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Firm Support Measures, Credit Payment Behavior, and Credit Risk

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Abstract

This paper examines the relationship between three government support measures (debt moratorium, credit guarantee programs, and payroll subsidies) and the firm's payment behavior on loans in Colombia. To do so, we take advantage of the COVID-19 pandemic and use it as a case study. Using highly granular data at the bank-firm level and a difference-in-difference approach, we find that firms subject to debt reliefs and government guarantee programs experienced a lower probability of default while these policies were in force. Subsequently, once the programs ended, the dynamic of the payment behavior of these firms was similar to that of those untreated. On the contrary, payroll subsidies did not affect firms' payment behavior. Regarding the effect on banks' risk assessment, our results suggest that participation in relief programs provided banks with new information about debtors' risk, which could indicate unintended consequences of government support programs.

Keywords: firm support, credit default, credit risk

JEL: G18, G21, G38

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1 Introduction

Economic and financial crises worldwide are costly. During periods of crisis, adverse effects on households and firms' performance due to employment and income losses are often recorded. In the long run, all types of crises, on average, lead to permanent impacts on GDP, poverty, and inequality (Reinhart and Rogoff, 2014; Cerra and Saxena, 2008). Consequently, governments have responded by developing and adopting several policies to contain social costs and stabilize the economy (Zhang et al., 2010). For instance, during the Great Recession of 2008, central banks enacted support measures to stabilize the banking system while governments adopted fiscal stimulus packages.

The COVID-19 pandemic shock led to a crisis similar to those characterized by large transitory supply shocks, in which the stimulus of demand does not activate the economy since the production of goods and services is temporarily low and instead only causes inflation or shortages (Guerrieri et al., 2022). In this context, policymakers and academics raised concerns about the effects of the crisis on firm survival, financial stability, and economic recovery (Caceres et al., 2020; Carletti et al., 2020; Tressel and Ding, 2021; Demmou et al., 2021). As a result, governments worldwide undertook several measures to mitigate the economic downturn resulting from disruptions in production and collapsing demand (Kalemli-Ozcan et al., 2020). These measures focused on keeping the economy alive by supporting enterprises, employment, and incomes through lending and financial support.

To date, several studies have analyzed the effectiveness of support measures during periods of crisis using the COVID-19 economic shock as a case study. Attention has been paid to the effects of debt forbearance –temporary suspension of debt repayments– on households and private consumption (Cherry et al., 2021; Albuquerque and Varadi, 2022) and, to a lesser extent, on firms (Kürşat et al., 2023). Likewise, the effects of job retention schemes on employment and income have been analyzed (Baena, 2022; Dao and Aiyar, 2022; Lam

and Solovyeva, 2023), as well as the impact of guaranteed loans on credit supply (Jimenez et al., 2022; Cascarino et al., 2022). Despite the vast literature, to the best of our knowledge, except for Kürşat et al. (2023) and Burga et al. (2023), little has been said about the effects of policy responses on the capacity of firms to meet their credit obligations and financial stability.

We intend to fill this gap by analyzing the relationship between government support measures and firms' performance using the COVID-19 experience in Colombia as a case study. Similar to other jurisdictions, between 2020 and 2021, several policies were enacted to mitigate the adverse economic effects caused by the pandemic shock in Colombia. In addition to monetary and fiscal policies, measures such as debt moratoriums, payroll subsidies, and government credit guarantees were implemented. We are interested in examining how these three policies affected the firms' credit payments and the bank's credit risk assessment during and after the policies' in-force period.[1]

We follow a difference-in-differences (DiD) approach using highly granular administrative data from Colombia during 2018Q4-2021Q4 to analyze how credit default and banks' risk assessment evolved for loans granted to firms that accessed any support measures compared to those that did not. We define credit default as 30 days or more past due on loan payments and banks' risk assessment as credits whose score differs from A.

The empirical strategy we propose exploits unobserved and observed heterogeneities to compare treated and untreated firms, ensuring that variations are explained by differences in government support policies rather than by bank-firm and firm-specific variables. In estimations, we include the economic cycle for each economic sector (i.e., sector-time fixed effects) and a rich set of firm financial situation and credit conditions variables to control for the fact that firm characteristics could have possibly driven the decision to participate

[1]For simplicity, throughout the document, when we mention *banks*, we refer to all credit institutions that take deposits from the public and grant credits to the public. These entities include commercial banks, investment banks, financial cooperatives, and financing companies.

in support measures and that the effect of the pandemic was highly differentiated among economic sectors (Bonet-Morón et al., 2020). In this sense, we reduce significant sources of bias when measuring the impact of government support measures.

Our empirical findings indicate a lower probability of credit default for firms subject to debt moratorium and firms with government-guaranteed credits. The former's effect vanishes in 2020Q3 once the policy ends, indicating a catch-up effect since differences in the credit default are no longer statistically significant between treated and untreated firms afterward. Meanwhile, the latter's effect lasts for one additional period until 2020Q4. The more persistent impact is related to the fact that government-guaranteed loans provided liquidity to firms that they used not only to build up savings buffers (Granja et al., 2022) but also to meet credit obligations.

Regarding the payroll subsidies, firms could improve their capacity to pay loans since lower labor costs eased liquidity constraints. However, we find no statistically significant difference in the probability of credit default between treated and untreated firms.

As for banks' credit risk assessment, results indicate that credits granted to treated firms are, on average, more likely to be reclassified as risky once the policies end. This suggests that the participation status provides banks with additional information about the level of risk borne by beneficiary firms. The effect is more significant when debt moratoriums and payroll subsidies are analyzed. For both programs, the increase in the probability of being classified as risky was expected since, in the first case, once debt forbearance ended, each bank was compelled to update the risk rating of the relieved debtors on a case-by-case basis. In the second case, subsidies were disbursed through banks, meaning they were aware of the firm's performance since receiving payroll subsidies was a signal of a shrink in income. By contrast, in 2020Q3, the probability of being classified as risky decreases for firms with government-guaranteed credits, and subsequently, the opposite effect occurs. The drop in 2020Q3 is explained by the fact that government guarantees reduce the banks' credit risk

perception since the guarantee constitutes additional credit protection (Jimenez et al., 2022).

We analyze the effects of government support measures for the entire sample and by firm size. We find that large firms mainly drive the aggregate results on credit default. The heterogeneities in the probability of credit default between large and medium-sized firms are due to the difference in credit conditions between the two. In fact, on average, large firms obtain better credit conditions from banks than medium-sized firms (Chodorow-Reich et al., 2022). Regarding credit risk, on average, firms subject to debt moratoriums are perceived as riskier once the relief ends, regardless of their size. However, the probability of being classified as risky increases more for medium-sized treated firms than for large treated firms.

The magnitude of the effects we find should be carefully analyzed since our DiD estimation, despite the inclusion of control variables and the compliance of parallel trends, could still be affected by firm-specific and time-varying unobserved factors driven by self-selection. Therefore, without bias, we suspect the effects on credit default could be lower. Our estimates would be an upper bound of the real impacts if, after controlling for all firm-specific and fixed effects variables, firms chose not to participate because they expected a lower credit default than the one we would observe for participating firms in the absence of treatment. Still, despite this potential bias direction, we find significant negative effects on credit default. By contrast, we suspect a possible underestimation bias for banks' risk assessment. The increase in risk perception could be greater since firms that chose not to participate may have anticipated a huge rise in banks' risk perception.

Regardless of the latter, our results suggest that debt moratoriums and government credit guarantee programs contribute to smoothing the credit cycle in periods of economic distress, such as the COVID-19 pandemic. The lower credit defaults associated with these support measures might have prevented a sharp deterioration in banks' financial statements. In fact, the gentle increase in non-performing corporate loans observed in Colombia during the pandemic strengthens this latter. In addition, the effects on banks' risk assessment call attention

to possible unintended consequences of support policies, in which banks reclassify relieved debtors just because they were treated (*stigma* effect). However, an additional exercise we present in this document suggests that banks, perhaps, reclassified treated firms based on their participation status and initial financial situation (*information* effect). This approach could benefit banks since the additional information available for their risk management could enhance their screening ability and allow them to assess credit risk accurately, minimizing the impact on their operations, financial performance, and reputation, which supports the idea that the ability to classify corporate borrowers by credit quality is greater during bad times and worse during good times (Becker et al., 2020). Despite this, policymakers may be especially careful when implementing support measures since information friction and *stigma* effects could arise. Under these scenarios, credit supply could be affected, exacerbating economic and credit cycles.

Our paper contributes to the broad literature on the effectiveness of support policies during periods of crisis. Some studies have focused on analyzing the effects of debt moratorium policies on households during the 2008 Great Recession (Collins and Urban, 2018; Mayer et al., 2014; Quercia and Ding, 2009), while others evaluate household delinquencies and private consumption during the COVID-19 pandemic (Cherry et al., 2021; Albuquerque and Varadi, 2022). However, as far as we know, only a few have focused on measuring the effects of debt relief policies on firm performance. Kürşat et al. (2023) evaluate the impact of debt moratorium policies on firms and banks and their ability to alleviate debt burdens during the COVID-19 pandemic in Colombia. The authors find that this program helped reduce firm defaults and improve debtors' new loan conditions.

Regarding public credit guarantee schemes, previous research has analyzed the distribution of credit under government-guaranteed credit policies during the COVID-19 pandemic. For the Chilean case, Huneeus et al. (2022) find that these measures rapidly increased credit to a broad class of firms, although adverse selection issues occurred (i.e., higher-risk firms

borrowed disproportionately). Likewise, Jimenez et al. (2022) point out that riskier firms and those in sectors most affected by the pandemic were more likely to obtain government-guaranteed loans in Spain. Additional documents also focus on self-selection in credit guarantee programs (Baixauli-Soler et al., 2023; Cascarino et al., 2022; Humphries et al., 2020; Chodorow-Reich et al., 2022). In contrast, little has been said about the effects of these policies on firms' credit default. To the best of our knowledge, Burga et al. (2023) are the only ones addressing this topic so far. They estimate the impact of loan guarantees on delinquency rates during the COVID-19 economic downturn in Peru and find that the program expanded the credit supply and reduced delinquency rates.

