DOES CREDIT PERFORMANCE CHANGE IN THE POST-COVID-19? EVIDENCE FROM JAVA ISLAND, INDONESIA

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ABSTRACT

This paper examines the impact of the COVID-19 pandemic on credit performance of banks in Java. We have used monthly panel data from January 2016 to December 2020 of the Java region. We find that the credit performance declines during the pandemic amid the economic downturn compared to the pre-COVID-19 period. Overall, our findings suggest that the delivery of credit types has been affected except working capital. Likewise, the credit for the main economic sectors is significantly influenced by the pandemic.

Keywords: Business matching; Credit performance; Impact evaluation; Intermediary function.
JEL Classifications: E0; E5; E6.

I. INTRODUCTION

The current COVID-19 pandemic has been a challenging issue that influenced the economy. Therefore, an enormous body of literature focuses on the impact of the pandemic on economic activities. Overall, large-scale of studies have discussed the negative effects of the pandemic, for example, increased risk in the financial industry (Lan *et al*., 2020); increased bubble activity in the exchange rate market and persistency in the market (Narayan, 2020a/b); abnormal returns in the stock market (Yan and Qian, 2020); and inefficiency in the oil market (Gil-Alana *et al*., 2020). The literature employs a wide range of economic agents and macroeconomic indicators in order to understand the impact of the pandemic on economic performance of different countries. Some of these studies include the following: corporate performance (Shen *et al*., 2020); real output (GDP) and consumption (Barro *et al*., 2020); and level of economic activities and the stock price of major stock markets (Ozili and Arun, 2020); amongst others[1].

Additionally, many studies have examined the impact of the COVID-19 pandemic on the financial sector. Altman (2020) assessed the impact of the pandemic on the performance of several key indicators pertaining to the nature of credit cycles, such as asset price decline, credit, and corporate default. Demirguc-Kunt *et al*. (2020) analyze underperforming bank stock prices around the world due to the impact of the COVID-19 pandemic on the banking sector. Khattak *et al* (2020) stated that banking competition and diversification complement each other in enhancing the stability of the Indonesian banking sector. Surjaningsih *et al*. (2018) show that credit risk in the commodity and other sectors is more sensitive to real economic growth in Indonesia than in the other sectors. Ekananda (2017) analyzes the dynamic relationship between the macroeconomic variables and the soundness of the banks in Indonesia.

However, none of the above studies examined the impact of the pandemic using regional data.. Even though, the understanding of regional issues is crucial to support the decision-making process to deliver a precise policy intervention, particularly for an archipelago country, such as Indonesia. The Central Bank of Indonesia (CBI) uses decentralized decision-making process to deliver a precise policy which is undertaken through aggregation of regional data as an integrated policy framework including monetary, macroprudential, and payment systems. Periodic regional data collection and quarterly report allows for consensus building and policy decisions.[2]

Investigating the regional economics, Ariani *et al*. (2019) claim that sub-national economy contributes to national macroeconomics in Indonesia, such as economic growth and inflation. Additionally Fetisov and Oreshin (2007) reveal that an understanding of Russian economics contributed greatly to the successful realization of large-scale programs, such as the construction of the Trans-Siberian Railway. This issue constitutes a research gap on the impact evaluation assessment within the regional scope. Our goal is to fill this research gap and construct an

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[1] For a survey of the COVID-19 literature, see Narayan (2021) and Phan and Narayan (2020).
[2] Source: Bank Indonesia https://www.bi.go.id/en/tentang-bi/profil/governance/process.aspx

alternative real sector financing for the Java region in Indonesia. Java Island[3] is selected to be discussed because of its economic size, which contributes approximately 60% of Indonesia's GDP (Indonesia Statistics, 2021). Table 1 shows the main economic sectors for each province.

Table 1.
Economic Sectors in Java's Provinces

This table reports four sectors that are dominant in the Java economy, i.e.: industry, trade, construction, and agriculture. Even though some exceptions in several provinces, such as financial services in DKI Jakarta province (capital city), the transportation sector in Banten, and the accommodation sector in DIY Jogjakarta.

