banks are able to actively manage their lending activity on an individual basis. However, there is also a significant number of reclassifications, which vary by bank. As expected, most of these reclassifications are toward higher government guarantees, although not all of them, which suggests that some program characteristics, such as differential deductible fees depending on firm size, are relevant in shaping banks' incentives.

We then estimate the marginal costs of evaluating a loan and reclassifying a firm, potentially against the administrator's classification. We show that these costs increase significantly and discontinuously when the reclassification entails challenging the administrator's classification, which suggests that the threat of ex-post auditing of the guarantees is effective in aligning banks' incentives.

The paper is structured as follows. After this brief introduction, the next section describes Chile's FOGAPE COVID government guarantee program. Section 3 presents the rich administrative data we use and defines our working sample. Next, we provide reduced-form evidence of firm size reclassification. In section 5, we develop a model that explains our reduced-form evidence. We end the paper with conclusions.

2 FOGAPE COVID Guarantee Program

The Small and Medium Enterprise Guarantee Fund (FOGAPE) was created in 1980. FOGAPE guarantees loans, leasing operations, and other financial products that public and private financial institutions offer to small and medium-sized firms. The primary funding sources of FOGAPE are government contributions, fees for guarantee services, and returns on fund investments. Banco Estado, Chile's main public bank, manages the program, and the Financial Market Commission (CMF), the country's financial regulator, supervises it.

FOGAPE allocates guarantees to banks, who decide on firm applications based on their internal criteria. Over time, the program has adjusted the borrower's eligibility, coverage rates, and usage restrictions.

In response to the COVID-19 pandemic, the Chilean government expanded FOGAPE's size and scope to enhance firms' access to financial markets. On April 24, 2020, Law 21,229 temporarily modified FOGAPE (FOGAPE COVID). This law increased the fund's capital by USD 3 billion, allowing for up to USD 33 billion in guarantees—approximately 10 percent of Chile's GDP. FOGAPE COVID expanded eligibility to include medium-sized and some large firms (up to 1,000,000 UF in sales), which had traditionally been ineligible.[1] To qualify for the program, firms must meet the following eligibility requirements: they cannot have overdue loan payments exceeding 30 days within the banking system, they must not have an individual risk classification of C1 or lower, and they cannot be undergoing reorganization or liquidation.[2]

FOGAPE COVID has established several conditions for loans granted with government guarantees. These include a maximum interest rate of the monetary policy rate (MPR) plus 3%, a limit on the total amount of FOGAPE COVID loans based on the firm's annual sales (see Table A.1 in the Appendix A for details), financing restricted to working capital only, a grace period of at least six months, and loan terms between 24 and 48 months.[3]

The program stipulates that guarantee rates are determined by firm size, with smaller firms receiving higher guarantee rates. There are four size categories: micro (below UF 2,400 in annual sales), small (UF 2,400–25,000), medium (UF 25,000–100,000), large I (UF

[1] UF is a unit of account used to adjust values for inflation in Chile. As of May 2024, 1 UF is approximately USD 30.

[2] Banks must assign a risk rating to borrowers when their exposure to the borrower is significant. Borrowers with overdue payments exceeding 90 days or those likely to require debt restructuring receive an individual risk rating ranging from C1 to C6.

[3] In April 2020, the MPR was 0.5%, resulting in an effective interest rate of 3.5%, which was favorable compared to market rates for most firms.

100,000–600,000), and large II (UF 600,000–1,000,000). The guarantee rate for loans to micro and small firms is 85%. The guaranteed rate for loans to medium-sized firms is 80%, for large I firms it is 70%, and for large II firms it is 60%. The program also includes a deductible for banks on each size-specific portfolio of guaranteed loans, designed to ensure that banks internalize some of the costs in case of default. Initially, these deductibles were higher for smaller firms, likely due to their higher default risk. However, as of June 30, 2020, all firm sizes were subject to a standardized deductible of 2.5%. The deductible significantly impacts the effective guarantee rates. For example, for small firms with an 85% guarantee and a 2.5% deductible, a 20% default rate results in an effective coverage rate of 75%. Table 1 presents the guarantee rates and deductibles by firm size.

Table 1: Guarantee Rates and Deductibles by Firm Size

Type of firms	Net annual sales (UF)		Guarantee rate (%)	Deductible (%)
	Above	Below		
Micro and small	0	25,000	85	5 (2.5 after 6/30/2020)
Medium	25,000	100,000	80	3.5 (2.5 after 6/30/2020)
Large I	100,000	600,000	70	2.5
Large II	600,000	1,000,000	60	2.5

Notes: This table reports guarantee rates and deductibles for FOGAPE COVID by firm size.

A distinctive feature of the program is the flexibility in calculating annual sales for firms, which can be based on one of three reference periods: October 2018 to September 2019, January 2019 to December 2019, or the 12 months preceding the loan application. Banks can use an application run by Chile's tax authority (SII) to query a firm's classification using its ID for any of the reference periods. Banks may consult the application several times, querying for different annual sales measures. Moreover, banks may use a classification different from the one suggested by the application if they have supporting information. This flexibility, combined with changes in effective coverage when firms change size categories, can incentivize banks to reclassify firms. The firm's repayment probability can influence such reclassification, as banks might find it more profitable to upgrade or downgrade a firm based on its likelihood of default. Documentation costs may also influence reclassification decisions.

To understand the program's impact on aggregate firms' credit access, Figure 1 shows the evolution of the commercial loans of FOGAPE and non-FOGAPE for the year 2020 in Chile.[4] Panel A shows that the COVID loans of FOGAPE were concentrated during the first four months of operation (May to August) and helped mitigate the contraction in credit

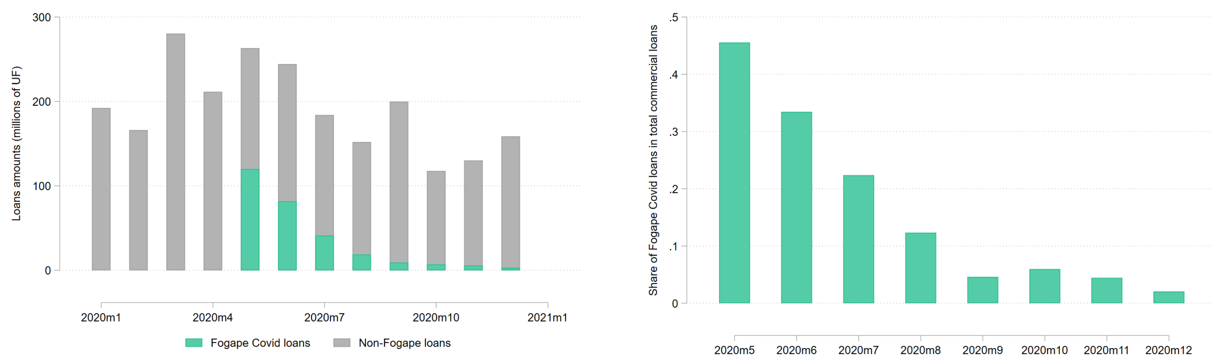
[4]We classify commercial loans as those extended to firms in Chilean pesos, US dollars, euros, or UF, excluding factoring loans and repurchase agreement operations.

caused by the pandemic. Panel B shows the share of FOGAPE COVID loans relative to all commercial loans. FOGAPE COVID loans represented 45% of commercial loans granted in May 2020 and 19% during the period from May to December 2020.

Figure 1: FOGAPE COVID vs. Non-FOGAPE COVID Commercial Loans

A. Loan amounts

B. Share of commercial loans



Notes: This figure shows the evolution of commercial loan amounts in Chile in 2020, categorized into FOGAPE COVID and non-FOGAPE COVID loans. The data includes commercial loans denominated in Chilean pesos, US dollars, euros, or UF, excluding factoring loans and repurchase agreement operations.

The importance of FOGAPE COVID as a funding source varied by firm size. It was more important for small- and medium-sized firms (42% and 39% of total commercial loans in May–December, respectively), followed by micro firms (22%), and lastly, large firms (14%).[5] The lower share for large firms is expected, as they may have access to other funding sources at costs similar to FOGAPE, and many large firms are not eligible for the program due to their size. The results for micro firms are more puzzling but may be related to eligibility conditions, such as the requirement of no overdue loan payments for 30 days to access the program or banks being more reluctant to finance these smaller firms even with government guarantees.