Finally, as for literature on payroll subsidy programs, attempts to describe the job retention schemes adopted in different jurisdictions have been made (OECD, 2020). Likewise, several documents have analyzed the effects of these programs on employment (Baena, 2022; Dao and Aiyar, 2022) and income (Lam and Solovyeva, 2023).[2] However, there are few analyses of the impact on other firm performance variables.

Our contribution is twofold. First, we provide valuable information on the effect of relief programs on the corporate loan portfolio. This analysis is relevant since business failure represents important economic costs for societies, particularly in periods of crisis. Therefore, studying the effect of support programs on corporate credit default is crucial to designing policies to reduce those costs. Second, our analysis focuses on three government support measures in force during the COVID-19 pandemic rather than on one single measure, ensuring that omitted relief programs are not contaminating the effects. In addition, by analyzing credit default and credit risk, we present an unexplored transmission channel in the literature on government-guaranteed programs and payroll subsidies. Likewise, our findings are relevant for policymakers since we provide valuable insight into the effects of more than one different policy in the event of an economic crisis driven by liquidity shocks.

[2]Valuable studies have also focused on analyzing the impacts of paycheck protection programs on employment and income (Chetty et al., 2020; Granja et al., 2022).

The rest of the paper is organized as follows. Section 2 describes the main government support measures enacted for firms in Colombia during the COVID-19 pandemic. Section 3 describes the data we use. Section 4 elaborates on the empirical strategy, and Section 5 presents the results. Finally, in Section 6 we briefly conclude.

2 Firm support during COVID-19 in Colombia

In the spread of the COVID-19 pandemic in March 2020, concerns about the decline in firms' and workers' income due to the shutdown in business activity led governments worldwide to launch several support programs. The first COVID-19 case in Colombia was confirmed on March 6, 2020, and the government declared a state of emergency on March 17.[3]

In the early stages of this COVID-19 crisis, according to The Business Impact of COVID-19 Survey carried out by the Network of Chambers of Commerce (*Confecámaras*), most firms recorded a decrease in their total sales, and consequently, some decided to reduce their staff. In response to this situation, the government implemented a job retention scheme known as PAEF (*"Programa Apoyo al Empleo Formal"*) and credit lines through the National Guarantee Fund (FNG) for firms to pay payroll and working capital expenses. In addition, the Financial Supervisor (Financial Superintendence of Colombia) enacted debt moratoria for households and firms. These programs were created to mitigate the adverse effects on the production sector; however, each had its eligibility criterion and impacted the beneficiaries differently. The rest of this section describes each program in detail.

[3]Decree No. 637 of 2020, through which the state of economic, social, and ecological emergency was declared.

Payroll subsidies under PAEF

Regarding the job retention scheme, the PAEF was launched in May 2020 to partially subsidize eligible firms' payrolls. The benefit was up to 40% of the current monthly legal minimum salary per employee, with the possibility of receiving a maximum of three transfers. Beneficiaries comprising firms and employees had to fulfill several requirements to get the subsidy.

As for employees, they had to earn at least one current monthly legal minimum salary, and the employer had to pay the social security contributions for the entire month on that income. In addition, the employer could not have suspended the employees' contracts during the month prior to the application. As for firms, firstly, they had to be established before January 1, 2020, and the commercial registry must have been renewed at least in 2019. Second, a decline in income of more than 20% had to be recorded.[4] Third, firms had to have a deposit product, savings account, or checking account in a bank to be able to receive the subsidy, and government entities could only represent up to 50% of their capital. The employees considered to calculate the subsidy had to correspond to at least 80% of the workers appearing in the National Health and Pension Contributions registry as of February 2020.

This first scheme was thought to be in force until July 2020. However, the government extended the program until March 2021 with some modifications to the application requirements. In particular, the employees considered to calculate the subsidy had to correspond to at least 50% (no longer 80%) of the workers listed in the National Health and Pension Contributions registry. Furthermore, to continue receiving the subsidy, firms had to submit their application every month and could receive a maximum of 11 (no longer three) transfers. Additionally, the maximum subsidy of 40% of the current monthly legal minimum

[4]To determine if the income decreased by more than 20%, two calculation methods were established. The first consists of comparing the income received the month immediately before the application with the same month of the previous year. The second consists of comparing the income received the month immediately prior to the application with the average income for January and February 2020.

salary increased to 50% for female workers or companies associated with highly affected industries (sports, tourism, gastronomy, art, entertainment, and recreation). However, despite the modifications to the application requirements, the subsidies were never available to the informal sector, bankrupt companies, and personal companies with less than three employees.

A second scheme was implemented from May to December 2021 and was similar to the latest version of the first one. However, it was mainly focused on small and medium-sized enterprises (SMEs). Therefore, in addition to the aforementioned requests, firms had to have a maximum of 50 employees.

The total amount of subsidies disbursed under both PAEF schemes reached around COP 7.5 trillion (0.8% of GDP in 2020), which benefited 192,988 employers, representing 4,617,436 workers.[5] The direct effect of the program was to reduce labor costs by providing liquidity to firms, which reduced the number of jobs at risk of being laid off. Besides this, easing liquidity constraints could have strengthened the ability of firms to meet their financial obligations, which could have reduced the materialization of credit risk.

Government credit guarantees

Another policy enacted to mitigate the adverse effects of the COVID-19 pandemic was government credit support for enterprises to meet their payroll payments and working capital expenses, such as utilities and supplier expenses, among others. This policy was implemented considering the decrease in firms' income and difficulties in obtaining financing. Therefore, it consisted of granting credit guarantees through the FNG, which supported between 80% and 90% of the credits granted to firms by banks. Three different credit lines were defined: two for companies and one for independent workers, who also faced high credit granting restrictions. All three of these were in force from April 2020 to December 2021.

[5] `https://www.paef.ugpp.gov.co/ver20/index.php`.

The first credit line was focused on credits granted solely to payroll payments. The maximum amount of the credit was COP 2 billion or 25 current monthly legal minimum salaries (around COP 22 million in 2020) for SMEs per financial intermediary. The term was 12 to 36 months, and the guarantee was 90% of the credit. The second credit line focused on credits intended to pay working capital expenses. The maximum amount of the credit was COP 2.4 billion, the term between 12 to 36 months, and the guarantee was 80% of the credit. The third one concentrated on independent workers, the total amount of the credit was 25 current monthly legal minimum salaries, the credit maturity was 24 months maximum, and the guarantee was 80% of the credit. In all cases, the commissions charged by the FNG for the issuance of guarantees were assumed for the most part (75%) by the national government to alleviate the financial burden of the firms. Likewise, banks could defer the payment of the 25% that remained the entrepreneur's responsibility. Eligible for the credit guarantees were natural or legal persons, small or medium-sized enterprises domiciled in Colombia, or firms operating in any sector of the economy. In addition, the firms had to record annual sales of a maximum of COP 51.9 billion and independent workers to contribute to social security for at least three consecutive months of the last six.

In total, during the pandemic period, the FNG supported, through the three different credit lines, COP 37 trillion in disbursed loans (4.4% of GDP in 2020), benefiting more than 892,000 entrepreneurs and self-employed workers.[6]

Debt moratorium program

Regarding the debt moratorium policy, on March 17, 2020, the Financial Superintendence of Colombia allowed supervised credit institutions to postpone the borrowers' loan payments to preserve their payment capacity and financial stability.[7] The program gave debt forbearance in the loans' principal and interest rates, and the eligibility criterion was solely to present

[6]See this link.
[7]External Circular Letter 7 of March 17.

less than 60 days overdue on Feb 29, 2020.[8]

To debtors subject to debt moratorium, banks could not increase interest rates on loans, charge interest on interest, or report them in risk central bureaus. However, banks were compelled to continue accruing interest during the suspension period to ensure that debt forgiveness did not become a general practice. The policy design contained the increase in credit risk recorded during the early stages of the COVID-19 crisis. Nevertheless, once the debt forbearance ended (August 31, 2020), each bank updated the risk rating of the relieved debtors on a case-by-case basis, considering their financial condition, such as their payment capacity.[9]

Since all performing debtors with less than or equal to 60 days past due on their credit could access debt forbearance, the program's reach was massive. According to the Financial Superintendence of Colombia, the policy benefited around 12 million debtors, which meant 16.9 million credits that accounted for COP 224.9 trillion (22.5% of GDP in 2020).[10] Of this amount, the payment holiday in the corporate loan portfolio represented 37.6% (COP 84.7 trillion), in the consumer loan portfolio 34.1% (COP 76.7 trillion), in the housing loan portfolio 21.1% (COP 47.5 trillion), and in the microcredit loan portfolio the 7.2%. These repayment deferrals were intended to mitigate financial distress by easing liquidity constraints and strengthening borrowers' ability to pay, thereby contributing to financial stability.

[8]Initially, the External Circular Letter 7 established 30 over-due days; however, the External Circular Letter 14 of March 30 increased it to 60 over-due days.

[9]External Circular Letter 22 of March 17.

[10]`https://www.superfinanciera.gov.co/inicio/sala-de-prensa/publicaciones-/historico-medidas-de-la-superfinanciera-ante-coyuntura-por-covid-/cifras-de-seguimiento-a-las-medidas-10103899`.

3 Data

To evaluate the effects of the support programs that took place in Colombia during the COVID-19 crisis on firms' financial performance, we employ four data sets from 2018Q4 to 2021Q4. The first one corresponds to the Colombian credit registry, which consists of quarterly information on all loans extended to firms. It comprehends (at the loan level) credit variables, such as loan amount, interest rates, residual maturity, credit rating, default days, and credit guarantees. This latter is relevant since it allows us to identify those firms that accessed the government guarantees through the FNG during this period. To do so, we look for those who did not have credits supported by the FNG before the pandemic (2018Q4-2019Q4) but did have during the pandemic (2020Q1-2021Q4).

The second database was provided by the Financial Superintendence of Colombia and contains information on the debtors subject to the debt moratorium program. Therefore, it allows us to identify firms that received payment holidays from March to December 2020. The third one consists of the list of all firms that receive payroll subsidies under both PAEF schemes.[11] In general, even though we are able to identify firms subject to any of the three government support measures analyzed, we lack information on the exact date of access. Therefore, our study uses the treatment status as an absorbing state and focuses solely on the performance evolution of treated corporates during the whole analysis period (Sun and Abraham, 2021).

