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Corporate Loan Default Determinants in Indonesia

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This paper investigates the determinants of corporate loan default using Otoritas Jasa Keuangan Financial Information Services System (SLIK) database. We find that borrower characteristic is significant predictor for corporate loan default especially associated with public ownership (listed company) and business size (MSMEs or large company). Loan characteristic is also significant predictor for corporate loan default especially loan associated with government program and compatibility of loan project / purpose with borrower business expertise. Furthermore, COVID-19 pandemic period has significant impact to increase corporate loan default. Meanwhile, government loan restructuring is decreasing corporate loan default during COVID-19 period and it confirms the effectiveness of policy.

Keywords: probability of default, loan default, corporate loan, restructuring, COVID-19

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1. Introduction

The unforeseen events from the COVID-19 outbreak damages the global economy. The COVID-19 pandemic has also caused an unprecedented health and economic crisis. This pandemic has brought about severe adverse effects in global economy as well as face to face interaction among people. In the pandemic era, people have to suspend their social interactions at work places, schools, shops and restaurants, public transportations and other places.

That condition has caused an unprecedented level of decline in sales among business sectors. To reduce the severe impact of the pandemic, the governments and central banks have suggested implementing countercyclical policies by providing financial support for economic activities and increased public expenditures (e.g. World Bank, 2020; Bank of Japan, 2021).

Nevertheless the ending of the pandemic and the path to economic recovery remain highly uncertain. The COVID-19 economic impacts have contributed to a sharp rise in defaults of corporate and household debt. This condition in turn will erode the asset quality of banks (OECD, 2021). In recent developments, as the pandemic continues into 2021, banks could face a substantial increase in non-performing loans (NPLs).

Studies of the COVID-19 economic impact to the economy and financial sectors have been explored (e.g. Siregar et.al, 2021; OECD, 2021; BIS, 2020; Kristofi, 2021; Kozak, 2021). Nevertheless most of the studies focus heavily to the banking resilience and financial system stability. Few studies explore corporate loan default dan estimate probability of default at individual level. Bank of Japan (2021) estimate the impact of the COVID-19 pandemic on firms' (Micro, Small and Medium Enterprises / MSMEs) default probability of the corporate cash fund scarcity based on big data from Tankan Survey. The study finds decline in sales due to COVID-19 increases the default probability of firms. Nehberecka (2021) investigates the COVID-19 pandemic impact to the probability of default of non-financial companies.

This study seeks to assess the determinant factors of corporate loan default and their probability of default prior and during COVID-19. To the best of our knowledge, there is no strong paper that specifically addresses the issue in the region using big data of individual corporate loans in the pandemic era.

The rest of the paper is organized as follows, brief explanation of corporate bank loan during COVID-19 in Indonesia in Section 2. Then we present and discuss the research method and empirical results, in section 3 and 4, respectively. Finally, in section 5, we provide conclusions and policy implications.

2. Corporate Bank Loan during COVID-19 in Indonesia

Debt renegotiation is an efficient solution to resolve firms' distress and avoid costly bankruptcy. Moreover, traditional bank loans are easier to restructure in financial distress than public debt and trade credit from institutional lenders (Demiroglu & James, 2015; Hotchkiss et al,. 2008). Indeed, the economic impact of the COVID-19 pandemic is affected to both supply-side and demand-sides shocks. This shocks cause most businesses regardless their size (micro, small, medium or large enterprises) and economy sector nearly collapse because of more than 30 percent decrease in revenues.[1] Consequently, it impact to the borrowers performance and capacity in carrying out their credit obligations.