Economic Sectors (%)	Jabar	Jetang	Jatim	DKI	Banten	DIY
Agriculture	8.89	13.97	11.70	0.08	5.87	9.78
Industry	41.67	34.46	30.26	12.29	31.07	12.88
Construction	8.39	10.70	9.47	11.71	11.06	10.35
Trade	14.89	13.62	18.20	16.93	12.86	8.49
Transportation	5.48	2.85	3.28	3.61	9.40	5.32
Accommodation	2.86	3.10	5.77	4.59	2.40	9.81
Financial Services	2.77	2.94	2.70	10.73	3.10	3.99
Others	15.06	18.36	18.63	40.07	24.25	39.36

During the pandemic, the intermediary function of the banking sector in the Java area has been constrained, which is indicated by the decelerating of credit growth. Bank Indonesia in The Monetary Policy Review (December 2020) suggests the low credit growth as stemming from weak corporate demand and risk averseness by the banking sector. Meanwhile, the Third-Party Funds (TPFs) in the banking deposits are in abundances depicting the depositors' cautious motive in spending money due to the uncertainty in the economic condition. Muhyiddin and Nugroho (2021) argue that the TPF continues to grow positively, while credit growth slows down, which implies abundant liquidity in the banking sector. It further suggests that the banking surplus funding increases due to the regulatory easing such as reduction in the minimum statutory reserves. Consequentially this resulted in the loan to deposit rRatio (LDR) reducing during the COVID-19 pandemic period.

The aim of this research is to examine the impact of the COVID-19 pandemic on credit performance. The hypothesis is that credit performance changes during the pandemic period. The Differences-In-Difference (DID) method is employed as an impact evaluation approach to examine the credit delivery using monthly data over the period January 2016 to December 2020. Our findings reveal that the credit performance declines during the pandemic amid the economic downturn compared to the pre-COVID-19 period. Furthermore, we extend our empirical

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[3] Java Island, is one of the 6 biggest islands in Indonesia, consists of 6 provinces, i.e.: DKI Jakarta (capitol), Jawa Barat, Jawa Tengah, Jawa Timur, Banten, and DIY Jogjakarta. It is supported by the main economic sector, namely the manufacturing industry (28%), trade (16%), construction (10%), and agriculture (8%). Java's Regional Gross Domestic Product (*RGDP*) tends to slow down since early 2020 due to the COVID-19 outbreak. Indonesia Statistics records that the 2020 economic contraction -2.51% (yoy) of Java's *RGDP* is slightly deeper than -2.07 (yoy) of Indonesia's GDP.

analysis using sector level data and reveal that the main economic sectors in Java has been affected by the pandemic as well.

These findings make two contributions to the literature. Firstly, investigating the impact of pandemic on credit performance at regional level and sectoral level has not been undertaken in ASEAN region as per our understanding. Secondly, the policy implicationof this study suggests that business matching as an alternative route instead of the relaxing regulation to overcome the dilemma is a possibility. These contributions support the findings of Ariani *et al.* (2019) where they document that macroeconomic factors significantly affect economic growth and regional inflation in Indonesia by utilizing macro data of 33 provinces in Indonesia. Likewise, our findings complements the Fetisov and Oreshin (2007) regional research which provides an initial idea about the modern economic situation on different regions of the Russian economy, as well as a detailed description of the state-of-the-art instruments of regional management in Russia.

This paper proceeds as follows. Section II discusses data and methodology. We discuss our main findings in Section III. Finally, Section IV sets forth our concluding remarks.

II. DATA AND METHODOLOGY
A. Data Set
Our study employs regional credit performance data which includes five-year monthly panel dataset which spans the period January 2016 to December 2020 for six provinces of Java Island. More specifically, our dataset includes following variables: total credit data in nominal value, credit decomposition data which includes working capital, investment, consumption, and Small-Medium Enterprises (SME) credit, and credit by the most economic sectors, namely trading, industry, agriculture, and construction credit. Additionally, we collect quarterly Regional Gross Domestic Product (*RGDP)* which was released in 2010 as the base year from the Indonesia Statistic. We have firstannualized RGDP and converted it into monthly frequency. The monthly credit data from each Java province is sourced from the Regional Financial & Economic Statistics released by The CBI.

Sharma *et al.* (2018) document that unit root evidence is important to understanding the nature and impact of shocks. Hence, we follow their suggestion and examine the null hypothesis of "unit root" using panel unit root tests, namely Im, Pesaran and Shin (IPS) and Levin, Lin and Chu (LLC). Our findings are reported in Table 2, and we document that *credit* and *RGDP* follow stationary process.

Table 2.
Panel Unit Root Test Result

This table reports unit root test for stationary testing. The result shows that Credit data in level and first differences are statistically significant at the 5% level, except in the level of Im, Pesaran and Shin (IPS) method. *RGDP* data in level is statistical significance at the 5% level for both Levin, Lin and Chu (LLC) and IPS methods, and *** represents statistical significance at 1% level.