The last dataset we employ corresponds to the Colombian business registry, which contains information on the firms' annual balance sheets. These data concentrate on medium and large companies,[12] and comprehend variables, such as profitability, liquidity, size, economic sector, among others.

[11] This information is publicly available on the Pension and Parafiscal Management Unit website.

[12] According to the Decree 1074 of 2015, companies that register sales or assets higher than 30,000 monthly minimum wages must present financial statements to the Colombian Superintendence of Companies.

We merge these four datasets at the firm level, considering solely those with any loans as of 2019Q4. This is done as our goal is to analyze the effects of subsidies and bailout programs on firms' financial performance. Therefore, we aim to control for firm-specific initial variables and credit conditions. The final database is a quarterly panel from 2018Q4 to 2021Q4 at a bank-firm level consisting of 400,143 observations, 39 banks, 14,535 firms, and 37,268 bank-firm relationships. Although our study is silent about smaller and informal firms, it is still highly relevant from the financial stability perspective since the pool included represents 46% of banks' credit portfolio to the private corporate sector in December 2019.

Regarding the scope of the government support measures analyzed, firms that received payment holidays under the debt moratorium policy account for 73% of the observations, those that received payroll subsidies under both PAEF schemes represent 70%, and firms with loans guaranteed by the FNG 48%. In addition, the firms that received more than one support account for the 55%. The data suggest the implementation of these policies was massive.

We define two variables of interest, default days and credit ratings, to analyze the effects of government support measures on firms' financial performance. These are selected since we are interested in analyzing whether these programs contributed to strengthening borrowers' ability to pay by easing liquidity constraints, thereby contributing to financial stability, and also in analyzing if firms subject to any of the facilities were perceived as more or less risky once they ended. In particular, for default days, we focus on the probability of default, which we define as an indicator variable equal to one if the loan is 30 or more days past due. Similarly, for credit ratings, we construct an indicator variable equal to one if the loan has a rating other than A.[13] This variable denotes the probability of being classified as a risky loan.

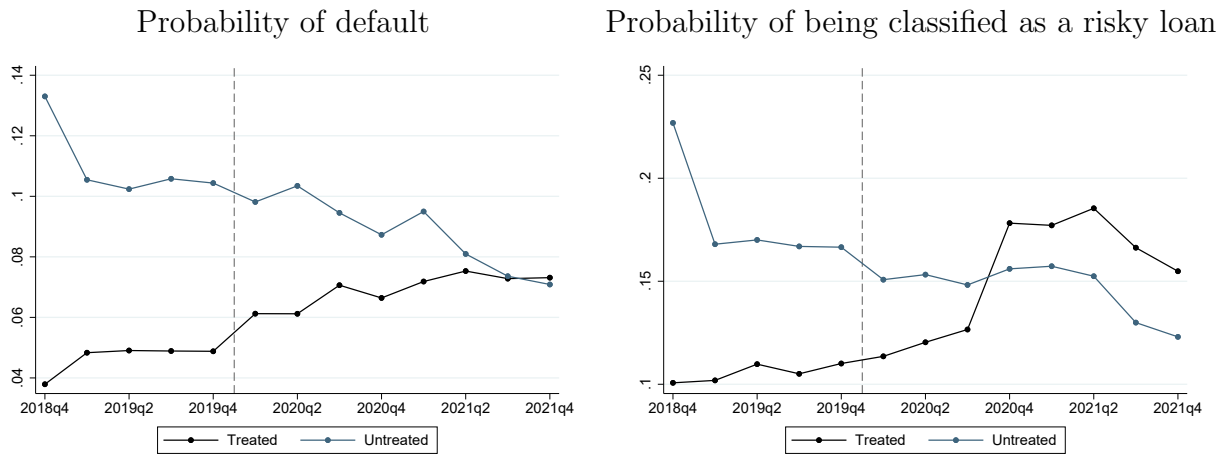
Figure 1 illustrates the dynamics of the probability of default and the probability of

[13]In Colombia, banks report the credit rating of each loan on a scale from A to E, in which A corresponds to the lowest risk level.

being classified as a risky loan between treated and untreated firms. In both cases, for the period prior to the COVID-19 pandemic, the treated and untreated firms registered a similar dynamic, although the average credit granted to the former presented a lower probability of default and classification as a risky loan.

During the implementation of the programs (i.e., during 2020), the probability of default increased in both groups of firms but at different times. For the untreated ones, this variable peaked in 2020Q2, while for those in the debt moratorium program, it remained relatively constant during the time the policy was in force (2020Q1-2020Q2) and then increased until 2021Q2. Regarding the probability of being classified as a risky loan, at the end of 2020, there was a sharp increase in the perception of risk for credits receiving any treatment. In contrast, banks' risk perception for the remaining ones decreased since 2021Q1. For the final period of analysis, it seems that both variables for the two groups of firms converge again to the same dynamic. However, this may be highly influenced by firm-specific variables as their own characteristics could have affected not only their payment behavior but also their decision to apply for any government support measures.

Figure 1: Trends between treated and untreated firms



Notes: Authors' calculations.

Considering the relevance of the firms' initial conditions, Tables 1 to 3 show that firms subject to any of the government support measures differ on average from the untreated ones. When focusing on all firms' initial financial situation, the treated ones, regardless of the program, recorded lower profitability, interest coverage ratio[14] and liquidity, and higher indebtedness before the COVID-19 pandemic (i.e., 2019Q4). In addition, firms with a lower logarithm of assets, a proxy of size, were more likely to receive credits guaranteed by the FNG and payroll subsidies (Tables 1 and 2).

Regarding credit conditions, some differences are also observed between both groups of firms. For instance, the debt moratorium policy focused on firms with higher loan amounts and lower maturities and interest rates (Table 3). In contrast, the credits guaranteed by the FNG were mainly directed to firms with lower credit amounts and interest rates but worse historical payment behavior, which means they recorded days of default greater than 30 during the last five years (Table 2). For firms under PAEF, differences are statistically significant only in interest rates: the treated ones recorded lower rates than the untreated ones (Table 1).

As some policies focused mainly on SMEs,[15] we split the sample into two groups to analyze the characteristics of firms treated under either of the three programs, differentiating by large and medium-sized enterprises.[16] According to the data, among large firms, 75.6%, 68.1%, and 38.6% of observations were under debt moratorium, payroll subsidies, and credits guaranteed by the FNG, respectively. In the case of medium-sized firms, these proportions change up to 70.4%, 71.7%, and 61.4%. In line with the design of the PAEF and government guarantee programs, the percentage of credits for medium enterprises that participated in

[14]Defined as the ratio between net operating income and financial costs.

[15]See the description of the PAEF and FNG programs in Section 2.

[16]Following Colombian financial regulation, small and medium-sized firms correspond to those with assets of less than 5,000 and 15,000 current legal monthly minimum wages, respectively. Considering that our sample includes information mainly from large and medium-sized firms, we define two categories. The first one corresponds to medium-sized firms that are those with assets of less than 15,000 current legal monthly minimum wages. The second one corresponds to large firms. Therefore, our analysis does not focus strictly on small and informal firms.

these policies is higher than that of large ones.

In general, as of 2019Q4, treated large firms, regardless of the policy, recorded a lower interest coverage ratio, liquidity and assets, a higher indebtedness, worse historical payment behavior, and lower interest rates. For medium-sized firms, although the treated ones, on average, recorded a lower interest coverage ratio and higher assets and loan amounts, several differences are observed depending on the policies. For instance, contrary to what is observed for the beneficiaries of payroll subsidies within the framework of the PAEF, those who received debt moratoriums and credits guaranteed by the FNG presented higher indebtedness and lower liquidity and interest rates.

Overall, for policymakers, the characterization we provide between treated and untreated firms by size and policy is relevant for the design of support measures in the future. Moreover, this characterization allows us to address selection bias due to observables in our empirical strategy.

Table 1: Mean differences between treated and untreated firms (payroll subsidies under PAEF)

	All firms			Large firms			Medium-sized firms		
	Treated	Unreated	Difference	Treated	Unreated	Difference	Treated	Untreated	Difference
Firms' financial situation									
Return over assets	0.03	0.03	0.00**	0.03	0.03	0.00**	0.04	0.03	-0.01***
Interest coverage ratio	4.00	4.86	0.86***	3.73	4.69	0.96***	4.39	5.15	0.76***
Debt-to-assets ratio	0.58	0.57	-0.01***	0.59	0.57	-0.02***	0.57	0.59	0.01**
Cash-to-assets ratio	0.06	0.06	0.00**	0.05	0.05	0.00	0.07	0.07	0.00
Log of assets	23.75	23.94	0.19***	24.68	24.89	0.20***	22.56	22.53	-0.03**
Credit conditions									
Historical payment behavior	0.25	0.24	-0.01	0.26	0.24	-0.03***	0.22	0.24	0.02***
Log of loan	19.64	19.61	-0.03	20.39	20.37	-0.02	18.67	18.46	-0.21***
Interest rate	0.12	0.12	0.01***	0.11	0.11	0.01***	0.13	0.13	0.01***
Maturity	3.01	3.03	0.01	2.78	2.84	0.05	3.31	3.32	0.01

Authors' calculations. The table depicts the difference in mean for financial situation and credit condition variables between firms that received payroll subsidies under PAEF and those that did not. The difference is calculated as the subtraction between the untreated and the treated. *, **, and ***, indicate significance at the 10%, 5%, and 1% respectively.