Most economies, including Indonesia, address the COVID-19 economy impact with policies related to bank restructuring. OJK as Indonesia financial sector authority issued series of policies related to bank loan restructuring: Regulation of the Financial Services Authority (POJK) Number 11/POJK.03/2020 regarding national economy stimulus as countercyclical policy of coronavirus disease 2019, which is revised by Regulation of the Financial Services Authority (POJK) Number 48/POJK.03/2020 that authorizes bank to restructure any loans (maximum total loan amount is IDR 10 billion) of borrower that is exposed by COVID-19 shock, starting from March 2020 to March 2022. This regulation allow banks to offer relaxation in loan term to their borrowers, thus the borrowers have time to withstand the effects of supply chain shocks due to lockdown. Per June 2021, total restructured outstanding loan is IDR 791.93 trillion from 5.03 million borrowers.[2]

3. Research Method

3.1. Data

The analysis in this paper uses data primarily from Otoritas Jasa Keuangan (OJK / Indonesian Financial Services Authority) Financial Information Services System (SLIK) database. SLIK database contains the universe of monthly Indonesia customers' debt history whose information are exchanged amongst financial institutions, both banks and non-banks. It is a centralized borrower's credit scoring reported by all financial institutions registered in the system. Through SLIK, financial institutions will check prospective customers' credit scoring to assess their creditworthiness during underwriting process. The database includes borrower's personal information, historical financing facilities (loan, debt securities, irrevocable LC, bank guarantee, and other financing facilities), collateral information, guarantee information, corporate owners or management, and financial reports. The database contains dynamic information such as the performance of each facilities, outstanding amount, restructuring frequency, interest rate, past due amounts updated on a monthly basis. In addition, the dataset also provides static information recorded at the time the loan was originated, such as facilities' initial amount, loan ID, Customer ID. So far, SLIK database have never been used for research in Indonesia, particularly for the analysis of the determinant of loan default. We refer to

[1] Micro and Small Enterprise Survey conducted by OJK in 2020 and 2021
[2] From www.ojk.go.id

Bastos (2010), Adelino et al. (2016), Ertan, Loumioti, and Barbaglia et al. (2021) for the existing works that exploit borrower's database for a variety of loan default.

In this study we focus on productive loan of commercial bank for non-bank corporate borrowers. We exclude interbank loan in order to get overview of real sector condition. This is an important part of bank loan, given the high concentration of productive loan in Indonesia.[3] We use loan level and borrower level data set providing information about loan granted, borrower, and loan project as object to be financed underlying each loan at the time of the origination. In particular, loan level information includes data on loan ID, principal loan amount, loan starting date, loan type/purposes, interest rate, and its type (e.g., fixed rate for life, fixed with future periodic resets, or floating), the loan term, the status, sector of economy, restructuring frequency, restructuring date, number of day past due, amount of past due, and performance of the loan, whether it is performing, defaulted or in arrears, and for how many months it has been in arrears. Borrower level information includes personal borrower information: Tax ID, address, business age, go public status, bank-related borrower's type. The most important thing is the SLIK data include not only loan characteristics at origination but also the performance of loans after origination. Furthermore, the system stores historical data for loan that has been paid up, write-off, sell to other financial institutions or as securitization. Thus, it is allowing us to look at ex post delinquency and defaults. We collected loan-level information from SLIK over the period from January 2019 until June 2021. Table 1 shows the description of dataset we employ for this study.

[3] Indonesia Economic and Financial Statistics (SEKI) September 2021: % Productive bank loan to all bank loan for Dec 2015 to Dec 2020 and Sep 2021 are 72%, 81%, 71%, 66%, 70%, 85%, and 80% respectively. Source: https://www.bi.go.id/en/statistik/ekonomi-keuangan/seki/Default.aspx