Variables	LLC		IPS	
	Level	**1st Difference**	**Level**	**1st Difference**
Credit	-3.4282***	-10.6268***	0.5472	-12.3424***
	(0.0003)	(0.0000)	(0.7079)	(0.0000)
RGDP	-4.1407	3.8083	-5.6948***	3.6163)
	(0.0000)	(0.9999)	(0.0000)	(0.9998)

B. Methodology

DID analysis is one of the most widely applicable methods of analyzing impact evaluation. DID method is a Quasi Experiment (Bertrand *et al.*, 2002), namely an experimental approach without experiment control. Even though, other methods, such as Regression Discontinuity Design (RDD), Instrument Variables (IV) (Khandker *et al.*, 2010), can be utilised for impact evaluation the DID is considered the most appropriate method to assess whether the credit performance changes during the pandemic period. Quantitative impact evaluation uses the DID method that is commonly used in impact evaluation (Baker, 2000). Therefore, we use panel data DID method to examine the cross-sections data of total credit in Java five provinces, credit decompositions, and credit of main economic sectors during pre- and post-COVID period.

The DID method requires two groups, namely the treatment group and the control group, and a minimum of two observation periods before-after treatment. The data can be repeated using cross-sectional samples of the population concerned or panel data which is a set of data considering multiple cross-sectional points in time over a range of time points. Wooldridge (2012) uses two types of data structure and discusses the potential advantages of having a panel rather than repeated cross-sections DID approaches. In this case, the treatment group is the credit performance affected by the COVID-19 pandemic. Furthermore, there is a control group in the credit performance not affected by the pandemic. The characteristics of the treatment group and the control group must be similar.

The DID method assumes that parallel trends/slopes do not change (trends over time are the same in both groups). This is such pseudo experimental design because it is not a real different separated group (treatment and control group) but only separating the data period.

We follow Darjana *et al.* (2022) and propose the following regression model:

$$Y_{it} = \alpha + \beta Treated_{it} + \gamma Post_{it} + \delta(Treated * Post)_{it} + \varepsilon_{it} \qquad (1)$$

Here, Y_{it} is a dependent variable, $Treated_{it}$ is a variable indicating whether a unit is treated, $Post_{it}$ is a dummy variable indicating the post-treatment period, $(Treated*Post)_{it}$ is an interaction variable, and δ is a DID estimator. Then, DID estimation is that:

$$E\ (Y_{i,t=1} - Y_{i,t=0}\ |\ t = 0)\ =\ \beta \qquad\qquad (2)$$

$$\frac{E\ (Y_{i,t=1} - Y_{i,t=0}\ |\ t = 1)\ =\ \beta\ +\ \delta}{\Delta\ Y_{it}\ =\ \delta} \qquad\qquad (3)$$

Coefficient of DID interaction variable is represented with δ or DID estimator, i.e. the change in Y_{it} for treated (t=1) units less the change in Y_{it} for control units (t=0). That is also called the average treatment effect (ATE) in terms of DID method.

III. MAIN FINDINGS

In this section we discuss our results and findings, also including the robustness tests. We undertake our study by using three measures for level of credit for a period of five years 2016-2020 with monthly frequency. Firstly,credit in total nominal value, second is credit decomposition which is working capital, investment, consumption, and SMEs credit and third is credit by economic sectors, namely trade, industry, agriculture, and construction credit. We use three panel data DID approaches for estimation, namely Common Effect Model (CEM), fixed effect model (FEM), and Random Effect Model (REM). To identify the the most appropriate method, Chow Test (CEM vs FEM), Hausman Test (FEM vs REM), and Breusch Pagan – LM Test (REM vs CEM) are undertaken.

A1. Total Credit
The REM model estimation has been chosen followed by the Haussman Test and the Breusch Pagan – LM Test. The model appears to be the most appropriate for the available panel data periods (see Table 3).

Table 3.
Panel Data Model selection

This table reports panel data regression model estimation with three selection tests. Those three have significancy at 5% level and the REM has been selected as a result.