The financing conditions offered by FOGAPE COVID were quite advantageous, especially for smaller firms. In 2020, the average interest rate for FOGAPE loans was 3.5%, with an average loan term of 40 months. In contrast, the average interest rates for non-FOGAPE loans were significantly higher: 11.9% for micro firms, 10.6% for small firms, 8.3% for medium-sized firms, and 4.9% for large firms. The average loan terms were also shorter: 29 months for micro and small firms, 20 months for medium-sized firms, and 9 months for large firms.[6]

Figure 2 shows information about FOGAPE COVID loans by firm's classification.[7] When

[5] See Figure B.1 in appendix B.

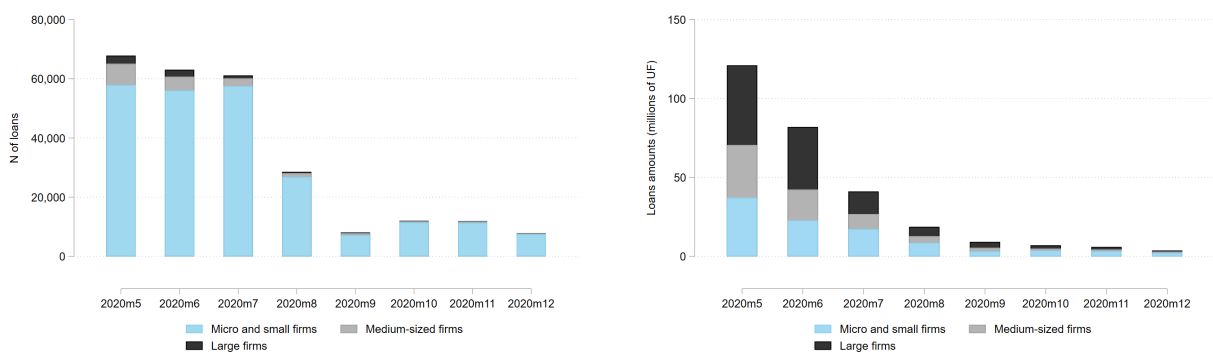
[6] Non-FOGAPE loans include commercial loans in Chilean pesos at a fixed rate, excluding factoring loans and repurchase agreement operations.

[7] For confidentiality reasons, we combined large I and large II firms into a single group called large firms.

we focus on the number of loans, panel A shows that most loans were granted to micro and small firms. In May–December 2020, 90% of the loans were granted to micro or small firms, 7% to medium-sized firms, and 3% to large firms. However, when we consider total loan amounts, the share of larger firms increases significantly (panel B). In May–December 2020, 34% of the total loan amounts were granted to micro or small firms, 25% to medium-sized firms, and 41% to large firms.

Figure 2: FOGAPE COVID Loans, by Firm Size

A. Loan count | B. Loan Amount



Notes: This figure shows the number and amount of FOGAPE COVID loans, categorized by firm type. Firms are classified based on their annual sales as follows: micro and small firms with sales below UF 25,000, medium-sized firms with sales between UF 25,000–100,000, and large firms with sales between UF 100,000–1,000,000.

There are also large differences in loan sizes across firm types. The average loan was UF 416 (approximately USD 16,000) for micro or small firms, UF 4,160 UF (approximately USD 166,000) for medium-sized firms, and UF 6,665 (approximately USD 665,000) for large firms.[8]

3 Data

We use several administrative datasets from different sources in Chile.

First, we use data on FOGAPE COVID loans from the Financial Market Commission (CMF), the financial supervisory agency in Chile. Banks participating in the program are required to report to the CMF every month, providing details on all loans granted under FOGAPE COVID and their characteristics. This dataset includes the bank ID, firm ID, operation date, loan characteristics (such as loan amount, interest rate, term, grace period, and guaranteed amount), and the firm's classification for FOGAPE (small, medium, large I,

[8]See Figure B.2 in appendix B.

or large II).

Second, we use data on firm debt (credit registry) from the CMF. Each month, banks must report the outstanding debt for each debtor, across various types of debt (e.g., contingent debt, commercial loans, leasing, or factoring), and classify it as either performing or non-performing (overdue by 90 days or deemed difficult to recover by the bank). In addition, banks report provisions for each debtor-type of debt combination, which are based on the probability of default and the loss given default, both of which depend on the bank's risk analysis of each debtor or group of debtors.

Using this data, we construct several key variables: a dummy for FOGAPE loan default (*default*), a dummy for whether the firm had a credit history with the lending bank prior to receiving the FOGAPE loan (*credit history with bank*), a dummy for whether the firm had a credit history with any bank (*credit history*), and the ratio of provisions to debt before the FOGAPE loan (*ratio provisions-debt*). A firm is classified as defaulting on the FOGAPE loan if the bank reports that its commercial debt has been overdue for six consecutive months during the 41-month period following the loan. For credit history with the bank, we consider a prior relationship if the firm had any loan with the bank in the 12 months preceding the FOGAPE loan. For the provisions variable, we calculate the average provisions made by the bank in the 12 months before the FOGAPE loan. This variable, available only for firms with prior credit history with the bank, measures the ex-ante default risk perceived by the bank at the time of the loan.

Finally, we use tax data from Chile's tax authority (SII), which requires firms to report their monthly income and expenses via the F29 form for VAT purposes. We use this information to calculate firms' sales (in UF). Based on the program's guidelines, we compute (i) net trade revenues between October 1, 2018, and September 30, 2019 (*Sales 1*), (ii) net trade revenues for the 2019 calendar year (*Sales 2*), and (iii) net trade revenues for the 12 months preceding the loan application (*Sales 3*).

Our sample consists of firms classified as small or medium under the FOGAPE loan program. We further restrict the sample to firms with annual sales below 25,000 UF across all three reference periods. Thus, all selected firms will be classified as small or medium with any sales measures.

Table 2 shows descriptive statistics for our final sample, which includes 216,378 loans issued to 189,583 firms. Of these firms, 92% are classified as small, with average annual sales of approximately 7,000 UF (roughly $210,000). The average FOGAPE loan amount is 750 UF ($22,500), with an average guaranteed amount of 615 UF (82% of the loan). The average interest rate is 3.6%, the average loan term is 41 months, and the average grace period is 7 months. Additionally, the default rate is 18%, 70% of the firms had a prior relationship with the lending bank, 75% had a credit history with any bank, and the average provisions-to-debt ratio before the FOGAPE loan is 2.5%.

Table 2: Descriptive statistics

	Mean	SD
A. Firm-level variables		
Sales 1 (UF)	7,109	13,455
Sales 2 (UF)	7,252	13,561
Sales 3 (UF)	7,216	13,614
Small (Fogape)	0.924	0.266
B. Loan-level variables		
Amount (UF)	750	1,317
Interest rate (%)	3.6	0.4
Grace period (in months)	7	11
Loan term (in months)	41	8
Guarantee amount (UF)	615	1,055
C. Bank-firm level variables		
Default	0.177	0.382
Credit history	0.752	0.432
Credit history with bank	0.699	0.459
Ratio provisions-debt	0.025	0.035
Observations	216,378	
Firms	189,583	

Notes: This table shows descriptive statistics for firms with FOGAPE COVID loans. The sample uses data from the CMF on FOGAPE loan characteristics and firm classifications, the CMF credit registry on firm debt and provisions, and tax data from SII on firms' sales. The sample is restricted to firms classified as small or medium with annual sales below 25,000 UF across the three sales measures.

4 Reduced-Form Analysis

4.1 Framework and Aggregate Results

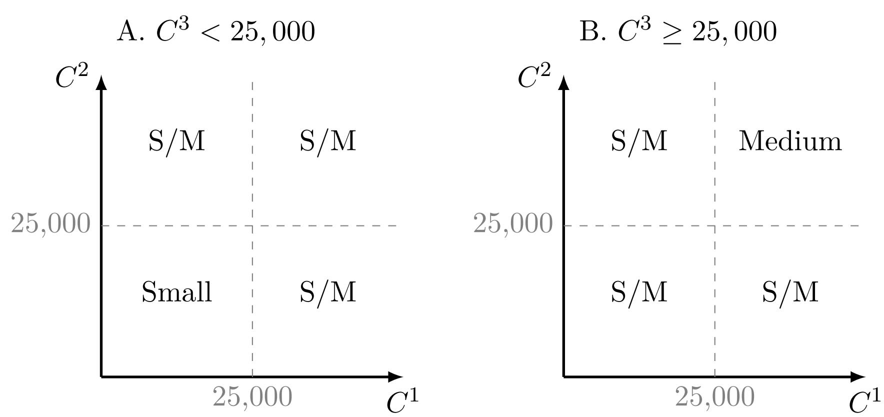
We explore banks' incentives to strategically choose the size of the applicant firm—thus, the credit guarantee conditions. We focus on banks' decision to classify firms as either small- or medium-sized.