Table 1. Explanatory Variables used to estimate probability of default

Features	Attribute	Type	Description
Loan Quality	Dynamic	Categorical	Loan classification based on borrower business prospect, performance, and payment capability. 1 if the loan is categorized as non-performing loan (NPL) and 0 otherwise
Borrowers Characteristics			
Business Age	Dynamic	Numerical	Number of months since the borrower is founded to month observation
Bank Related Parties	Dynamic	Categorical	Borrower relationships with the bank such as same ownerships, same group. 1 for confirmed relationships, 0 for independent relationships
Go Public	Dynamic	Categorical	1 for listed corporate, 0 for non-listed corporate
MSME	Dynamic	Categorical	Borrower business size. 1 for micro, small, and medium enterprises (MSMEs), 0 for non-MSMEs
Loan Characteristics			
Econ. Sector	Static	Categorical	Similarity of primary economy sector of borrower business line and loan economy sector. 1 for same economy sector, 0 for different economy sector
Gov. Loan Program	Static	Categorical	Loan type. 1 for government program loan, 0 for non-government loan
Interest Rate	Dynamic	Numerical	Loan Interest rate, observable monthly (percentage)
Plafond	Static	Numerical	Loan amount at originated (billion IDR)
Outs. Loan	Dynamic	Numerical	Current loan amount, observable monthly (billion IDR)
Term Loan	Static	Numerical	A set period of payment term last, in months
Due Freq.	Dynamic	Numerical	How many time borrower experience past due payment
Days Past Due	Dynamic	Numerical	The number of days by which borrower have missed payment
Rest. Freq.	Dynamic	Numerical	How many time loan has been restructured
Days to Rest.	Dynamic	Numerical	The number of days by which loan has been restructured for the first time since it originated

3.2. Empirical Strategy

We use standard logistic regression analysis to determine the effect of borrower and loan characteristic to probability of corporate loan default:

$$y_{it} = c + X_{it}\beta + \gamma_1 z_{it} + \gamma_2 \mathbf{1}_{t\geq \text{April 2020}} + \gamma_3 \mathbf{1}_{t\geq \text{April 2020}} z_{it} + \varepsilon_{it}$$

where y_{it} is default indicator of loan quality i at month t (observations are arranged by loan ID-month). The value of y_{it} is binary, which is $y_{it} = 0$ for loan quality 1 or 2, and $y_{it} = 1$ for loan quality 3, 4, or 5. This default indicator is also in line with non-performing loan (NPL) definition set by regulator[4]. X_{it} is covariates matrix, it consists of borrower and loan characteristic. z_{it} is variables of interest, due frequency, days past due, restructuring frequency, and days to restructuring. There are four model in total, which we apply one variable of interest for each model. $\mathbf{1}$ is dummy variable that indicates the COVID-19 pandemic period, defined from April 2020 where government starts to apply social restriction.[5] We also add the interaction $\mathbf{1}$ and z_{it} to distinguish effects of variable of interest before pandemic and during pandemic. For set of coefficients, c is scalar intercept, β is vector of coefficients of covariates, γ_1 is coefficient for variable of interest z_{it}, γ_2 is coefficient for COVID-19 indicator $\mathbf{1}$, and γ_3 is coefficient for variable interaction $\mathbf{1}$ and z_{it}.

The borrower characteristic consists of business age, bank related parties, go public, and MSMEs. Business age is measured by months, from the time when the business entity was first established until the month observation. Bank related parties is a dummy variable, the value is 1 if borrower has connection with bank and 0 otherwise. The connection can be bank shareholder, bank subsidiary, shareholder of bank subsidiary, family relationship with bank/bank subsidiary controller or administrator, or having financial dependency with bank. Go public is dummy variable which the value is 1 if borrower has public share, and 0 otherwise. MSME is also a dummy variable, the value is 1 if borrower is classified as micro, small, or medium enterprise.

The loan characteristic consists of economic sector, government loan program, interest rate, plafond, outstanding loan, and term loan. The economic sector is dummy variable which the value is 1 economic sector of loan project is corresponding with the economic sector of borrower company business line. Government loan program is also a dummy variable, the value is 1 if the loan is categorized as government

[4] Regulation of the Financial Services Authority (POJK) Number 40/POJK.03/2019 regarding valuation of commercial bank asset quality. For loan quality classification, 1 (performing loan), 2(special mention), 3 (sub-standard), 4(doubtful), 5(default)

[5] Government Regulation Number 21/2020 and Minister of Health Regulation Number 9/2020 regarding guideline of large scale social restriction

program. Interest rate is credit interest in percentage, plafond is total amount of loan in billions IDR, outstanding loan is also in billions IDR, and term loan is length of loan contract in months.