Table 2: Mean differences between treated and untreated firms (credits guaranteed by the FNG)

	All firms			Large firms			Medium-sized firms		
	Treated	Unreated	Difference	Treated	Unreated	Difference	Treated	Untreated	Difference
Firms' financial situation									
Return over assets	0.03	0.03	0.00***	0.03	0.03	0.00	0.04	0.03	0.00**
Interest coverage ratio	3.35	5.02	1.67***	3.10	4.59	1.49***	3.60	6.09	2.49***
Debt-to-assets ratio	0.60	0.57	-0.03***	0.60	0.57	-0.03***	0.60	0.55	-0.04***
Cash-to-assets ratio	0.05	0.06	0.01***	0.04	0.05	0.01***	0.06	0.08	0.02***
Log of assets	23.38	24.19	0.82***	24.26	25.04	0.79***	22.61	22.47	-0.14***
Credit conditions									
Historical payment behavior	0.26	0.23	-0.03***	0.28	0.24	-0.04***	0.24	0.20	-0.04***
Log of loan	19.54	19.70	0.16***	20.26	20.46	0.20***	18.92	18.18	-0.74***
Interest rate	0.11	0.12	0.01***	0.11	0.11	0.01***	0.12	0.14	0.02***
Maturity	3.04	3.00	-0.03	2.83	2.79	-0.04	3.22	3.45	0.23***

Authors' calculations. The table depicts the difference in mean for financial situation and credit condition variables between firms that received credits guaranteed by the FNG and those that did not. The difference is calculated as the subtraction between the untreated and the treated. *, **, and ***, indicate significance at the 10%, 5%, and 1% respectively.

Table 3: Mean differences between treated and untreated firms (debt moratorium program)

	All firms			Large firms			Medium-sized firms		
	Treated	Unreated	Difference	Treated	Unreated	Difference	Treated	Untreated	Difference
Firms' financial situation									
Return over assets	0.03	0.04	0.00***	0.03	0.03	0.01***	0.03	0.04	0.00
Interest coverage ratio	3.26	6.92	3.66***	3.13	6.81	3.68***	3.50	7.07	3.57***
Debt-to-assets ratio	0.59	0.54	-0.05***	0.60	0.53	-0.06***	0.59	0.55	-0.04***
Cash-to-assets ratio	0.05	0.09	0.04***	0.04	0.07	0.04***	0.06	0.10	0.04***
Log of assets	23.85	23.71	-0.14***	24.72	24.84	0.12***	22.59	22.48	-0.11***
Credit conditions									
Historical payment behavior	0.24	0.24	0.00	0.26	0.24	-0.02***	0.22	0.25	0.03***
Log of loan	20.07	18.55	-1.52***	20.76	19.36	-1.40***	19.07	17.68	-1.39***
Interest rate	0.11	0.14	0.04***	0.10	0.13	0.03***	0.12	0.15	0.04***
Maturity	2.98	3.15	0.18***	2.76	2.95	0.19***	3.30	3.38	0.09

Authors' calculations. The table depicts the difference in mean for financial situation and credit condition variables between firms that received payment holidays under the debt moratorium program and those that did not. The difference is calculated as the subtraction between the untreated and the treated. *, **, and ***, indicate significance at the 10%, 5%, and 1% respectively.

4 Empirical strategy

As shown in Section 2, the government support measures during COVID-19 for Colombian firms were available for a broad set of enterprises. In addition, the eligibility criteria of each policy were established based on variables that materialized days or months before, meaning the programs were not influenced by any prior knowledge or anticipation of the COVID-19 pandemic. However, in the end, the decision to participate was upon each firm, implying that estimating policy effects is challenging. For instance, in terms of observable variables, the participating firms were significantly different from the untreated ones since they had, on average, a more fragile financial position at the beginning of the COVID-19 pandemic (See Section 3). Moreover, in terms of unobservable variables, the treated firms may have had more access to financial information and were, therefore, aware of all kinds

of support measures. In consequence, a simple comparison between borrowers subject to support programs and those who did not participate would lead to biased results of the effects of the policy measures.

We employ a difference-in-differences (DiD) approach to address the potential sources of bias. This methodology exploits unobserved and observed heterogeneities to compare treated and untreated firms, ensuring that variations are explained by differences in the government support policies rather than by bank-firm and firm variables that could explain not only the self-selection into programs but also the outcomes.

Formally, we follow an event-study DiD specification to analyze the effects of government support measures on credit default (Default) and risk assessment (Risky), in which, as defined in Section 3, the first one stands to the probability of being 30 days overdue and the second one to the probability of being classified as a risky loan. The models we estimate are as follows:

$$\begin{aligned}\text{Default}_{fbt} = &\sum_{q\neq 2018\text{Q4}} \rho_q(\mathbf{1}[t=q]\cdot \text{Moratorium}_f) + \sum_{q\neq 2018\text{Q4}} \psi_q(\mathbf{1}[t=q]\cdot \text{Guarantees}_f) + \\ &\sum_{q\neq 2018\text{Q4}} \omega_q(\mathbf{1}[t=q]\cdot \text{Payroll}_f) + \sum_{q\neq 2018\text{Q4}} \alpha_q(\mathbf{1}[t=q]\cdot X_f^{2019}) + \\ &\sum_{q\neq 2018\text{Q4}} \phi_q(\mathbf{1}[t=q]\cdot X_{fb}^{2019}) + \sum_{q=1}^{4} \theta_q \text{Risky}_{fbt-q} + \kappa_{fb} + \gamma_{st} + \varepsilon_{fbt} \quad (1)\end{aligned}$$

and

$$\begin{aligned}\text{Risky}_{fbt} = &\sum_{q\neq 2018\text{Q4}} \rho_q(\mathbf{1}[t=q]\cdot \text{Moratorium}_f) + \sum_{q\neq 2018\text{Q4}} \psi_q(\mathbf{1}[t=q]\cdot \text{Guarantees}_f) + \\ &\sum_{q\neq 2018\text{Q4}} \omega_q(\mathbf{1}[t=q]\cdot \text{Payroll}_f) + \sum_{q\neq 2018\text{Q4}} \alpha_q(\mathbf{1}[t=q]\cdot X_f^{2019}) + \\ &\sum_{q\neq 2018\text{Q4}} \phi_q(\mathbf{1}[t=q]\cdot X_{fb}^{2019}) + \kappa_{fb} + \gamma_{st} + \varepsilon_{fbt}, \quad (2)\end{aligned}$$

where t stands for quarter, b for bank, f for firm, $\mathbf{1}[\cdot]$ corresponds to an indicator function and ε_{fbt} to the error term. The variables Moratorium_f, Guarantees_f, and Payroll_f are dummy variables equal to 1 if firm f accessed to debt moratorium, government guarantees, and payroll subsidies, respectively, during the COVID-19 pandemic. We include all three programs since, during this period, it was common for firms to access more than one support measure. The parameters of interest correspond to ρ_q, ψ_q, and ω_q since they capture the dynamic effect of each support measure *relative* to the excluded period, corresponding to 2018Q4.

Considering that the effect of the pandemic was highly differentiated among economic sectors, we also include sector-time fixed effects γ_{st} to control for the economic cycle within each sector. Likewise, taking into account the differences between treated and untreated, we include bank-firm fixed effects κ_{fb} and initial firms' financial and credit conditions, i.e., X_f^{2019} and X_{fb}^{2019}. Regarding the former, the control variables included correspond to the most relevant ones according to the corporate finance literature on firms' default (Cathcart et al., 2020; Traczynski, 2017; Bottazzi et al., 2011), such as return on assets (profitability), cash-to-asset ratio (liquidity), interest coverage ratio (debt burden), debt-to-asset ratio (indebtedness), and historical payment behavior, which is equal to 1 if the firm recorded a 30-day overdue before 2020.

As for the initial firms' credit conditions, we include the logarithm of the loan amount, interest rate, residual maturity, and credit rating dummies. In addition, following Bottazzi et al. (2011), who argue that credit risk classification represents a short-term default forecast made by the bank, we include the credit rating for four previous periods in equation (1). This is done to control for the information observed by banks (but not by us) about the payment capacity of debtors.

We complement the aforementioned analysis by calculating not only the dynamic effect of government support measures on credit default and risk assessment but also the overall

effect over the post-treatment period. To do so, we also follow a DiD approach. Specifically, we estimate the following models:

$$\text{Default}_{fbt} = \rho(\text{Post}_t \cdot \text{Moratorium}_f) + \psi(\text{Post}_t \cdot \text{Guarantees}_f) + \omega(\text{Post}_t \cdot \text{Payroll}_f) + \alpha(\text{Post}_t \cdot X_f^{2019}) + \phi(\text{Post}_t \cdot X_{fb}^{2019}) + \sum_{q=1}^{4} \theta_q \text{Risky}_{fbt-q} + \kappa_{fb} + \gamma_{st} + \varepsilon_{fbt} \quad (3)$$

and

$$\text{Risky}_{fbt} = \rho(\text{Post}_t \cdot \text{Moratorium}_f) + \psi(\text{Post}_t \cdot \text{Guarantees}_f) + \omega(\text{Post}_t \cdot \text{Payroll}_f) + \alpha(\text{Post}_t \cdot X_f^{2019}) + \phi(\text{Post}_t \cdot X_{fb}^{2019}) + \kappa_{fb} + \gamma_{st} + \varepsilon_{fbt}, \quad (4)$$

where Post_t corresponds to a dummy variable equal to 1 for periods after 2019, and the coefficients ρ, ψ, and ω stand for the average post-treatment effect from 2020Q1 to 2021Q4. This approach allows us to calculate the overall effect of each support measure[17] and evaluate whether the effects were persistent or not.

We cluster standard errors of all regressions at the bank-firm level to account for the serial correlation of panel data. Furthermore, regarding the parallel trend assumption, which we rely on to make a casual interpretation of the effects we are estimating, our dynamic specification allows us to determine whether this assumption holds before the COVID-19 pandemic (i.e., before 2020Q1). This is if the average non-performing and risky loans of firms subject to the policies had the same trend as those untreated in the absence of treatment, once we control for within bank-firm, sector-time, initial financial performance, and credit conditions. In other words, if ρ_q, ψ_q, $\omega_q \approx 0$ for all $q < 2020q1$.

We present the results of equations (1) to (4) for the entire sample and by firm size. The

[17]The overall effect refers to the total effect of the period of analysis. It is not a long-term effect since to determine this, it is necessary to include more periods ahead as well as some other factors. For instance, Kürşat et al. (2023) argue that the debt moratorium could produce over-indebtedness in the long term, something that should be considered when analyzing the long-term effects.

latter is done considering that the majority of government support measures implemented during the COVID-19 pandemic targeted SMEs. Therefore, we are interested in analyzing the effects by firm size. However, as mentioned in Section 3, we can only differentiate our sample by large and medium-sized firms; this is how the analysis is presented.