For each firm i, banks observe three classification suggestions from the government, (Z_i^1, Z_i^2, Z_i^3), each being a function of past sales measures, (C_i^1, C_i^2, C_i^3), as described in section 2. Specifically, a criterion l suggests medium size classification whenever past sales are (weakly) greater than UF 25,000; that is, $Z_i^l = \mathbb{1}\{C_i^l \geq 25,000\}$.

As a result of FOGAPE classification rules, banks' discretion in classifying borrowing firms varies. When all classification criteria align, the bank must adhere to their suggestion. Deviation requires documented justification. If criteria conflict, the bank freely chooses between small- or medium-size.

For illustration, Figure 3 displays a bank's level of discretion as a function of past sales measures. To ease exposition, we condition on either $C^3 < 25,000$ or $C^3 \geq 25,000$, and plot banks' areas of discretion as a function of C^1 and C^2. Panel A presents classification suggestions under the condition $C^3 < 25,000$. The graph is divided into four quadrants, with the bank only instructed to classify a firm as small in the southwest quadrant, where all three criteria coincide. Discretion is granted in the remaining quadrants, due to conflicting criteria. Panel B displays suggested classifications when $C^3 \geq 25,000$. In this case, the bank is instructed to classify the firm as medium only if both C^1 and C^2 exceed 25,000. Otherwise, the bank retains discretion.

Figure 3: Suggested Classification by Past Sales



Notes: This figure illustrates a bank's level of discretion as a function of past sales measures. Banks' areas of discretion are plotted as a function of C^1 and C^2, conditioning on either $C^3 < 25,000$ (panel A) or $C^3 \geq 25,000$ (panel B).

To get a sense on how many firms lie in the discretion and non-discretion areas, and on the extent to which banks comply with instructed classification, Table 3 shows the sum of classification criteria, $\sum_l Z^l$, as well as banks' actual classification, small or medium. When $\sum_l Z^l = 0$, all three criteria suggest to classify the firm as small. When $\sum_l Z^l = 3$, all criteria suggest medium size. In these two cases the bank is expected to comply. Whenever $\sum_l Z^l = 1, 2$, the bank has discretion in classification.

Consistent with the data description in section 3, the vast majority of firms are identified as small by the classification criteria, i.e. $\sum_l Z^l = 0$. Of those 196,647 firms, in 99.6% of cases the bank complies with the instruction. The cases where banks enjoy discretion, i.e. $\sum_l Z^l = 1, 2$, amount to 5,599. Banks classify firms as small in about half of these cases. There are 14,132 firms identified as medium by all three criteria, i.e. $\sum_l Z^l = 3$. Banks follow advice in 92% of the cases.

Table 3: Firm Classification Criteria and Actual Classification

	Small	Medium	Total
$\sum_j Z_j = 0$	195,896	751	196,647
$\sum_j Z_j = 1, 2$	2,870	2,729	5,599
$\sum_j Z_j = 3$	1,089	13,043	14,132
Total	199,855	16,523	216,378

Notes: This table displays the sum of classification criteria, $\sum_l Z^l$, and banks' actual classification, small or medium. For past sales measure l, $Z_i^l = \mathbb{1}\{C_i^l \geq 25,000\}$ denotes medium size classification for firm i. When $\sum_l Z^l = 0$, all three criteria suggest to classify the firm as small. When $\sum_l Z^l = 3$, all criteria suggest medium size. When $\sum_l Z^l = 1, 2$, the three criteria do not align.

Table 3 reveals two key insights. First, banks overwhelmingly adhere to instructions when classifying firms as small. Second, while banks generally comply with instructions for medium-size classifications, there is a notable number of instances where firms are incorrectly classified as small, deviating from the established criteria.

Next section sheds more light onto banks' reclassification and risk shifting behavior. We disaggregate the descriptives from Table 3, and attempt to uncover relations between banks' classification decisions, incentives, and implied costs.

4.2 Classification Probabilities

Motivated by the aggregate findings, we delve into banks' classification behavior, examining whether and how decisions differ between areas of discretion and non-discretion. For instance, referring to Figure 3, panel A, we compare classifications in the southeast (discretionary) and southwest (non-discretionary) quadrants. In the southeast quadrant, no particular classification pattern is expected, whereas in the southwest quadrant, where banks are instructed to classify firms as small, we expect adherence to this advice with probability one. Furthermore, we investigate how classification decisions vary along the distribution of past sales measures, and especially as they approach the boundary where the level of discretion changes.

We estimate the probability of classifying a firm as small as a function of past sales measures. We focus on areas where discretion changes. For instance, referring to Figure 3, panel A, we examine classification decisions in the southwest and southeast quadrants, by conditioning on both $C_i^2 < 25,000$ and $C_i^3 < 25,000$, and estimate classification probabilities over the C_i^1 distribution. We also examine classification decisions among northwest and northeast quadrants in Figure 3, panel B, by conditioning on $C_i^2 \geq 25,000$ and $C_i^3 \geq 25,000$, and estimate classification probabilities over the C_i^1 distribution. We perform analogous exercises for the C_i^2 and C_i^3 measure distributions.

In practice, we estimate the following equations,

$$E\left[s_{ij} \mid Z^m = 0, Z^n = 0\right] = f\left(C^l, Z^l; \beta \mid Z^m = 0, Z^n = 0\right), \tag{1}$$

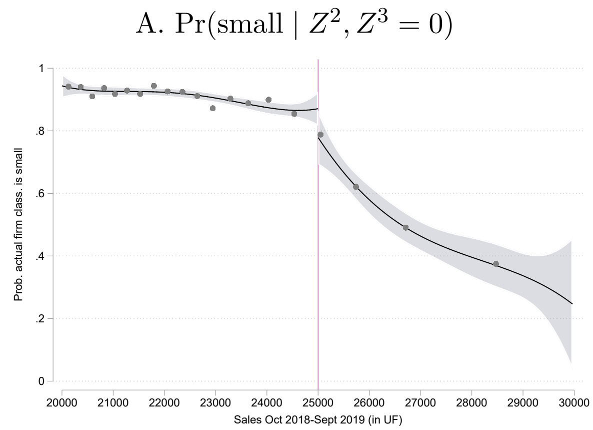
$$E\left[s_{ij} \mid Z^m = 1, Z^n = 1\right] = g\left(C^l, Z^l; \gamma \mid Z^m = 1, Z^n = 1\right), \tag{2}$$

where equation (1) concerns classification decisions among small-instructed non-discretionary and discretionary areas, and equation (2) concerns classification decisions among discretionary and medium-instructed non-discretionary areas. The variable s_{ij} takes the value of one if firm i is classified as small by bank j, and zero otherwise, $f(\cdot)$ and $g(\cdot)$ are flexible functions of sales measures and size suggestions, C^l and Z^l, with parameters β and γ, and $m \neq n \neq l$. We approximate $f(\cdot)$ and $g(\cdot)$ with a quartic polynomial on C^l interacted with Z^l, to allow for different function shapes in the discretionary and non-discretionary zones.

Figure 4 displays estimation results graphically. For ease of exposition, we present results only for C^1 conditioning on values of Z^2 and Z^3. Corresponding results for C^2 and C^3 measures are found in Figure B.5 in Appendix B. Panel A plots estimates from equation (1) for the probability of small-size classification, over the distribution of C^1, conditioning on Z^2 and Z^3 suggesting small size. When $C^1 < 25,000$, all three criteria instruct small size. When $C^1 \geq 25,000$, criteria disagree and the bank enjoys discretion. Estimates show that banks adhere to the small-size instruction in about 90% of the cases. This probability only slightly decreases as the C^1 measure approaches the discretionary zone. In the discretionary zone, banks classify firms as small with increasing probability as the sales measure approaches the non-discretionary zone.