For definition of variable of interest, due frequency is frequency of credit delinquency (exceed due date), days past due is number of days from due date until date observation of credit delinquency, restructuring frequency is how many times the credit is restructured, and days to restructuring is number of days from time loan origination until first restructuring date. The value of variable of interest is set 0 if there is no credit delinquency or credit restructuring.

4. Results

4.1. Descriptive Statistics and Correlation Matrix

Table 2 presents the descriptive statistic of loan quality, borrower characteristic, loan characteristic, and our variable of interest. The table includes the results in time period pre COVID-19 and during COVID-19. For borrower characteristic, bank related parties, go public, and MSMEs have the similar values for two periods. The reason is two time periods data mostly share the same borrowers, only small percentage of new borrowers enter during COVID-19 period. Only variable business age which is higher in the mean (4.35 months difference) during COVID-19 period. From the definition of business age and the fact that two time periods mostly share the same borrowers, its value will be higher in later period (COVID-19).

For loan characteristic, economic sector and government loan program are slightly lower during COVID-19 period. From pre COVID-19 to COVID-19 period, interest rate has the mean 11.40% then decreasing to 10.70%, plafond has the mean 26.40 billion IDR then decreasing to 18.21 billion IDR, outstanding loan has the mean 7.02 billion IDR then increasing to 7.50 billion IDR, and term loan has the mean 50.97 months then increasing to 53.69 months. Clearly there is credit contraction during COVID-19 period, it makes the bank lowering credit interest, and decreasing loan originated amount (plafond). The increasing of outstanding loan and term loan is the results of credit restructuring program during COVID-19 period. The borrowers postpone the payment of interest and or principle, therefore their outstanding loan and term loan are automatically increasing.

Table 3 presents the correlation matrix of borrower characteristic, loan characteristic, and variable of interest. We estimate models separately based on variable of interest and observe correlations excluding interaction among those four variable of interest, which resulting relatively low values (the absolute values are lower than 0.3). Therefore there is no multicollinearity problem in the model regression.

Table 2. Descriptive Statistics of Variables: pre COVID-19 and during COVID-19

Variable	obs		mean		sd		25 percentile		median		75 percentile	
	pre covid	covid	pre covid	covid	pre covid	covid	pre covid	covid	pre covid	covid	pre covid	covid
Loan Quality	1266938	1220214	0.04	0.05	0.20	0.22	0	0	0	0	0	0
Borrower characteristic												
Business Age	1250003	1216826	182.40	186.75	155.17	159.34	74.03	74.77	138.03	143.20	250.40	252.67
Bank Related Parties	1266938	1220214	0.02	0.02	0.14	0.13	0	0	0	0	0	0
Go Public	1266938	1220214	0.03	0.02	0.18	0.15	0	0	0	0	0	0
MSME	1266938	1220214	0.51	0.51	0.50	0.50	0	0	1	1	1	1
Loan characteristic												
Econ. Sector	1266938	1220214	0.49	0.48	0.50	0.50	0	0	0	0	1	1
Gov. Loan Program	1266938	1220214	0.02	0.01	0.13	0.12	0	0	0	0	0	0
Interest Rate	1222262	1191890	11.40	10.70	5.70	5.36	9.25	8.75	11.10	10.50	12.75	12.25
Plafond	1233126	1183382	26.40	18.21	2524.64	536.43	0.20	0.19	0.84	0.81	4.00	4.00
Outs. Loan	1266938	1220214	7.02	7.50	61.15	68.02	0.08	0.07	0.38	0.37	1.89	1.89
Term Loan	1266938	1220214	50.97	53.69	41.86	44.55	24.33	24.37	36.53	41.37	60.90	62.97
Due Freq.*	89309	133920	12.33	9.19	25.32	21.35	1.00	1.00	2.00	1.00	11.00	6.00
Days Past Due*	96442	105445	411.64	401.38	808.05	722.22	30.00	26.00	89.00	90.00	432.00	432.00
Rest. Freq.*	50181	220451	1.34	1.49	0.98	10.33	1.00	1.00	1.00	1.00	1.00	1.00
Days to Rest.*	37364	180833	1263.73	1138.96	1093.70	1208.96	558.00	374.00	1030.00	801.00	1669.00	1475.00