Despite all the considerations mentioned above, we acknowledge that our DiD estimation could still be affected by firm-specific and time-varying unobserved factors driven by self-selection. Therefore, the magnitude of the effects should be carefully read. We suspect that the direction of bias for credit default is overestimation. If, after controlling for all of the aforementioned factors, firms chose not to participate because they expected a lower default than the one we would observe for participating firms in the absence of treatment, our estimates would be an upper bound of the real effects. Still, we find significant negative effects on default despite this potential direction of bias. For banks' risk assessment, we suspect a possible underestimation bias. The increase in risk perception could be greater since firms that chose not to participate may have anticipated a huge increase in banks' risk perception. Unfortunately, we cannot provide strong evidence in this regard; however, the differences in observables that we document in Section 3 support our claims.

5 Results

This section presents the results concerning the impact of government support measures deployed during the COVID-19 pandemic: debt moratorium, government guarantee credits, and payroll subsidies on the firms' payment behavior. First, results are presented for the entire sample. We then conduct our analysis by firm size. Estimates are calculated following the DiD specifications presented in Section 4, robust standard errors are clustered at the bank-firm level, and control variables, such as initial firms' financial and credit conditions, firm-bank and sector-time fixed effects, are included.

Main results

Figure 2 panel (a) depicts the dynamic effect on the probability of default, while in panel (b), we present the effect on banks' credit risk assessment. The analysis of the pre-intervention trends in outcomes suggests that the parallel trends assumption is broadly satisfied in both panels. This means that, on average, credit default and credit risk perception are not associated with support measures in the period before the COVID-19 pandemic.[18]

Our empirical findings indicate a lower credit default during 2020Q2 for firms subject to debt moratorium and during 2020Q4 for firms with credits guaranteed by the FNG. In contrast, no statistically significant difference is found between treated and untreated groups for firms receiving payroll subsidies. This latter could be explained by the fact that subsidized firms were those whose income decreased by more than 20%, so initially an increase in credit default was expected. However, this rise was not observed, and instead, results do not suggest any change in the credit default dynamic, perhaps due to the job retention scheme that, by reducing labor costs, contributed to unemployment and prevented firms from defaulting as liquidity constraints were eased.

Regarding the debt moratorium program, firms with payment holidays record a 1.2 percentage point (pp) lower default probability during 2020Q2. However, given that this policy ended in August 2020, the effect vanishes in 2020Q3. Afterward, a catch-up effect is observed, as differences in the credit default are no longer statistically significant between treated and untreated firms. The effects on firms with government-guaranteed credits are similar to those described. Specifically, the credit default diminishes for those treated in 2020Q2 until 2020Q4, when the default probability decreases by 1.2 pp. In the subsequent

[18]Even though the pre-trends assumption is broadly satisfied, we point out some exceptions. For instance, in 2019Q4, the difference in the probability of credit default between firms under debt moratorium and the untreated ones is different from zero, as well as the difference in the probability of being classified as risky loans for firms with government-guaranteed credits during 2019Q1-2019Q3. In Appendix A, we argue that this is related to a *jumpy* behavior in the outcome variables recorded in some periods before the COVID-19 pandemic. However, we show that results remain similar even when we change the base period selection.

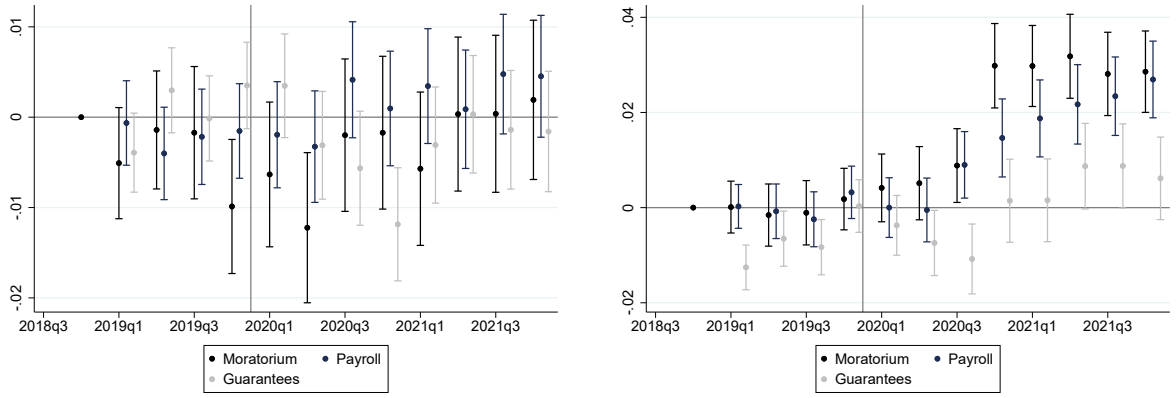
periods, however, no systematic differences in default are recorded between firms with and without government-guaranteed credits.

As for banks' credit risk assessment, results indicate that credits granted to firms treated under any of the three government support programs are, on average, more likely to be reclassified as risky once the policies end. In particular, for firms subject to debt moratorium and payroll subsidies, there is a higher probability of being classified as a risky loan since 2020Q3, corresponding to the period in which banks assessed the borrowers' ability to repay and reclassified those unlikely to resume payments. For the debt moratorium program, the probability of being rated other than A increases by around 3 pp at the end of 2020 and remains at similar levels afterward. Likewise, the banks' credit risk assessment is, on average, worse for firms receiving payroll subsidies. In fact, the treated firms' probability of being classified as a risky loan increases as of 2020Q3. In contrast, banks' risk perception decreases during 2020 for firms with government-guaranteed credits, and the opposite effect occurs thereafter.

The previous results suggest that policies enacted through banks, such as the debt moratorium and payroll subsidies, can provide additional information to these entities so that once the programs end, they are very likely to reclassify those debtors under treatment. Meanwhile, banks consider government guarantees additional credit protection in their risk assessment (Jimenez et al., 2022). Therefore, given that the guarantees had a term between 12 and 36 months, depending on the credit line granted, a reduction in the probability of being classified as risky for treated firms during the in-force period was expected, followed by a correction.

In addition to the dynamic effect, we are also interested in analyzing the overall effect of each government support policy. Table 4 depicts the results for the entire post-treatment study period (2020-2021). To analyze the effects on credit default and risk assessment, we present in Columns 1 and 4 the results without including firms' initial financial situation

Figure 2: Effects of government support measures during COVID-19 on Colombian firms



(a) Probability of credit default

(b) Probability of being classified as a risky loan

Authors' calculations. DiD estimates. Estimations include bank-firm and sector-time fixed effects. They also contain firm- and credit-level covariates as specified in equations (1) and (2). Robust standard errors are clustered at the bank-firm level. Confidence intervals are calculated at the 10% significance level.

and credit conditions, while in the remaining ones (Columns 2 and 3, and Columns 5 and 6) we gradually include the control variables that we present in Section 4.

Regarding the specification that does not include control variables, the government support measures are related to higher credit default and there is a large effect on risk assessment. However, when we control for firms' initial financial situation and credit conditions, the results change, which highlights the relevance of including these variables in the analysis. Specifically, we find no statistically significant difference in firms' payment behavior between treated and untreated, regardless of the program. This result and the dynamic effect previously analyzed point to a transitory positive effect of credit payment and an overall catch-up effect. In addition, we find that support measures are associated with a higher probability of being classified as risky, especially for debt moratoriums and payroll programs (2.0 pp and 1.4 pp, respectively). As for government guarantees, the effect has lower statistical power and magnitude (0.5 pp).

As mentioned above, the effects on the probability of being classified as risky could suggest that participation in support measures can provide banks with additional information that

negatively impacts the credit score of treated debtors once the policies end. This, in turn, could imply unintended consequences of these support policies. In particular, one could think of a *stigma* effect if banks, in their risk assessment, decided to reclassify treated firms just because the participation is a negative signal instead of analyzing the situation of each relieved firm on a case-by-case basis. However, if banks reclassified debtors based on their participation status and financial situation, the effects could be related to an *information* mechanism. We explore these channels in Appendix B. According to our findings, on average, firms that received any support measures and whose financial situation was weak are more likely to be reclassified as risky. This is the case, for instance, for less profitable firms under payroll subsidies and debt moratorium programs.

Table 4: Overall effects of government support measures during COVID-19 on Colombian firms

	Credit default			Risk assessment		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Post × Debt moratorium	0.0025	0.0012	0.0001	0.0314***	0.0267***	0.0195***
	(0.0021)	(0.0025)	(0.0033)	(0.0023)	(0.0027)	(0.0029)
Post × Government guarantees	0.0056***	-0.0029	-0.0033	0.0158***	0.0064**	0.0052*
	(0.0017)	(0.0020)	(0.0025)	(0.0024)	(0.0028)	(0.0029)
Post × Payroll subsidies	0.0072***	0.0051**	0.0031	0.0145***	0.0127***	0.0137***
	(0.0018)	(0.0020)	(0.0024)	(0.0024)	(0.0026)	(0.0027)
Observations	399,337	312,236	242,357	399,337	312,236	299,144
R-squared	0.657	0.662	0.653	0.703	0.709	0.688
Within adj. R-squared	0.0003	0.0091	0.0231	0.0027	0.0107	0.0127
Bank-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Initial Conditions × Post	No	Yes	Yes	No	Yes	Yes
Credit Initial Conditions × Post	No	No	Yes	No	No	Yes
Lags of risk rating	No	No	Yes	No	No	No

Authors' calculations. DiD estimates as specified in equations (3) and (4). Post corresponds to the entire post-treatment study period (2020-2021). Lags of risk rating correspond to the inclusion of four lags of banks' risk ratings for credit. Robust standard errors in parentheses are clustered at the bank-firm level. *** p<0.01, ** p<0.05, * p<0.1.

Heterogeneity analysis by firm size

Figure 3 depicts the results of the effect of the government support measures on credit default and banks' credit risk assessment by firm size. Panel (a) focuses on large firms, and panel (b) focuses on medium-sized firms. Overall, the large firms' results remain similar to those

recorded for the entire sample. For instance, the probability of credit default decreases during 2020Q2 for large firms subject to debt moratoriums and during 2020Q3 and 2020Q4 for large firms with credits guaranteed by the FNG. Likewise, similar to the aggregate results, there is no statistically significant difference in the probability of credit default between large firms receiving payroll subsidies and those not receiving them.