Panel B in Figure 4 plots estimates from equation (2) for the probability of small-size classification, over the distribution of C^1, conditioning on Z^2 and Z^3 suggesting medium size. When $C^1 < 25,000$, the bank is in a discretionary zone, since the Z^1 criterion contradicts the other two. When $C^1 \geq 25,000$, all three criteria instruct medium size. In the discretionary zone, banks classify firms evenly between small and medium. The probability of small-size decreases in the vicinity of the non-discretionary zone. In the non-discretionary zone, banks comply with the medium-size instruction in about 80% of the cases, when the sales measure is sufficiently far from the discretionary zone. This compliance rate reduces significantly to about 60% as the sales measure approaches the discretionary zone.

Figure 4: Classification Probability by Past Sales Measure C^1



Notes: Panel A displays estimated small-size classification probabilities over the distribution of C^1, conditioning on Z^2 and Z^3 suggesting small size. Panel B displays estimated small-size classification probabilities over the distribution of C^1, conditioning on Z^2 and Z^3 suggesting medium size.

We interpret these results as suggestive evidence that banks tend to reclassify firms as small. When small-size instructed, banks generally adhere. However, when banks are instructed to classify firms as medium, they do not always comply, and comply even less as they approach the discretionary zone. Documentation to justify non-compliance with size instruction is likely to be easier to provide when the sales measure is close to the discretionary zone. Our results are thus consistent with decreasing reclassification costs near the threshold.

We proceed by exploring whether banks reclassify firms based on their relationship lending status at the moment of loan application. Firms with prior credit history, either with the lending bank or in the broader financial market, are likely to have already revealed their type. The bank likely possesses more information on these firms compared to those lacking credit history. Consequently, banks might be less inclined to reclassify them as small to secure a higher guarantee rate. On the contrary, extending new loans to firms already carrying debt could elevate their default risk by increasing their overall debt burden and financial obligations. If this risk is significant, banks might be more prone to reclassify these firms as small.

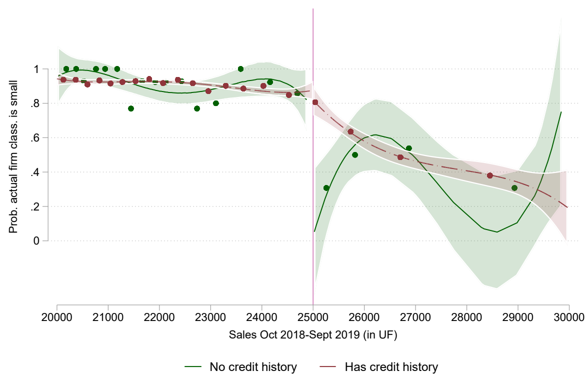
Figure 5 presents estimated firm classification probabilities over the distribution of sales measure C^1, among discretionary and non-discretionary zones, analogous to the evidence in Figure 4, but distinguishing between firms with existing credit history (in red) and firms with no credit history (in green). Panel A defines firms with credit history as firms having contracted loans with any bank in the period between October 2018 and September 2019.

Both plots A1 and A2 in panel A show no significant difference in small-size classification probabilities between firms with and without credit history. An opposite result is displayed in panel B, where banks reclassify firms with an existing lending relationship with bank as small-size with higher probability compared to firms with no prior lending relationship with the bank. This result is especially clear in plot B2, in both discretionary and medium-instructed non-discretionary zones.

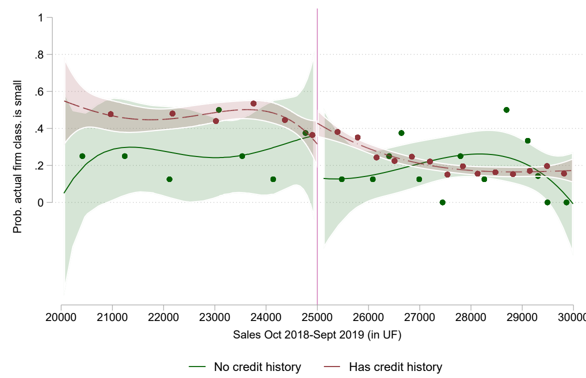
Figure 5: Classification Probability by Past Sales Measure C^1 and Credit History

A. Prior credit history in the financial market

A1. $\Pr(\text{small} \mid Z^2, Z^3 = 0)$

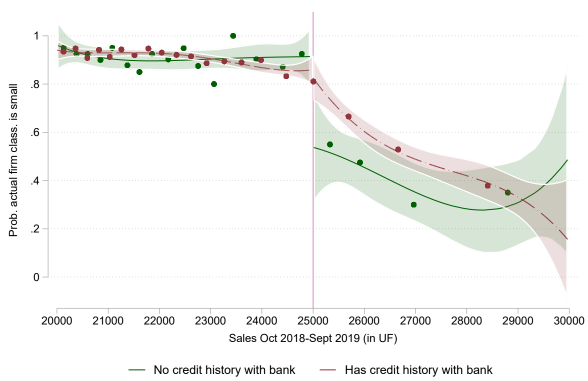


A2. $\Pr(\text{small} \mid Z^2, Z^3 = 1)$

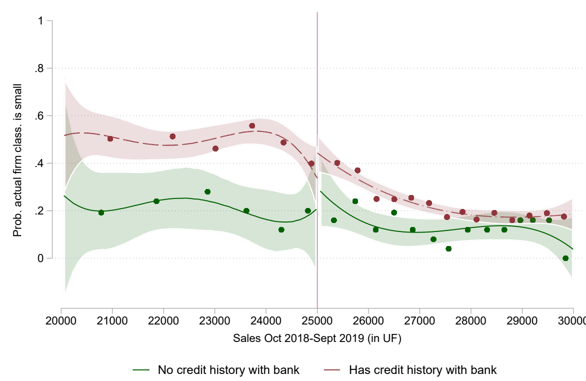


B. Prior lending relationship with the bank

B1. $\Pr(\text{small} \mid Z^2, Z^3 = 0)$



B2. $\Pr(\text{small} \mid Z^2, Z^3 = 1)$



Notes: Panel A presents estimated firm classification probabilities distinguishing between firms with an existing credit history in the financial market (in red) and firms new to the credit market (in green). Panel B presents estimated firm classification probabilities distinguishing between firms with prior lending relationship with the bank (in red) and firms without prior lending relationship with the bank (in green). Plots A1 and B1 display estimated small-size classification probabilities over the distribution of C^1, conditioning on Z^2 and Z^3 suggesting small size. Plots A2 and B2 display estimated small-size classification probabilities over the distribution of C^1, conditioning on Z^2 and Z^3 suggesting medium size.

The evidence just shown suggests that the overloaded debt burden effect dominates the type-revealing effect of firms' existing credit history. This result is driven by borrower with prior lending relationship with the bank.

5 A Model of Firm Size Classification

We develop a model of firm classification that sheds light onto our understanding of the incentives and costs faced by banks under the FOGAPE credit guarantee program. Let $s_{ij} = \{0, 1\}$ denote bank j's classification of firm i, with $s_{ij} = 1$ $(= 0)$ denoting small (medium) size. Guarantee and deductible rates are $\{M^s, M^m\}$ and $\{d^s, d^m\}$, respectively, where the superscript s (m) corresponds to small (medium) size classification, with $M^s > M^m$ and $d^s \leq d^m$. Firm's ex-post repayment of the loan is R_i, which is ex-ante unobserved by the bank. Loan size is L_i. The interest rate is fixed by the program at p. The vector $\left(\kappa^s_{ij}, \kappa^m_{ij}\right)$ collects the fixed costs associated to small- and medium-size classification. These costs are directly related to the required documentation and increased bureaucracy the bank has to engage in when deviating from suggested instruction. Finally, for simplicity, we assume away marginal costs associated to loan processing.

5.1 No Prior Lending Relationship with the Bank

A noteworthy aspect of the FOGAPE program is that it waives deductibles on loans for firms without existing debt with the lending bank at the time of application. For these firms, the problem of the bank is to choose the size of the firm that maximizes its expected profit. Note that this is a loan-level problem, as follows,

$$\max_{s_{ij} \in \{0,1\}} E\left[\Pi_{ij}\right] = \left\{E\left[R_i\right](1+p) + (1 - E[R_i])\left[s_{ij}M^s + (1 - s_{ij})M^m\right]\right\} L_i - s_{ij}\kappa^s_{ij} - (1 - s_{ij})\kappa^m_{ij}.$$

The expected profit function includes the bank's ex-ante expectation of firm repayment, $E\left[R_i\right]$. Whenever the firm repays, the bank earns $(1 + p)$ for every peso it lends. In the case the firm does not repay and is classified as small, the bank receives $M^s < 1$ scaled by the loan amount, L_i, and incurs in a fixed classification cost, κ^s_{ij}. Analogously, if the firm is classified as medium and does not repay, the bank receives $M^m L_i$, and incurs in classification cost, κ^m_{ij}.