This table presents the descriptive statistics of variables used in the model, in pre COVID-19 and during COVID-19 time period. The observation is in "loan ID-month" panel format. Loan quality is binary variable of default indicator. For borrower characteristic, business age is in months, bank related parties is dummy variable of having connection with bank, go public is dummy variable of having public share, and MSME is dummy variable of micro small medium enterprise. For loan characteristic, economic sector is dummy variable that loan project is corresponding with the economic sector of borrower company business line, government loan program is dummy variable of loan categorized as government program, interest rate is in percentage, plafond is in billion IDR, outstanding loan is in billion IDR, and term loan is in months. For variable of interest, due frequency is number of delinquency, days past due is number of days from due date until date observation, restructuring frequency is number of restructuring, and days to restructuring is number of days from time observation until first restructuring date. Sign * for variable of interest indicates that descriptive statistic is calculated only for loans that have credit delinquency or restructuring.

Table 3. Correlation Matrix

	Business Age	Bank Related Parties	Go Public	MSME	Econ. Sector	Gov. Loan Program	Interest Rate	Plafond	Outs. Loan	Term Loan	Due Freq.	Days Past Due	Rest. Freq.	Days to Rest.
Business Age	1													
Bank Related Parties	0.0411	1												
Go Public	0.0838	0.0448	1											
MSME	-0.0872	-0.0266	-0.1135	1										
Econ. Sector	0.0378	-0.0318	-0.0343	-0.0206	1									
Gov. Loan Program	-0.0438	0.0324	-0.0138	0.1004	-0.0442	1								
Interest Rate	-0.0012	-0.0030	-0.0066	0.0075	-0.0094	-0.0035	1							
Plafond	0.0034	0.0006	0.0037	-0.0100	0.0008	-0.0002	-0.0005	1						
Outs. Loan	0.0375	0.0260	0.0494	-0.0866	0.0368	-0.0063	-0.0038	0.0450	1					
Term Loan	0.0859	0.0020	0.0305	-0.0471	-0.0515	-0.0199	0.0024	0.0007	0.0585	1				
Due Freq.	0.0018	-0.0070	-0.0147	0.0323	-0.0334	-0.0029	0.0037	-0.0007	-0.0066	-0.0057	1			
Days Past Due	0.0011	-0.0060	-0.0128	0.0374	-0.0320	-0.0015	0.0039	-0.0009	-0.0082	-0.0108	0.8393	1		
Rest. Freq.	-0.0061	0.0018	-0.0048	0.0170	-0.0150	0.0007	-0.0001	-0.0001	0.0013	0.0343	0.0057	0.0036	1	
Days to Rest.	0.0104	0.0272	-0.0196	0.0777	-0.0519	-0.0047	-0.0016	-0.0005	0.0076	0.2979	0.0237	0.0120	0.1077	1

This table presents the correlation matrix of borrower characteristic, loan characteristic, and variable of interest. The definition of each variable is the same with definition in Table 1, except for variable of interest that is calculated from full sample not only for loans that have credit delinquency or restructuring.

4.2. Empirical Results

Table 4 presents the logistic regression results with four models. Model 1, 2, 3, and 4 are for variable of interest due frequency, days past due, restructuring frequency, and days to restructuring respectively. The results provide significancy analysis for probability of loan default.

For borrower characteristic, we find positive significances for business age, go public, and MSME in model 1, 2, 3, and 4. Bank related parties has positive significances for model 1 and 2, but negative significances for model 3, and 4. Bank related parties tend to increase probability of default due to possibility of subjectivity in under writing process. Go public firm and MSMEs also tends to increase probability of default than private firm and non-MSMEs. It is general consensus that micro, small, and medium enterprises inherently riskier than large company. In addition, bank may incorrectly assess MSMEs risk and characteristic due to asymmetric information (Stiglitz and Weiss, 1981).