Related to the effects on banks' credit risk assessment, similar to the results of the entire sample, credits granted to large firms subject to debt moratorium and payroll subsidies are, on average, more likely to be reclassified as risky once the policies end. In both cases, a greater probability of being classified as risky loans is recorded as of 2020Q3. Meanwhile, for large firms with government-guaranteed credits, a lower probability of being classified as risky is recorded during 2020, and there is no statistically significant difference in the subsequent periods.

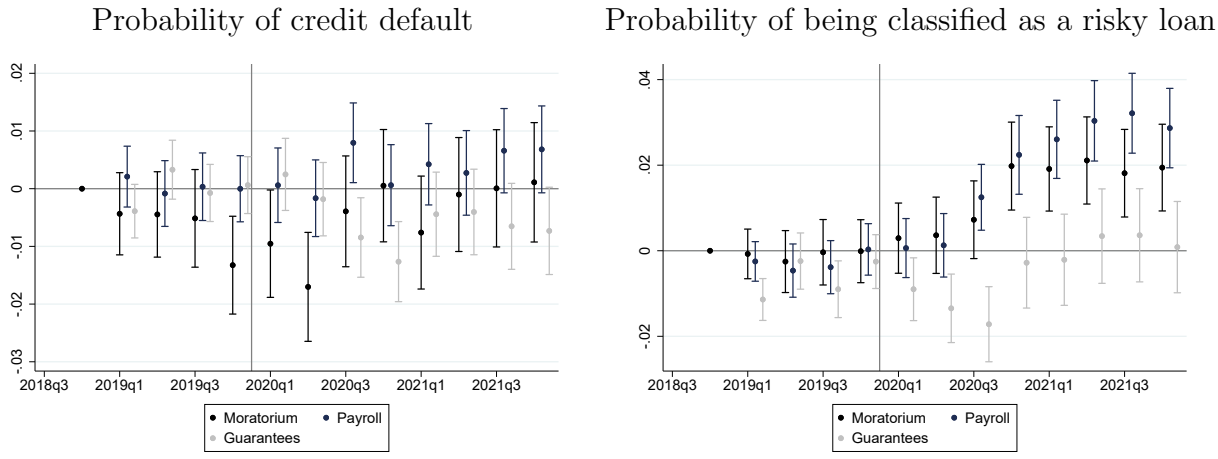
In contrast, the results for medium-sized firms differ from those of the entire sample. Regarding credit default, panel (b) shows no statistically significant difference in the probability of credit default between treated and untreated medium-sized firms during the entire analysis period, regardless of the program. As for credit risk, like the aggregate results, the probability of being classified as risky increases for medium-sized firms under debt moratorium and remains high. However, contrary to the aggregate results, for medium-sized firms subject to government support measures and those not subject to them, there is no statistically significant difference in the probability of being classified as a risky loan even though it increases as of 2021Q1. Likewise, for medium-sized firms that received payroll subsidies under PAEF, there is no statistically significant difference between the treated and untreated ones, except in the last quarter (2021Q4).

The heterogeneity in our findings on credit default across firm sizes could be related to differences in credit conditions. According to Section 3, on average, large firms obtain better credit conditions from banks than medium-sized firms. Therefore, large firms receiving debt

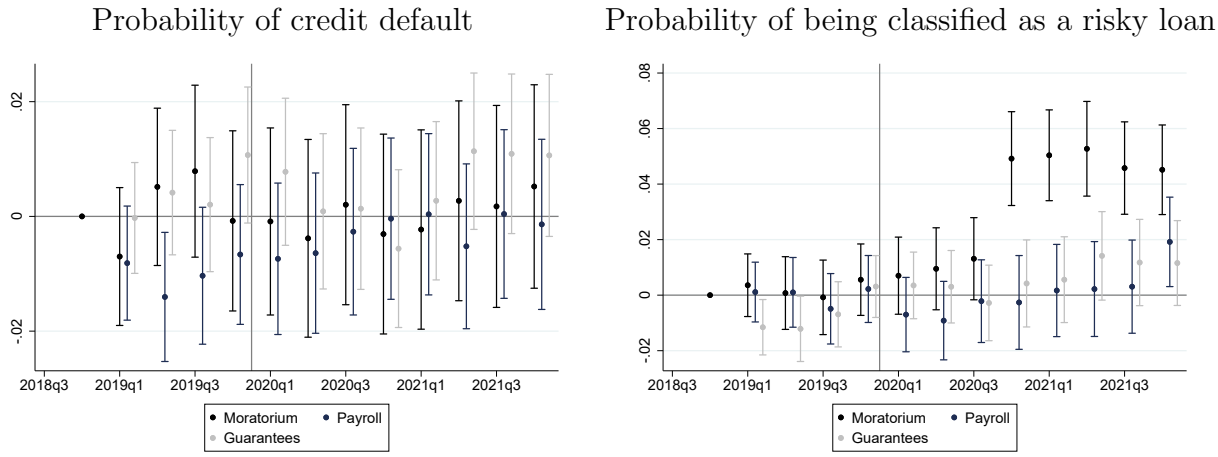
moratoriums and government-guaranteed credits could have experienced a greater decrease in financial expenses as, on the one hand, they had payment holidays and, on the other, they borrowed loans at lower rates. This latter considering that, in addition to the better credit conditions, government-guaranteed loans are disbursed at lower rates than existing loans since the guarantee abates credit risk (Cascarino et al., 2022). Consequently, large firms could have met their financial obligations better than medium-sized firms, reducing the probability of credit default.

As for the heterogeneities in credit risk, the hypothesis of better credit conditions could also explain that for large firms with government-guaranteed credits, the probability of being classified as risky decreases between 2020Q1 and 2020Q3, but it does not for medium-sized firms. Subsequently, however, a slight increase in the probability of being classified as risky is recorded for both as the guaranteed credits come to term. Conversely, the difference in credit risk between large and medium-sized firms that received payroll subsidies (i.e., for large firms, the probability of being classified as risky increases as of 2020Q3, while for medium-sized firms, rises only until 2021Q4) could be related to the fact that medium-sized firms received payroll subsidies for longer than large firms since both PAEF schemes included SMEs. Therefore, the effect on banks' risk assessment for medium-sized firms is recorded until the program ends (2021Q4). Lastly, the results do not vary significantly by size for firms under debt moratoriums. In fact, the probability of being classified as risky for large and medium-sized firms increases once the reliefs end since banks update the risk rating of both.

Figure 3: Heterogeneous effects of government support measures during COVID-19 by firm size



(a) Large size firms



(b) Medium-sized firms

Authors' calculations. DiD estimates by firm size. Estimations include bank-firm and sector-time fixed effects. They also contain firm- and credit-level covariates as specified in equations (1) and (2). Robust standard errors are clustered at the bank-firm level. Confidence intervals are calculated at the 10% significance level.

Finally, as we did for the entire sample, we analyze the overall effect of each government support policy by firm size. Table 5 depicts the results for the entire post-treatment study period (2020-2021). For large (medium) firms, we present the effects on credit default in Column 1 (3) and the effects on banks' risk assessment in Column 2 (4).

The effects on credit default are broadly similar to those of the entire sample and do not vary significantly between firm sizes. We find no statistically significant difference in firms' payment behavior between those treated under PAEF and debt moratorium and those untreated for both firm sizes, which is in line with the catch-up effect previously mentioned. In contrast, according to the negative dynamic effect found, the credit default decreases for large firms that received credits guaranteed by the FNG, and there is no effect for medium-sized firms.

The effects on banks' risk assessment vary slightly depending on the firm size. For large firms, debt moratoriums and payroll subsidies are associated with a higher probability of being classified as risky. Meanwhile, debt moratoriums and government guarantees are associated with a higher probability of being classified as risky for medium-sized firms. This finding suggests that, on average, firms under debt moratoriums are perceived as riskier once the relief ends, regardless of their size. However, the probability of being classified as risky increases more for medium-sized treated firms than for large treated firms, which could be related to the credit conditions hypothesis.

Table 5: Overall effect of government support measures during COVID-19 on Colombian firms

	Large firms		Medium-sized firms	
VARIABLES	Credit default	Risk assessment	Credit default	Risk assessment
Post × Debt moratorium	0.0003	0.0134***	-0.0013	0.0302***
	(0.0037)	(0.0035)	(0.0070)	(0.0051)
Post × Government guarantees	-0.0048*	-0.0001	0.0012	0.0111**
	(0.0027)	(0.0037)	(0.0052)	(0.0046)
Post × Payroll subsidies	0.0029	0.0212***	0.0050	0.0004
	(0.0025)	(0.0031)	(0.0056)	(0.0049)
Observations	160,655	188,106	81,702	111,038
R-squared	0.654	0.707	0.654	0.662
Within adj. R-squared	0.0295	0.0154	0.0156	0.0101
Bank-Firm FE	Yes	Yes	Yes	Yes
Time-Sector FE	Yes	Yes	Yes	Yes
Firm Initial Conditions x Post	Yes	Yes	Yes	Yes
Credit Initial Conditions x Post	Yes	Yes	Yes	Yes
Lags of risk rating	Yes	No	Yes	No

Authors' calculations. DiD estimates as specified in equations(3) and (4) by firm size. Post corresponds to the entire post-treatment study period (2020-2021). Lags of risk rating correspond to the inclusion of four lags of banks' risk ratings for credit. Robust standard errors in parentheses are clustered at the bank-firm level. *** p<0.01, ** p<0.05, * p<0.1.

6 Conclusion

Several studies have analyzed the effectiveness of support measures during periods of crisis using the COVID-19 economic shock as a case study. Much attention has been paid to the effects on households and private consumption, and less effort has been made to measure the effects on firms' credit performance. This paper aims to fill this gap by analyzing the relationship between government support measures and firms' credit default and credit risk using the COVID-19 experience in Colombia.

Following a DiD approach and using highly granular administrative data from Colombia during 2018Q4-2021Q4, results show a transitory lower probability of credit default followed by a catch-up effect for firms subject to debt moratorium and with government-guaranteed credits, indicating that these programs contribute to smoothing the credit cycle in periods of economic distress, such as the COVID-19 pandemic. In addition, we find that credits granted to firms that received support measures are more likely to be reclassified as risky after the end of the support since banks reclassified treated firms based on their participation status and initial financial situation. Heterogeneity analyses by firm size indicate that large firms mainly drive the aggregate results on credit default, and firms subject to debt moratoriums are perceived as riskier once the relief ends, regardless of their size.