The solution to the bank's problem is

$$s^*_{ij} = \mathbb{1}\left\{(1 - E[R_i])L_i(M^s - M^m) \geq \kappa^s_{ij} - \kappa^m_{ij}\right\},$$

which states that the incentives for small-size classification increase with the riskiness of the firm, the size of the loan, and the larger the difference in guarantee rates between small and medium firms. In addition, small-size classification incentives decrease (increase) with small (medium) classification costs.

5.2 Existing Lending Relationship with the Bank

The problem is different for firms that already have an existing lending relationship with the bank. For these firms, any loans extended under the program will carry deductibles. These deductibles are applied to the bank's entire portfolio of applicable loans, as opposed to being assessed on a per-loan basis.

The bank chooses a vector $s_j = \{s^*_{1j}, ..., s^*_{Ij}\} \in \{0,1\}^I$ to maximize the following expected profit function at the bank-level, $E\left[\Pi_j\right]$,

$$\sum_i \left(E[R_i](1+p)L_i - s_{ij}\kappa^s_{ij} - (1-s_{ij})\kappa^m_{ij}\right) +$$

$$\begin{cases} 0 & \text{if } \sum_i s_{ij}\left[(1-E[R_i]) - d^s\right]L_i < 0, \\ & \sum_i (1-s_{ij})\left[(1-E[R_i]) - d^m\right]L_i < 0 \\ & \\ (1-d^s)\sum_i s_{ij}(1-E[R_i])M^s L_i & \text{if } \sum_i s_{ij}\left[(1-E[R_i]) - d^s\right]L_i \geq 0, \\ & \sum_i (1-s_{ij})\left[(1-E[R_i]) - d^m\right]L_i < 0 \\ & \\ (1-d^m)\sum_i (1-s_{ij})(1-E[R_i])M^m L_i & \text{if } \sum_i s_{ij}\left[(1-E[R_i]) - d^s\right]L_i < 0, \\ & \sum_i (1-s_{ij})\left[(1-E[R_i]) - d^m\right]L_i \geq 0 \\ & \\ (1-d^s)\sum_i s_{ij}(1-E[R_i])M^s L_i + & \text{if } \sum_i s_{ij}\left[(1-E[R_i]) - d^s\right]L_i \geq 0, \\ (1-d^m)\sum_i (1-s_{ij})(1-E[R_i])M^m L_i & \quad \sum_i (1-s_{ij})\left[(1-E[R_i]) - d^m\right]L_i \geq 0. \end{cases}$$

This is a piece-wise profit function, contingent upon whether the default rate for each firm size (small and medium) exceeds its respective deductible rate. The initial component of the profit function represents the bank's total revenue when loans are repaid, minus classification costs. This constitutes the bank's sole earnings if the proportion of defaulted loan amount remains below the deductible rate for both small and medium-sized firms. However, if the small firm default rate surpasses its deductible, the government compensates the bank at the guarantee rate, M^s, for each peso lent to and not repaid by small firms, after the bank absorbs the deductible. An analogous mechanism applies to medium-sized firm loans. Consequently, the bank's profit function is partitioned into four distinct pieces, determined by the interplay between default rates and deductibles for each firm size group.

The solution to this problem is a vector of firm size classification,

$$s^*_j = \{s^*_{1j}, ..., s^*_{Ij}\} \in \{0,1\}^I \text{ s.t. } E\left[\Pi_j(s^*_j)\right] \text{ is maximal.}$$

5.3 Estimation

We model firm repayment using a linear-in-the-parameters function,

$$R_i = X_{ij}\beta_i + \psi_i, \tag{3}$$

where X_{ij} collects observable (to the econometrician) variables related to the bank and the firm that determine firm repayment, β_i is a heterogeneous vector of coefficients of repayment responses to covariates, and ψ_i summarizes unobservable repayment determinants. We estimate equation (3) by OLS.

We parameterize classification costs, $(\kappa_{ij}^s, \kappa_{ij}^m)$, so that they reflect the varying implied costs incurred by banks when assigning firm size across the discretion and non-discretion zones, as illustrated in Figure 3. In addition, we aim to account for the non-zero slope in bank decisions as past sales measures approach the boundaries between these zones, as was shown in section 4.2.

The following equations present our modeling of classification costs,

$$\kappa_{ij}^s = h^s(Z_i, C_i, W_{ij}; \alpha^s) + \epsilon_{ij}^s,$$
$$\kappa_{ij}^m = h^m(Z_i, C_i, W_{ij}; \alpha^m) + \epsilon_{ij}^m,$$

where $h^s(\cdot)$, $h^m(\cdot)$ are flexible functions, W_{ij} is a vector of bank-firm determinants of costs, α^s and α^m are parameters to be estimated, and ϵ_{ij}^s and ϵ_{ij}^m are idiosyncratic error terms.

We assume $\epsilon_{ij}^s - \epsilon_{ij}^m \sim N(0, \sigma_{sm}^2)$. Thus, the probability of small-size classification for applicants without an existing lending relationship with the bank is,

$$\Pr(s_{ij} = 1) = \Phi\left(\frac{(1 - E[R_i])L_i(M^s - M^m) + h^m(Z_i, C_i, W_{ij}; \alpha^m) - h^s(Z_i, C_i, W_{ij}; \alpha^s)}{\sigma_{sm}}\right). \tag{4}$$

Notice that since theory imposes a coefficient of one accompanying the term $(1-E[R_i])L_i(M^s - M^m)$, the standard deviation parameter, σ_{sm}, is identified.

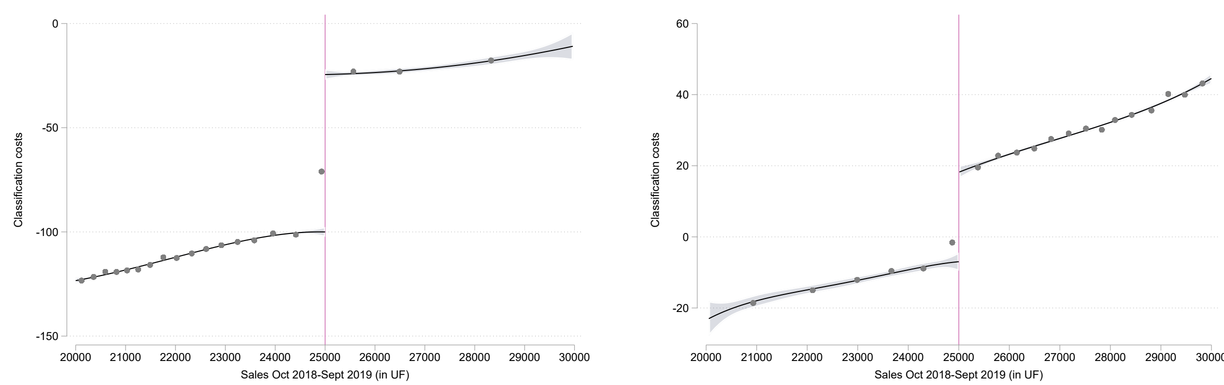
5.4 Results

Tables A.2 and A.3 in appendix A show the estimation results from equations (3) and (4), respectively. Estimates for the repayment equation show in general that shorter loan terms, larger grace periods, and less risky firms increase repayment probabilities. Estimates for the small-size classification equation show that medium-size instruction reduces small-size classification probability, small-size instruction does the opposite, and closeness to discretionary zones determines classification.

Figure 6 uses estimates from equation (4) to plot estimated classification costs over the distribution of C^1.[9] Panel A conditions the analysis on Z^2 and Z^3 suggesting small size, while panel B conditions on Z^2 and Z^3 suggesting medium size. Note that the plotted classification costs are the differences between small-size classification costs and medium-size classification costs, i.e. $\hat{h}^s - \hat{h}^m$. The results validate the model. Classification costs for small size are smaller than medium-size classification costs when banks are small-sized instructed (panel A). The opposite is observed in the medium-size non-discretionary zone (panel B). Discretionary zones have small-size classification costs that are slightly less than the costs to classify firms as medium. Finally, medium-size classification costs discontinuously increase (relative to small-size classification costs) when either going from the small-size instructed zone to the discretionary zone (panel A), or going from the discretionary zone to the medium-size non-discretionary zone (panel B).