For loan characteristic, we find negative significances for economic sector, government loan, and outstanding loan in model 1, 2, 3, and 4. This findings confirm that in distributing loan, bank should be considered project underlying the loan associated with company expertise (same economic sector). Meanwhile government loan tend to decrease probability of default because the government subsidy (interest rate, loan insurance program) is one of tools to bridge high risk borrower to get relatively low interest (Kim and Lim, 2021). In other side negative significancy for outstanding loan means payment relatively lowering probability of default, however the economic impact of outstanding loan is relatively not significant. The Interest rate is positive significant in model 3 and 4 (restructuring) but not significant in model 1 and 2 (delinquency). The significancy of interest rate in model 3 and 4 (restructuring) may due to changes in interest rate as a results of loan restructuring and its economic impact is also relatively not significant. Plafond is not significant in model 1, 2, 3, and 4. This results also confirm that plafond (loan amount) is clearly not related to probability of default. Term loan is positive significant in model 2, but negative significant in model 3, and 4, and not significant in model 1. Positive significancy for days past due mostly because many companies is exposed to business downturn during COVID-19 made them difficult to fulfill their obligation. For restructuring view (model 3 and 4), restructured loans have longer term loan or granted for grace period of payment and eventually lowering their probability of default. Kim and Lim (2021) find that amortization schedule implemented on mortgage government program is successfully reducing the foreclosure rate.

Covid indicator is positive significant with 1% in all models reflecting that COVID-19 time period essentially increase probability of default. In addition, all variable of interest (due frequency, days past due, restructuring frequency, and days to restructuring) are positive significant with 1%. Going further, we find that due frequency and restructuring frequency have higher effect than days past due and days to restructuring. Furthermore, we observe interaction between covid indicator and variable of interest. The results show all models also significant with 1%. The coefficient of due frequency is 0.395 and -0.005 for its interaction with covid indicator, therefore the total impact of due frequency is 0.395 in pre COVID-19 period and decrease to 0.390 (from 0.395-0.005) in COVID period. With same calculation, we have 0.016 in pre COVID-19 and 0.017 in COVID-19 for days past due, 0.990 in pre COVID-19 and 0.003 in COVID-19 for restructuring frequency, and 0.024 in pre COVID-19 and 0.006 in COVID-19 for days to restructuring. These results shows that in general, impact of credit delinquency and restructuring is lower in COVID-19 period than in pre COVID-19 period. Additionally, the decreasing effect is considerably higher for credit restructuring (from 0.990 to 0.003) than credit delinquency (from 0.395 to 0.390) which confirms the effectiveness of Regulation of the Financial Services Authority (POJK) Number 11/POJK.03/2020 application.

4.3. Robustness Check

For robustness, we also analyze the logistic regression with different observation, CIF-month and borrower ID-month. CIF-month represents monthly loan dataset aggregated by CIF (Costumer Identification File). Therefore one CIF may have several loan IDs. Other observation, borrower ID-month represents monthly loan dataset aggregated by borrower ID (corporate tax ID). One borrower ID may have several CIFs because they may have loan from more than one bank. Table 5 presents the results for observation based on CIF-month and Table 6 presents the results for observation based on borrower ID-month. We find that the results from CIF-month and borrower ID-month are consistent with loan ID regression.

5. Conclusion and Policy Implications

In this study we analyze the determinant of corporate loan default using SLIK database. We employ logistic regression approach to estimate the significancy and probability of default. The variables used in this research consist of borrower characteristic (business age, bank related parties, go public, and MSME), loan characteristic (economic sector, government loan, interest rate, plafond, outstanding loan, and term loan), and variable of interest (due frequency, days past due, restructuring frequency, and days to restructuring). Our finding shows the following: (1) borrower characteristic is strong predictor for corporate loan default especially associated with public ownership (listed company) and business size (MSMEs or large company), (2) loan characteristic is also strong predictor for corporate loan default especially loan associated with government program and compatibility of loan project / purpose with borrower business expertise, (3) COVID-19 period has strong impact to increase corporate loan default, (4) government loan restructuring policy is effectively decreasing corporate loan default during COVID-19 period.