Test	Hypothesis	Significance	Result
Chow	H0: CEM H1: FEM	Prob.>F 0.0000	FEM
Haussman	H0: FEM H1: REM	Prob.>Chi2 0.0147	REM
Breusch-Pagan LM	H0: CEM H1: REM	Prob.>Chibar2 0.0000	REM

The DID estimation results are reported in Table 4 and indicates that all variables are statistically significant. In the regression, dependent variable Y_{it} is the level of the regional economy or Regional Gross Domestic Product (*RGDP*); $Credit_{it}$ represents the total credit variable; T_Covid_{it} is the dummy variable, taking value one over the period January 2020 – December 2020 and a value of zero otherwise; $T\_Covid.Credit_{it}$ is the interaction variable. The model has the following specifications:

$$Y_{it} = \alpha + \beta\ Credit_{it} + \gamma\ T\_Covid_{it} + \delta\ T_{Covid}.Credit_{it} + e_{it} \tag{5}$$

$$Y_{i,2016-2019} = \alpha + \beta\ Credit_{it} \tag{6}$$

$$Y_{i,2020} = (\alpha + \gamma) + (\beta + \delta)\ Credit_{it} \tag{7}$$

Table 4.
DID Estimation Results

This table reports estimating results (namely, coefficients, Standard Deviation (SD)) for independent variables selected from the REM model specification chosen. The Asterix sign (*) means that the coefficient has statistically significant at a 5% significance level. The data are split into two samples: Panel A denotes the pre-pandemic sample period (2016:01-2019:12) while the pandemic sample period (2020:01-2020:12) is in Panel B.

	Panel A: Pre-COVID Period	**Panel B: COVID Period**
	Coefficients (SD)	**Coefficients (SD)**
Credit	1.79*	1.79
	(0.05)	(0.05)
T_Covid	-	75.25*
		(13.03)
T_Covid*Credit	-	-0.52*
		(0.02)
Constant	364.67*	364.67
	(225.10)	(225.10

Additionally, we find that the interaction variable, $T\_Covid.Credit_{it}$ is statistically significant at the 5% level. This suggests that credit performance is significantly changing in the pandemic period (2020) compared with the pre-pandemic period (2016 to 2019). A negative sign, however, has changed the $Credit_{it}$ coefficient to 1.27, slightly lower than 1.79 in the previous period. It indicates that the credit disbursements in 2020 decline along with the *RGDP* downturns in the Java region.

The estimation result of DID can be illustrated by the graph in Figure 1. The slope of the treatment line (1.27) has a lower gradient than the control line (1.79) due to the pandemic effect.

Figure 1.
Illustration of Total Credit DID Results

This graph shows that during the pandemic period treatment line has lower slope than that of the control line. It indicates that the COVID-19 has been negative impact on the *RGDP* along with the credit perfomance. The both lines that are similar slope before the pandemic period has fulfilled the parallel trend DID assumption.
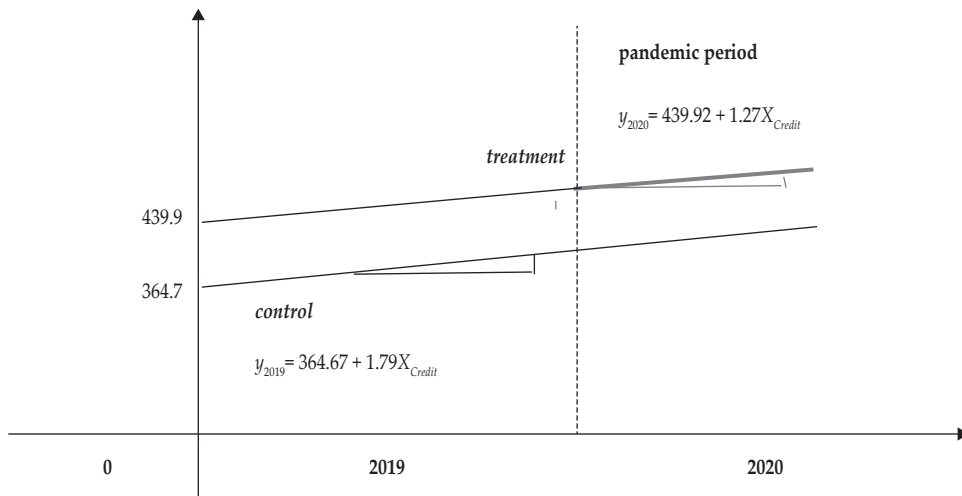
A2. Credit Decomposition

For examining the credit decomposition data Chow and the Haussman test suggests that the FEM panel data model is most appropriate except for SMEs credit, see Table 5. Our findings suggest that all credit types are statistically significant at 5% at level for both pre- and post pandemic, except credit of working capital, which covers 45% of total credit, see Table 6.

Table 5.
Panel Data Model selection

This table reports panel data regression model estimation with three selection test. Those three have significancy at 5% level and the FEM has been selected for credit decomposition, except CEM for SMEs credit.