Figure 6: Classification Costs by Sales Measure C^1

A. $(\hat{h}^s - \hat{h}^m \mid Z^2, Z^3 = 0)$ B. $(\hat{h}^s - \hat{h}^m \mid Z^2, Z^3 = 1)$



Notes: Panel A displays estimated classification costs, $\hat{h}^s - \hat{h}^m$, over the distribution of C^1, conditioning on Z^2 and Z^3 suggesting small size. Panel B displays estimated classification costs, $\hat{h}^s - \hat{h}^m$, over the distribution of C^1, conditioning on Z^2 and Z^3 suggesting medium size.

6 Conclusion

In this paper, we studied banks' risk-shifting behavior under the FOGAPE COVID credit guarantee program in Chile. Using rich administrative data, we showed that banks tend to reclassify firms to obtain higher loan guarantee rates. This behavior is amplified for firms with an existing credit history in the financial system.

Our analysis suggests that the costs and benefits of reclassification play a significant

[9] Figures B.6 and B.7 in appendix B plot estimated classification costs over the distribution of C^2 and C^3, respectively.

role in banks' decision-making processes. Banks are more likely to reclassify firms as small when the potential benefits of higher guarantee rates outweigh the costs associated with justifying these reclassifications. This tendency is amplified near the discretionary zone, where documentation to justify non-compliance with size instruction is easier to provide.

We have also developed a structural model to better understand the incentives and costs banks face when deciding to reclassify firms. Our model highlights the importance of firm and loan characteristics in determining reclassification behavior.

Our findings have important policy implications. They suggest that the design of credit guarantee programs should carefully consider the incentives they create for banks. Policymakers should aim to balance the need for credit access with the potential risks of moral hazard and adverse selection. Future research could explore alternative program designs that mitigate these risks while still providing necessary support to small and medium-sized firms.

References

Cao, J., L. Goldberg, S. Sinha, and S. Ungaro (2024): “Policy Insight 133: Government guarantee programmes for bank lending to firms: Lessons for future policymakers,” *CEPR Policy Insight No 133, CEPR Press, Paris & London*.

Deyoung, R., A. Gron, G. Torna, and A. Winton (2015): “Risk Overhang and Loan Portfolio Decisions: Small Business Loan Supply before and during the Financial Crisis,” *The Journal of Finance*, 70, 2451–2488.

Gertler, M. and S. Gilchrist (1994): “Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms*,” *The Quarterly Journal of Economics*, 109, 309–340.

Griffin, J. M., S. Kruger, and P. Mahajan (2023): “Did FinTech Lenders Facilitate PPP Fraud?” *The Journal of Finance*, 78, 1777–1827.

Huneeus, F., J. P. Kaboski, M. Larrain, S. L. Schmukler, and M. Vera (2022): “The Distribution of Crisis Credit: Effects on Firm Indebtedness and Aggregate Risk,” .

Joaquim, G. and F. Netto (2021): “Optimal Allocation of Relief Funds: The Case of the Paycheck Protection Program,” *FRB of Boston Working Paper No. 21-16*.

Mullins, W. and P. Toro (2018): “Credit Guarantees and New Bank Relationships,” Working Papers Central Bank of Chile, Central Bank of Chile.

OECD (2013): “Credit Guarantee Schemes,” *Financing SMEs and Entrepreneurs 2013, Chapter 3*.

A Additional Tables

Table A.1: Firm's maximum financing available under FOGAPE COVID

Firms with net annual sales below:	Maximum financing available under FOGAPE COVID:
1,000 UF	250 UF
10,000 UF	2,500 UF
25,000 UF	6,250 UF
100,000 UF	25,000 UF
200,000 UF	50,000 UF
400,000 UF	100,000 UF
600,000 UF	150,000 UF
1,000,000 UF	250,000 UF

Notes: This table reports the maximum financing available under FOGAPE COVID, depending on the firm's annual sales.

Table A.2: OLS Estimates of the Probability of Repayment: Linear Probability Model

	(1)
Log(Amount)	0.016***
	(0.001)
Loan term	-0.004***
	(0.000)
Grace period	0.000**
	(0.000)
External borrower	-0.014***
	(0.004)
Existing borrower × provisions=1	0.067***
	(0.008)
Existing borrower × provisions=2	0.114***
	(0.004)
Existing borrower × provisions=3	0.063***
	(0.003)
Existing borrower × provisions=4	0.023***
	(0.003)
Existing borrower × provisions=5	-0.035***
	(0.003)
Log(Sales 1)	0.012***
	(0.001)
Log(Sales 2)	-0.007***
	(0.001)
Log(Sales 3)	-0.001
	(0.001)
Exporter	0.034***
	(0.004)
Limited liability	-0.080***
	(0.002)
Constant	0.863***
	(0.005)
Observations	215,940

Notes: This table reports OLS estimates of a linear probability model for the probability of repayment of FOGAPE COVID loans. Robust standard errors are shown in parentheses. Significant levels: *p>0.10, **p>0.05, ***p>0.01

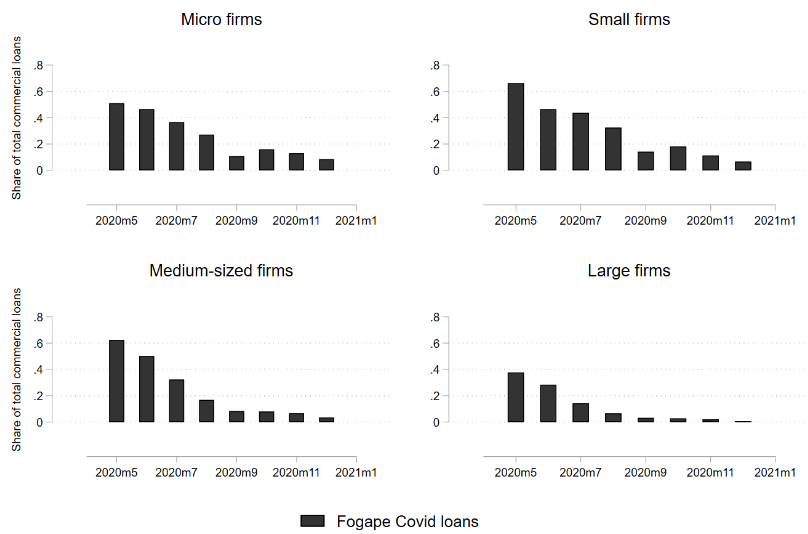
Table A.3: Maximum Likelihood Estimates of the Classification Probability: Probit Model

	(1)
$Constant$	15.181
	(0.029)
$AllMedium$	-22.686
	(0.036)
$AllSmall$	69.782
	(0.038)
$Sales1$	-471.512
	(0.343)
$Sales1^2$	-359.263
	(1.354)
$Sales1^3$	3,884.460
	(6.309)
$Sales1^4$	-4,153.902
	(8.773)
$Sales2$	-33.793
	(0.392)
$Sales2^2$	629.732
	(1.710)
$Sales2^3$	-1,230.128
	(7.527)
$Sales2^4$	762.607
	(9.819)
$Sales3$	-164.751
	(0.241)
$Sales3^2$	53.679
	(0.869)
$Sales3^3$	516.949
	(3.785)
$Sales3^4$	-501.461
	(4.414)
σ	66.016
	(0.002)
Observations	215,940

Notes: This table reports maximum likelihood estimates of a probit model for the classification probability of firm's sizes. Robust standard errors are shown in parentheses. Significant levels: *p>0.10, **p>0.05, ***p>0.01

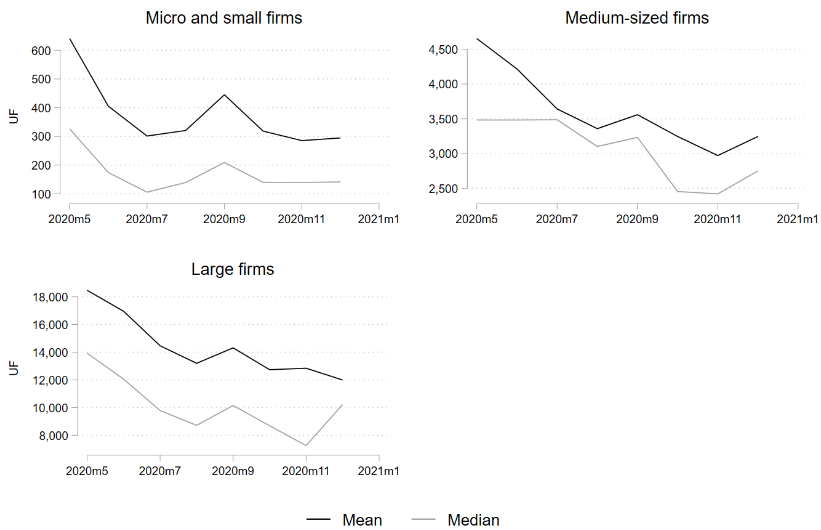
B Additional Figures

Figure B.1: Share of FOGAPE COVID Loans in Total Commercial Loans, by Firm Size



Notes: This figure shows the share of FOGAPE COVID loans on total commercial loans in the year 2020, categorized by firm size. Commercial loans are loans to firms denominated in Chilean pesos, US dollars, euros, or UF, excluding factoring loans and repurchase agreement operations. Firm sizes are defined as follows: micro firms have annual sales below 2,400 UF, small firms between 2,400 and 25,000 UF, medium firms between 25,000 and 100,000 UF, and large firms above 100,000 UF.