As a result, it is essential for bank to assess borrower characteristic thoroughly during under writing process to mitigate the potential borrower risk. In addition, bank should consider the compatibility of project loan with the borrower expertise (primary business line) in the loan approval decision and actively monitor that loan usage in line with its predetermined purpose. Loan restructuring policy indeed effectively lowering corporate loan default, however further research needs to be conducted to estimate the appropriate time to gradually withdraw the policy.

Table 4. Per loan ID-month observation

	1	2	3	4
(Intercept)	-3.908***	-4.296***	-3.274***	-3.154***
	(-364.309)	(-349.714)	(-376.439)	(-361.863)
Business Age	0.000*	0.000***	0.000***	0.000***
	(1.849)	(13.615)	(5.591)	(3.989)
Bank Related Parties	0.162***	0.120***	-0.140***	-0.168***
	(6.240)	(3.946)	(-6.027)	(-7.190)
Go Public	1.530***	1.621***	1.036***	1.028***
	(106.072)	(104.583)	(76.164)	(75.645)
MSME	0.183***	0.063***	0.288***	0.275***
	(22.509)	(6.644)	(45.101)	(43.135)
Economic Sector	-0.092***	-0.083***	-0.263***	-0.265***
	(-11.614)	(-9.076)	(-42.017)	(-42.346)
Government Loan Program	-0.090***	-0.061	-0.260***	-0.273***
	(-2.809)	(-1.602)	(-9.907)	(-10.406)
Interest Rate	0.000	0.000	0.002***	0.002***
	(1.514)	(0.742)	(7.887)	(8.810)
Plafond	-0.000	-0.000	-0.000	-0.000
	(-0.879)	(-0.916)	(-0.394)	(-0.137)
Outstanding Loan	-0.001***	-0.001***	-0.001***	0.000***
	(-6.202)	(-5.798)	(-8.197)	(-6.342)
Term Loan	0.000	0.001***	-0.001***	-0.002***
	(0.536)	(11.487)	(-15.105)	(-28.354)
Due Frequency	0.395***			
	(204.248)			
Days Past Due		0.016***		
		(228.310)		
Restructuring Frequency			0.990***	
			(121.788)	
Days to Restructuring				0.024***
				(94.444)
Covid	0.117***	0.054***	0.261***	0.172***
	(14.067)	(5.495)	(41.379)	(27.150)
Covid × Due Frequency	-0.005*			
	(-1.797)			
Covid × Days Past Due		0.001***		
		(14.602)		
Covid × Restructuring Frequency			-0.987***	
			(-121.250)	
Covid × Days to Restructuring				-0.018***
				(-61.005)
Number of observations	2487152	2487152	2487152	2487152
Pseudo R^2	0.4467	0.6157	0.0096	0.0072

This table presents the logistic regression results based on loan ID-month observation. Model 1, 2, 3, and 4 are for variable of interest due frequency, days past due, restructuring frequency, and days to restructuring respectively.