Our findings on the probability of being classified as a risky loan call attention to policy-makers when implementing support measures since information friction and stigma effects could arise. Under these scenarios, credit supply could be affected, exacerbating economic and credit cycles. Further research could explore whether the increase in credit risk perception affected banks' credit supply, worsening the viability of initially affected firms.

References

Albuquerque, Bruno and Alexandra Varadi, "Consumption effects of mortgage payment holidays: evidence during the COVID-19 pandemic," IMF Working Papers 2022/44, International Monetary Fund February 2022.

Baena, Sara, "El impacto del Programa de Apoyo al Empleo Formal (PAEF) sobre la preservación de empleos en Colombia ante el choque del COVID-19," Tesis de maestría en Economía, Universidad de los Andes 2022.

Baixauli-Soler, Samuel, Gabriel Lozano-Reina, Susana Álvarez Díez, and Diego Rodríguez-Linares, "Impact of public guarantees on optimal debt levels following the COVID-19 pandemic: efficiency in their allocation," *Spanish Journal of Finance and Accounting / Revista Española de Financiación y Contabilidad*, 2023, *0* (0), 1–27.

Becker, Bo, Marieke Bos, and Kasper Roszbach, "Bad times, good credit," *Journal of Money, Credit and Banking*, 2020, *52* (S1), 107–142.

Bonet-Morón, Jaime, Diana Ricciulli-Marín, Gerson Javier Pérez-Valbuena, Luis Armando Galvis-Aponte, Eduardo A Haddad, Inácio F Araújo, and Fernando S Perobelli, "Regional economic impact of COVID-19 in Colombia: An input–output approach," *Regional Science Policy & Practice*, 2020, *12* (6), 1123–1150.

Bottazzi, Giulio, Marco Grazzi, Angelo Secchi, and Federico Tamagni, "Financial and economic determinants of firm default," *J Evol Econ*, 2011, *21*, 373–406.

Burga, Carlos, Walter Cuba, Eduardo Díaz, and Elmer Sánchez, "Loan Guarantees and Bank Incentives: Evidence from Covid-19 Relief Funds in Peru," 2023.

Caceres, Carlos, Diego Cerdeiro, Dan Pan, and Suchanan Tambunlertchai, "Stress Testing U.S. Leveraged Corporates in a COVID-19 World," IMF Working Papers 2020/238, International Monetary Fund November 2020.

Carletti, Elena, Tommaso Oliviero, Marco Pagano, Loriana Pelizzon, and Marti G Subrahmanyam, "The COVID-19 Shock and Equity Shortfall: Firm-Level Evidence from Italy," *The Review of Corporate Finance Studies*, 08 2020, *9* (3), 534–568.

Cascarino, Giuseppe, Raffaele Gallo, Francesco Palazzo, and Enrico Sette, "Public Guarantees and Credit Additionality During the Covid-19 Pandemic," Temi di Discussione (Working Paper) 1369, Bank of Italy May 2022.

Cathcart, Lara, Alfonso Dufour, Ludovico Rossi, and Simone Varotto, "The differential impact of leverage on the default risk of small and large firms," *Journal of Corporate Finance*, 2020, *60*, 101541.

Cerra, Valerie and Sweta Chaman Saxena, "Growth dynamics: the myth of economic recovery," *American Economic Review*, 2008, *98* (1), 439–457.

Cherry, Susan, Erica Xuewei, Gregor Matvos, Tomasz Piskorski, and Amit Seru, "Government and private household debt relief during COVID-19," NBR Working Papers 28357, National Bureau of Economic Research 2021.

Chetty, Raj, John N Friedman, Michael Stepner et al., "The economic impacts of COVID-19: Evidence from a new public database built using private sector data," Technical Report, national Bureau of economic research 2020.

Chodorow-Reich, Gabriel, Olivier Darmouni, Stephan Luck, and Matthew Plosser, "Bank liquidity provision across the firm size distribution," *Journal of Financial Economics*, 2022, *144* (3), 908–932.

Collins, J. Michael and Carly Urban, "The effects of a foreclosure moratorium on loan repayment behaviors," *Regional Science and Urban Economics*, 2018, *68*, 73–83.

Dao, Mai and Shekhar S Aiyar, "The Effectiveness of Job-Retention Schemes: Covid-19 Evidence from the German States," *Available at SSRN*, 2022.

Demmou, Lilas, Sara Calligaris, Guido Franco, Dennis Dlugosch, Muge Adalet McGowan, and Sahra Sakha, "Insolvency and debt overhang following the COVID-19 outbreak: Assessment of risks and policy responses," OECD Economics Department Working Papers 1651, OECD Publishing 2021.

Granja, João, Christos Makridis, Constantine Yannelis, and Eric Zwick, "Did the paycheck protection program hit the target?," *Journal of Financial Economics*, 2022, *145* (3), 725–761.

Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning, "Macroeconomic implications of COVID-19: Can negative supply shocks cause demand shortages?," *American Economic Review*, 2022, *112* (5), 1437–1474.

Humphries, John Eric, Christopher A Neilson, and Gabriel Ulyssea, "Information frictions and access to the Paycheck Protection Program," *Journal of public economics*, 2020, *190*, 104244.

Huneeus, Federico, Joseph P Kaboski, Mauricio Larrain, Sergio L Schmukler, and Mario Vera, "The distribution of crisis credit: Effects on firm indebtedness and aggregate risk," 2022.

Jimenez, Gabriel, Luc Laeven, David Martinez-Miera, and Jose-Luis Peydro, "Public Guarantees, Relationship Lending and Bank Credit: Evidence from the COVID-19 Crisis," Working paper, SSRN February 2022.

Kalemli-Ozcan, Sebnem, Pierre-Olivier Gourinchas, Veronika Penciakova, and Nick Sander, "COVID-19 and SME failures," *IMF Working Papers*, 2020, *2020* (207).

Kürşat, Yasin, Mauricio Villamizar-Villegas, and José Villegas, "Debt Moratorium: Theory and Evidence," Borradores de economía 1253, Banco de la República de Colombia 2023.

Lam, W Raphael and Alexandra Solovyeva, "How Effective were Job-Retention Schemes during the COVID-19 Pandemic? A Microsimulation Approach for European Countries," 2023.

Mayer, Christopher, Edward Morrison, Tomasz Piskorski, and Arpit Gupta, "Mortgage Modification and Strategic Behavior: Evidence from a Legal Settlement with Countrywide," *American Economic Review*, September 2014, *104* (9), 2830–57.

OECD, *Job retention schemes during the COVID-19 lockdown and beyond*, OECD Publishing, 2020.

Quercia, Roberto and Lei Ding, "Loan Modifications and Redefault Risk: An Examination of Short-Term Impacts," *Cityscape: A Journal of Policy Development and Research*, 2009, *11* (3), 171–193.

Reinhart, Carmen M and Kenneth S Rogoff, "Recovery from financial crises: Evidence from 100 episodes," *American Economic Review*, 2014, *104* (5), 50–55.

Sun, Liyang and Sarah Abraham, "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 2021, *225* (2), 175–199. Themed Issue: Treatment Effect 1.

Traczynski, Jeffrey, "Firm Default Prediction: A Bayesian Model-Averaging Approach,"

Journal of Financial and Quantitative Analysis, 2017, *52* (3), 1211–1245.

Tressel, Thierry and Xiaodan Ding, "Global Corporate Stress Tests—Impact of the COVID-19 Pandemic and Policy Responses," IMF Working Papers 2021/212, International Monetary Fund August 2021.

Zhang, Yanchun, Nina Thelen, and Aparna Rao, "Social protection in fiscal stimulus packages: Some evidence," 2010.

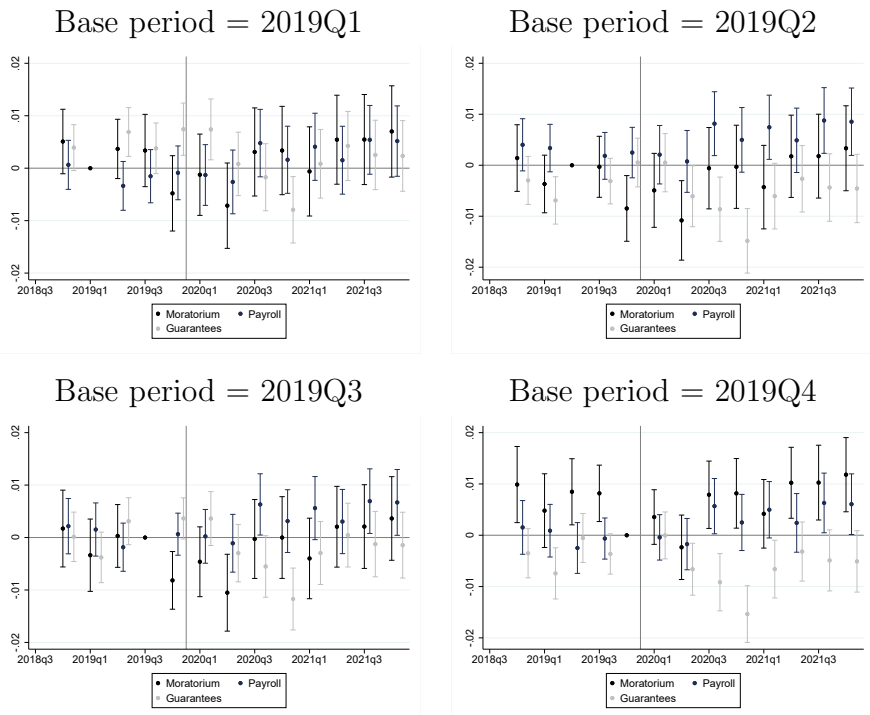
A Robustness to changes in base period

Figure 2 shows that the parallel trends assumption is broadly satisfied in the pre-treatment period. However, some exceptions are pointed out. For instance, in 2019Q4 the difference in the probability of credit default between firms under debt moratorium and the untreated ones is different from zero, as well as the difference in the probability of being classified as risky loans for firms with government-guaranteed credits during 2019Q1-2019Q3. In this Appendix, we argue that this is related to a *jumpy* behavior in the outcome variables recorded in some periods before the COVID-19 pandemic. Despite this, we show that results remain similar even if we modify the base period selection.