Figure B.2: Loan Size, by Firm Size

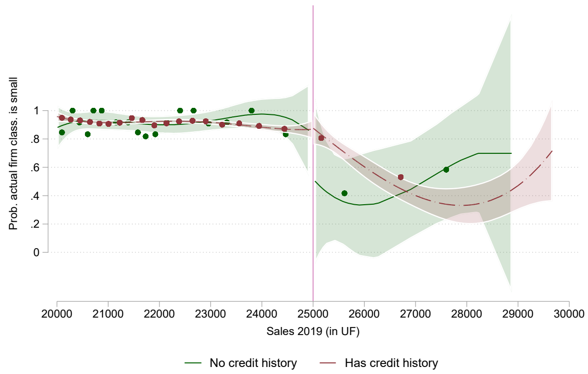


Notes: This figure shows the mean and median loan sizes of FOGAPE COVID loans (in UF), categorized by firm size. Firms are classified based on their annual sales as follows: micro and small firms with sales below UF 25,000, medium-sized firms with sales between UF 25,000–100,000, and large firms with sales between UF 100,000–1,000,000.

Figure B.3: Classification Probability by Past Sales Measure C^2 and Credit History

A. Prior credit history in the financial market

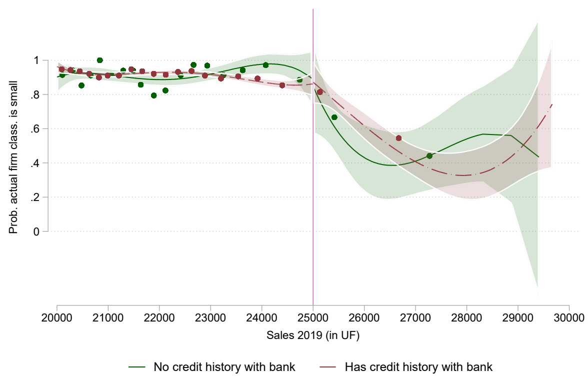
A2. $\Pr(\text{small} \mid Z^1, Z^3 = 0)$



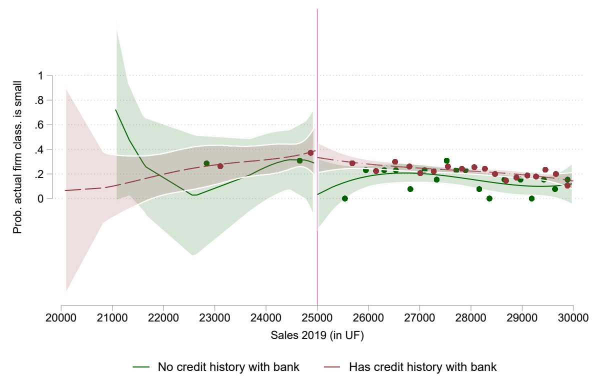
B. $\Pr(\text{small} \mid Z^1, Z^3 = 1)$

B. Prior lending relationship with the bank

B1. $\Pr(\text{small} \mid Z^1, Z^3 = 0)$



B2. $\Pr(\text{small} \mid Z^1, Z^3 = 1)$

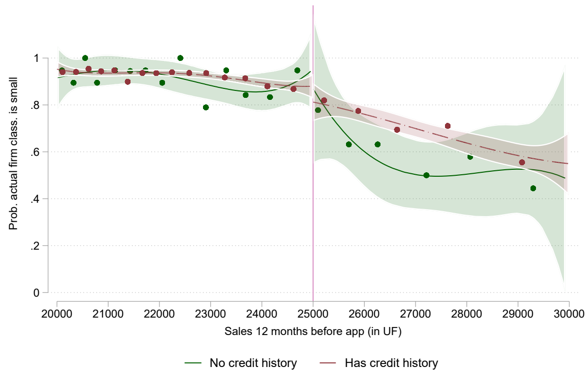


Notes: Panel A presents estimated firm classification probabilities distinguishing between firms with an existing credit history in the financial market (in red) and firms new to the credit market (in green). Panel B presents estimated firm classification probabilities distinguishing between firms with prior lending relationship with the bank (in red) and firms without prior lending relationship with the bank (in green). Plots A1 and B1 display estimated small-size classification probabilities over the distribution of C^2, conditioning on Z^1 and Z^3 suggesting small size. Plots A2 and B2 display estimated small-size classification probabilities over the distribution of C^2, conditioning on Z^1 and Z^3 suggesting medium size.

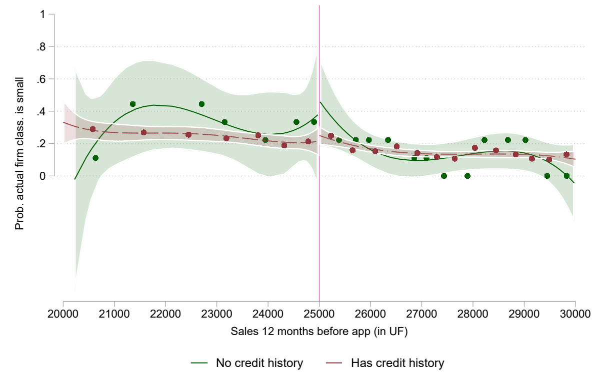
Figure B.4: Classification Probability by Past Sales Measure C^3 and Credit History

A. Prior credit history in the financial market

A2. $\Pr(\text{small} \mid Z^1, Z^2 = 0)$

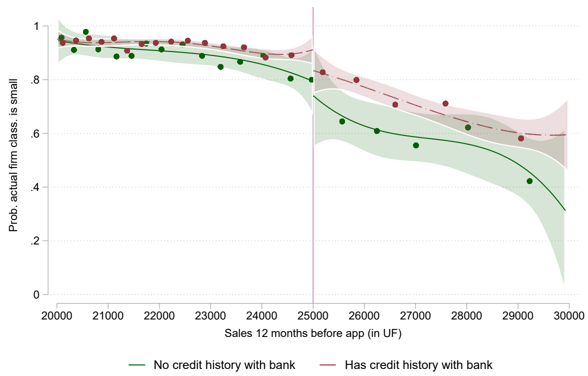


B. $\Pr(\text{small} \mid Z^1, Z^2 = 1)$

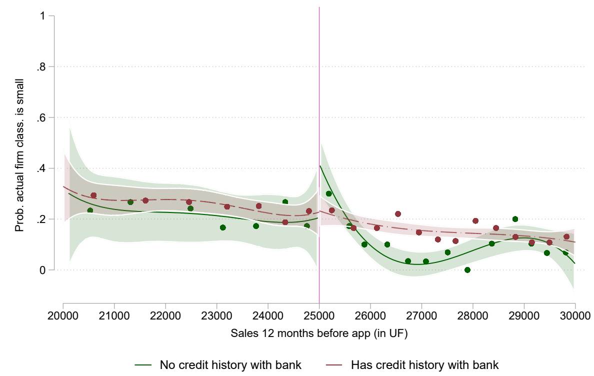


B. Prior lending relationship with the bank

B1. $\Pr(\text{small} \mid Z^1, Z^2 = 0)$



B2. $\Pr(\text{small} \mid Z^1, Z^2 = 1)$

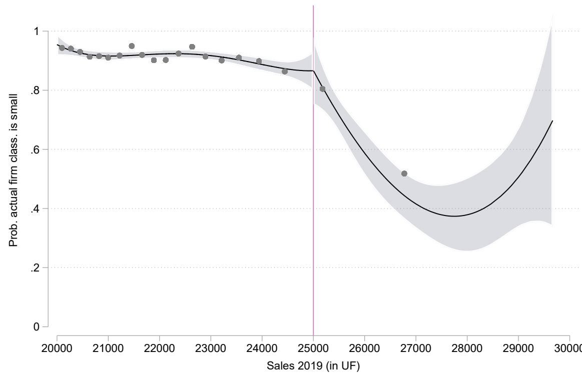


Notes: Panel A presents estimated firm classification probabilities distinguishing between firms with an existing credit history in the financial market (in red) and firms new to the credit market (in green). Panel B presents estimated firm classification probabilities distinguishing between firms with prior lending relationship with the bank (in red) and firms without prior lending relationship with the bank (in green). Plots A1 and B1 display estimated small-size classification probabilities over the distribution of C^3, conditioning on Z^1 and Z^2 suggesting small size. Plots A2 and B2 display estimated small-size classification probabilities over the distribution of C^3, conditioning on Z^1 and Z^2 suggesting medium size.