Table 5. Per CIF-month observation

	1	2	3	4
(Intercept)	-3.680***	-4.039***	-3.079***	-2.986***
	(-271.098)	(-258.768)	(-285.667)	(-275.512)
Business Age	0.000***	0.000***	0.000***	0.000***
	(-4.752)	(-5.821)	(12.334)	(11.686)
Bank Related Parties	0.278***	0.172***	-0.028	-0.106***
	(8.845)	(4.518)	(-1.029)	(-3.810)
Go Public	0.149***	0.181***	-0.122***	-0.127***
	(4.238)	(4.533)	(-4.028)	(-4.208)
MSME	-0.001***	0.001***	-0.002***	-0.003***
	(-5.230)	(7.207)	(-20.743)	(-30.418)
Economic Sector	0.036***	-0.018	0.190***	0.136***
	(3.565)	(-1.503)	(25.465)	(17.945)
Government Loan Program	0.000**	0.000***	0.000	0.000
	(-2.443)	(-2.885)	(-0.141)	(-0.051)
Interest Rate	0.388***	0.339***	0.398***	0.366***
	(37.454)	(28.389)	(49.528)	(45.353)
Plafond	-0.256***	-0.286***	-0.374***	-0.355***
	(-26.458)	(-25.386)	(-49.345)	(-46.818)
Outstanding Loan	-0.195***	-0.148***	-0.386***	-0.381***
	(-6.172)	(-4.060)	(-14.617)	(-14.438)
Term Loan	0.000*	0.000	0.002***	0.002***
	(1.778)	(1.404)	(9.063)	(10.181)
Due Frequency	0.000			
	(0.465)			
Days Past Due		0.000**		
		(2.227)		
Restructuring Frequency			-0.000***	
			(-4.079)	
Days to Restructuring				-0.000*
				(-1.899)
Covid	0.279***	0.012***	0.570***	0.021***
	(165.868)	(188.156)	(80.438)	(74.947)
Covid × Due Frequency	-0.004*			
	(-1.657)			
Covid × Days Past Due		0.001***		
		(9.728)		
Covid × Restructuring Frequency			-0.567***	
			(-79.935)	
Covid × Days to Restructuring				-0.016***
				(-50.327)
Number of observations	1511933	1511933	1511933	1511933
Pseudo R^2	0.4447	0.6150	0.0100	0.0076

This table presents the logistic regression results based on CIF-month observation. Model 1, 2, 3, and 4 are for variable of interest due frequency, days past due, restructuring frequency, and days to restructuring respectively.

Table 6. Per borrower ID-month observation

	1	2	3	4
(Intercept)	-3.570***	-3.939***	-2.958***	-2.878***
	(-257.564)	(-246.593)	(-270.032)	(-262.330)
Business Age	0.000***	0.000***	0.000***	0.000***
	(-3.279)	(-4.928)	(15.078)	(14.855)
Bank Related Parties	0.239***	0.139***	-0.047*	-0.105***
	(7.697)	(3.724)	(-1.760)	(-3.890)
Go Public	0.179***	0.207***	-0.017	-0.009
	(5.164)	(5.260)	(-0.580)	(-0.317)
MSME	-0.001***	0.001***	-0.002***	-0.003***
	(-5.903)	(6.817)	(-22.087)	(-28.565)
Economic Sector	0.033***	-0.018	0.193***	0.133***
	(3.267)	(-1.446)	(25.579)	(17.398)
Government Loan Program	0.000**	0.000***	0.000	0.000
	(-2.495)	(-2.865)	(-0.171)	(-0.057)
Interest Rate	0.340***	0.301***	0.335***	0.310***
	(31.820)	(24.456)	(40.625)	(37.529)
Plafond	-0.280***	-0.311***	-0.385***	-0.362***
	(-28.770)	(-27.439)	(-50.595)	(-47.574)
Outstanding Loan	-0.214***	-0.159***	-0.407***	-0.404***
	(-6.896)	(-4.460)	(-15.649)	(-15.558)
Term Loan	0.000*	0.000	0.002***	0.002***
	(1.743)	(1.396)	(8.528)	(9.929)
Due Frequency	0.000			
	(-0.189)			
Days Past Due		0.000		
		(0.975)		
Restructuring Frequency			0.000**	
			(-2.518)	
Days to Restructuring				0.000
				(-0.319)
Covid	0.272***	0.011***	0.570***	0.019***
	(162.602)	(184.507)	(82.145)	(69.130)
Covid × Due Frequency	-0.005**			
	(-2.345)			
Covid × Days Past Due		0.001***		
		(8.899)		
Covid × Restructuring Frequency			-0.567***	
			(-81.585)	
Covid × Days to Restructuring				-0.016***
				(-47.235)
Number of observations	1369754	1369754	1369754	1369754
Pseudo R^2	0.4485	0.6186	0.0113	0.0073

This table presents the logistic regression results based on borrower ID-month observation. Model 1, 2, 3, and 4 are for variable of interest due frequency, days past due, restructuring frequency, and days to restructuring respectively.

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