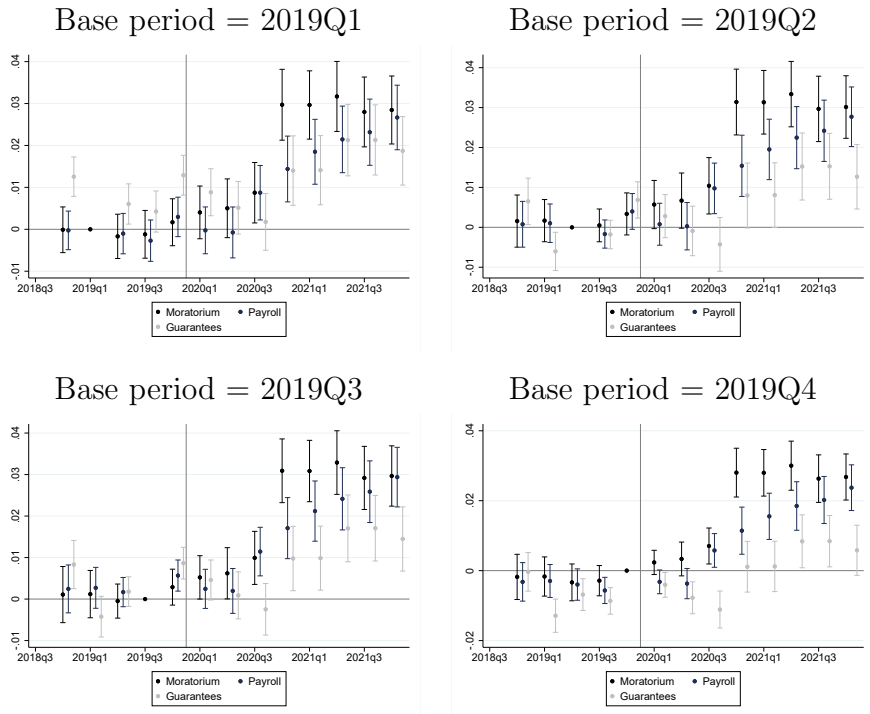
As a first exercise, we present the results of estimating equations (1) and (2) with different base period selections. Like the main results, panel (a) generally shows a transitory decrease in the probability of credit default for firms with debt moratoriums and government-guaranteed credits. However, when the base period is 2019Q4, an upward shift is recorded in the transitory results of the debt moratorium. Despite this, it remains true that relative to 2019Q4, during 2018Q4-2019Q3, the differential in the probability of credit default between treated and untreated firms was constant, and in 2020Q3, it decreased. Panel (b), conversely, shows an increase in the probability of being classified as risky for treated firms at the end of 2020 regardless of the base period selection.

As a second exercise, we estimate equations (1) and (2) using all the pre-treatment periods as a base (i.e., 2018Q4-2019Q4). Under this specification, each post-2020 estimate corresponds to the effect relative to the average pre-COVID-19 period. Figure A2 depicts the results. Similar to the main findings, relative to the pre-pandemic period, firms with debt moratoriums and government-guaranteed credits recorded a lower probability of credit default followed by a catch-up effect (panel a) and a higher probability of being classified as risky regardless of the support policy (panel b).

Figure A1: DiD estimates for different base periods



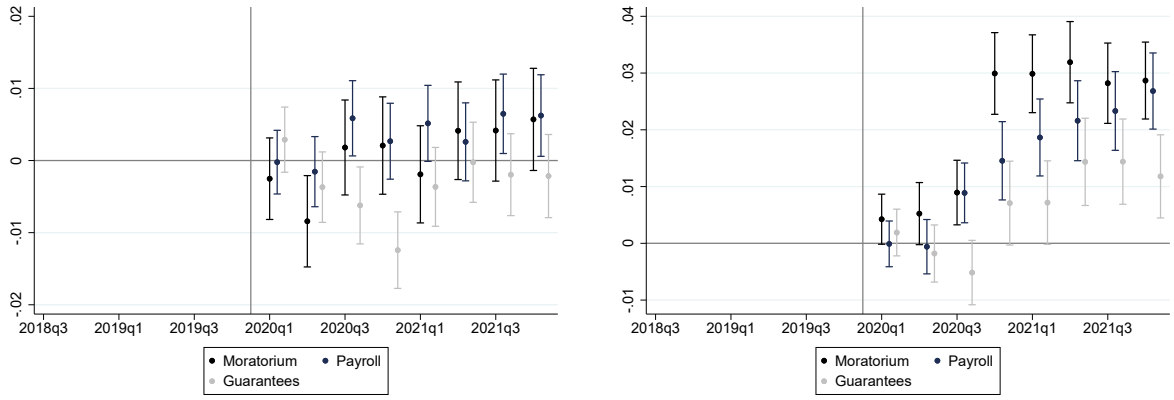
(a) Probability of credit default



(b) Probability of being classified as risky

Authors' calculations. DiD estimates as specified in equations (1) and (2) but changing the base period. Robust standard errors are clustered at the bank-firm level. Confidence intervals are calculated at the 10% significance level.

Figure A2: DiD estimates using 2018Q4-2019Q4 as base period



(a) Probability of credit default

(b) Probability of being classified as risky

Authors' calculations. DiD estimates as specified in equations (1) and (2) but changing the base period. Robust standard errors are clustered at the bank-firm level. Confidence intervals are calculated at the 10% significance level.

B Risk classification and financial situation of firms

The effects on the probability of being classified as risky could suggest unintended consequences of the support policies we analyze in this document. In particular, one could think of a *stigma* effect if banks, in their risk assessment, instead of analyzing the situation of each relieved firm on a case-by-case basis, decided to reclassify treated firms just because the participation is a negative signal. However, if banks reclassified debtors based on the participation status and their financial situation, then the effects we found could be related to an *information* mechanism. We explore these channels in this Appendix.

To explore to what extent the *stigma* or the *information* mechanism drove banks' risk assessment in the post-COVID-19 period, we include in equation (4) interaction terms between the entire post-treatment study period (2020-2021), the treatment status, and the initial characteristics of firms.[19] We estimate this specification to analyze whether firms' financial soundness affects the relationship between being classified as risky and support measures. If these terms are statistically significant, then the *information* mechanism hypothesis is stronger.

Table B1 depicts the results for the entire sample (Column 1) and by firm size (Columns 2-3). According to our findings, on average, firms that received any of the support measures and whose financial situation was weak were more likely to be reclassified as risky, reinforcing the *information* mechanism hypothesis. For instance, when analyzing the entire sample results, the probability of being classified as risky is lower for firms with higher initial profitability and assets that received debt moratoriums. Likewise, the effect of participating in government guarantees on credit risk classification is higher for more indebted firms. These results remain similar by firm size.

[19] Formally, we include $\text{Post}_t \cdot X_f^{2019} \cdot \text{Policy}_t$, where $\text{Policy}_t = \text{Moratorium}_f, \text{Guarantees}_f, \text{Payroll}_f$.

Table B1: Risk classification and financial situation of firms

VARIABLES	Entire sample (1)	Large firms (2)	Medium-sized firms (3)
Post × ROA × Moratorium	-0.234***	-0.364***	-0.0230
	(0.0570)	(0.0746)	(0.0869)
Post × Interest coverage ratio × Moratorium	-0.000183	-0.000310	-0.000418
	(0.000272)	(0.000310)	(0.000498)
Post × Debt-to-assets ratio × Moratorium	-0.00310	0.0102	-0.0361
	(0.0135)	(0.0165)	(0.0233)
Post × Cash-to-assets ratio × Moratorium	-0.0124	-0.0752*	0.0227
	(0.0357)	(0.0454)	(0.0521)
Post × Log of assets × Moratorium	-0.00751***	-0.00318	-0.0199***
	(0.00164)	(0.00239)	(0.00703)
Post × ROA × Guarantees	0.153***	0.297***	-0.109
	(0.0591)	(0.0812)	(0.0877)
Post × Interest coverage ratio × Guarantees	-0.000355	-0.000927**	0.000608
	(0.000340)	(0.000414)	(0.000545)
Post × Debt-to-assets ratio × Guarantees	0.0253*	0.0130	0.0481**
	(0.0149)	(0.0197)	(0.0245)
Post × Cash-to-assets ratio × Guarantees	0.0246	0.0475	0.0191
	(0.0392)	(0.0560)	(0.0515)
Post × Log of assets × Guarantees	-0.00399*	-0.00889**	0.0129*
	(0.00215)	(0.00423)	(0.00686)
Post × ROA × Payroll	-0.179***	-0.340***	0.00314
	(0.0557)	(0.0709)	(0.0879)
Post × Interest coverage ratio × Payroll	-1.16e-05	0.000432*	-0.000565
	(0.000245)	(0.000251)	(0.000469)
Post × Debt-to-assets ratio × Payroll	0.0177	0.0138	0.0254
	(0.0138)	(0.0167)	(0.0243)
Post × Cash-to-assets ratio × Payroll	-0.0613**	-0.0475	-0.0777*
	(0.0286)	(0.0332)	(0.0449)
Post × Log of assets × Payroll	0.00576***	0.00106	0.0125*
	(0.00167)	(0.00248)	(0.00737)
Observations	299,144	188,106	111,038
R-squared	0.688	0.708	0.662
Within adj. R-squared	0.0137	0.0174	0.0106
Bank-Firm FE	Yes	Yes	Yes
Time-Sector FE	Yes	Yes	Yes
Firm Initial Conditions x Post	Yes	Yes	Yes
Credit Initial Conditions x Post	Yes	Yes	Yes

Authors' calculations. DiD estimates as specified in equations (3) and (4), including interaction terms between the entire post-treatment study period (2020-2021), the treatment status, and the initial characteristics of firms. Estimates are conducted for the whole sample and by firm size. Robust standard errors in parentheses are clustered at the bank-firm level. *** p<0.01, ** p<0.05, * p<0.1.