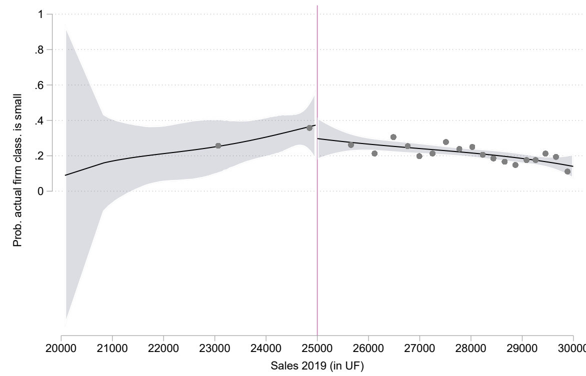
Figure B.5: Classification Probability by Past Sales Measures C^2 and C^3

A. Past sales measure C^2

A1. Pr(small | $Z^1, Z^3 = 0$)

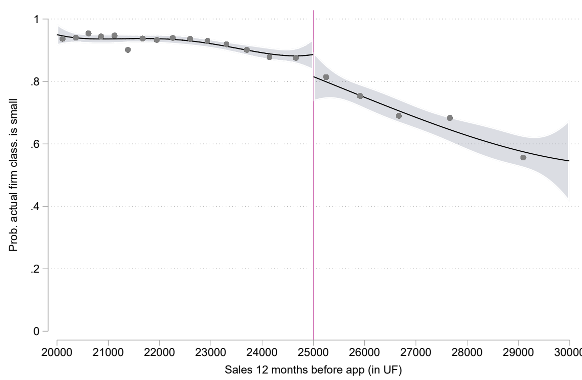


A2. Pr(small | $Z^1, Z^3 = 1$)

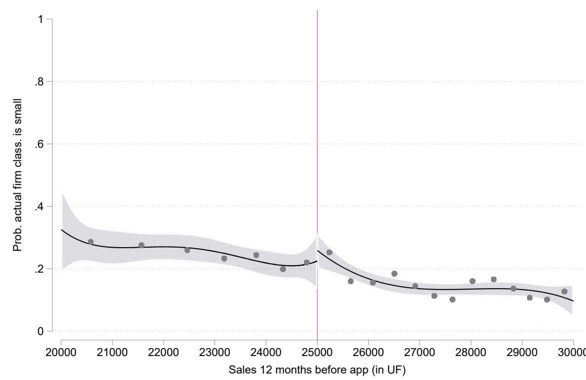


B. Past sales measure C^3

B1. Pr(small | $Z^1, Z^2 = 0$)



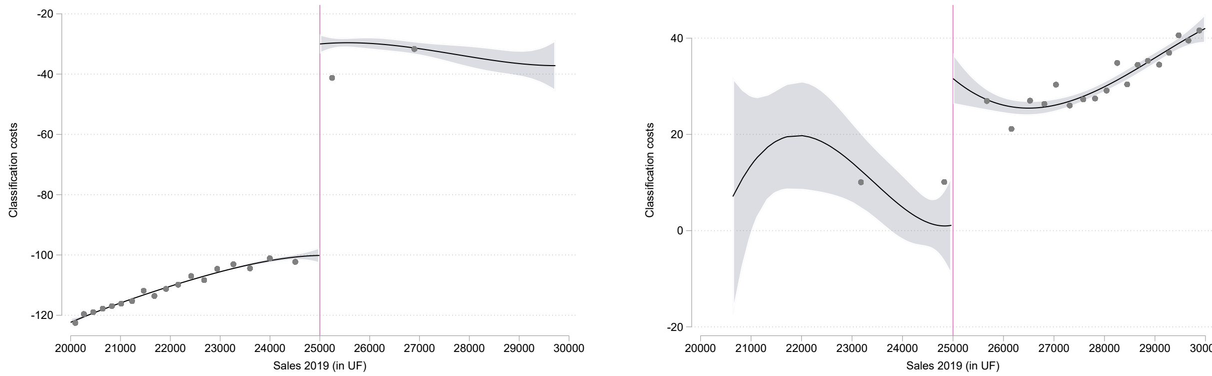
B2. Pr(small | $Z^1, Z^2 = 1$)



Notes: Panel A1 displays estimated small-size classification probabilities over the distribution of C^2, conditioning on Z^1 and Z^3 suggesting small size. Panel A2 displays estimated small-size classification probabilities over the distribution of C^2, conditioning on Z^1 and Z^3 suggesting medium size. Panel B1 and B2 display similar figures for C^3 conditional on Z^1 and Z^2.

Figure B.6: Classification Costs by Sales Measure C^2

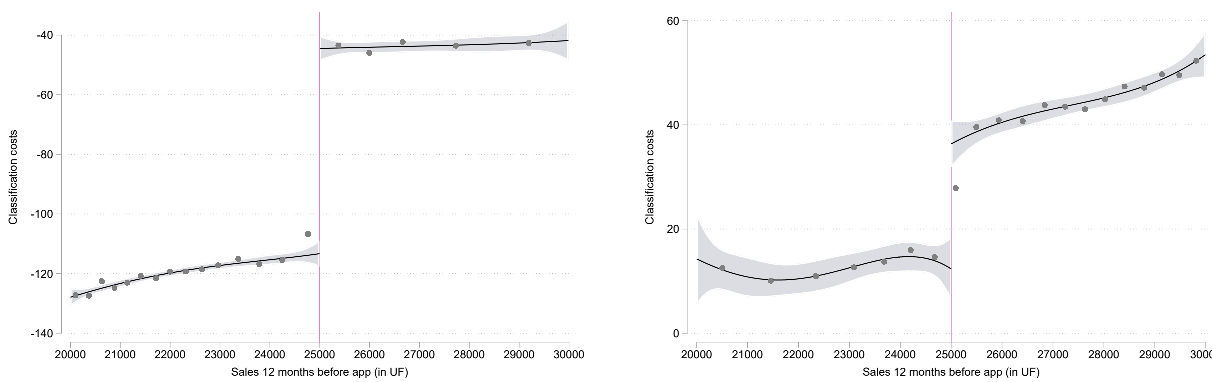
A. $(\hat{h}^s - \hat{h}^m \mid Z^1, Z^3 = 0)$ B. $(\hat{h}^s - \hat{h}^m \mid Z^1, Z^3 = 1)$



Notes: Panel A displays estimated classification costs, $\hat{h}^s - \hat{h}^m$, over the distribution of C^2, conditioning on Z^1 and Z^3 suggesting small size. Panel B displays estimated classification costs, $\hat{h}^s - \hat{h}^m$, over the distribution of C^2, conditioning on Z^1 and Z^3 suggesting medium size.

Figure B.7: Classification Costs by Sales Measure C^3

A. $(\hat{h}^s - \hat{h}^m \mid Z^1, Z^2 = 0)$ B. $(\hat{h}^s - \hat{h}^m \mid Z^1, Z^2 = 1)$



Notes: Panel A displays estimated classification costs, $\hat{h}^s - \hat{h}^m$, over the distribution of C^3, conditioning on Z^1 and Z^2 suggesting small size. Panel B displays estimated classification costs, $\hat{h}^s - \hat{h}^m$, over the distribution of C^3, conditioning on Z^1 and Z^2 suggesting medium size.