Test	Working Capital		Investment		Consumers		SMEs	
	Significancy	Result	Significancy	Result	Significancy	Result	Significancy	Result
Chow	Prob.>F 0.0000	FEM	Prob.>F 0.0000	FEM	Prob.>F 0.0000	FEM	Prob.>F 0.0000	FEM
Haussman	Prob.>Chi2 0.9249	FEM	Prob.>Chi2 0.9943	FEM	Prob.>Chi2 0.8242	FEM	Prob.>Chi2 0.0000	-
Breusch-Pagan LM	Prob.>Chibar2 0.0000	REM	Prob.>Chibar2 0.0000	REM	Prob.>Chibar2 0.0000	REM	Prob.>Chibar2 0.0000	REM

Table 6.
DID Estimation Results of Credit Decomposition

This table reports estimating result (coefficients) for independent variables selected from the model specification. The FEM is the most appropriate for all panel data estimation models. The asterix sign (*) means that the coefficient has statistically significant in 5% at level. Coefficients in Panel B consist of each *constant + T_Covid_{it}* and *$Credit_{it}$ + $T\_Covid.Credit_{it}$* of credit decomposition, respectively.

	Panel A: Pre-COVID Period	**Panel B: COVID Period**
Working Capital	3.12	3.06
Investment	4.53*	4.09*
Consumers	6.24*	6.59*
SMEs	9.57*	10.23*
Constant (1)	477.94*	567.47*
Constant (2)	748.01*	896.60*
Constant (3)	481.68*	526.92*
Constant (4)	500.54*	465.47*

The insignificance of working capital credit means that there is no relatively changing performance of the credit before and during the pandemic period. This can be owing to a hypothesis that the banking sector expects the real sector capacity to absorb its credit delivery. This is evident as several industries exhibited high demand such as information & communication, food & beverages, medical device, and pharmaceutical industries during the pandemic. Additionally this could be owing to the support policies of the central bank to prop up the economy (See Rizvi, Narayan & Juhro 2021 for a detail of policy interventions by Bank Indonesia).

A3. Credit By Economic Sector
For inquiry on credit by economic sector, FEM panel data model is selected referring to the Chow and the Haussman test for all credit by economic sectors, see Table 7

Table 7.
Panel Data Model Selection

This table reports panel data regression model estimation with three selection test. Those three have significancy at 5% level for the credit of main sectors, namely, trade, industry, agriculture, and construction. The FEM has been selected as panel data DID model for those four sectors as results.

Test	Trade		Industry		Agriculture		Construction	
	Significancy	Result	Significancy	Result	Significancy	Result	Significancy	Result
Chow	Prob.>F 0.0000	FEM	Prob.>F 0.0000	FEM	Prob.>F 0.0000	FEM	Prob.>F 0.0000	FEM
Haussman	Prob.>Chi2 0.9893	FEM	Prob.>Chi2 0.5680	FEM	Prob.>Chi2 0.1333	FEM	Prob.>Chi2 0.7590	FEM
Breusch-Pagan LM	Prob.>Chibar2 0.0000	REM	Prob.>Chibar2 0.0000	REM	Prob.>Chibar2 0.0000	REM	Prob.>Chibar2 0.0000	REM

All credit of primary sectors (trade, industry, agriculture, construction) is significantly influenced by the pandemic, see Table 8.

Table 8.
DID Estimation Results of Credit by Economic Sectors

This table reports estimating result (coefficients) for independent variables selected from the model specification. The FEM is the most appropriate for all panel data estimation models. The asterix sign (*) means that the coefficient has statistically significant in 5% at level. Coefficients in Panel B consist of each *constant + T_Covid$_{it}$* and *Credit$_{it}$ + T_Covid.Credit$_{it}$* of credit by economic sectors, respectively.

	Panel A: Pre-COVID Period	COVID Period
Trade	8.92*	10.19*
Industry	3.92*	4.22*
Agriculture	28.49*	26.07*
Construction	7.39*	6.87*
Constant (1)	415.10*	371.40*
Constant (2)	833.36*	948.76*
Constant (3)	646.91*	795.94*
Constant (4)	790.50*	920.04*

It is observed that credit in trade and industry sectors have a higher coefficient in pandemic suggesting a larger credit decline in the pandemic period than that of the previous period. Conversely, agriculture and construction sectors have smaller changes in credit decreasing during the pandemic period. That may have occurred owing to resilience of the agriculture sector and the credit restructuring for construction provided by the policy makers.

B. Robustness Check

To further test for robustness we create a dummy treatment group for the panel data estimation model following Jiang *et al*. (2019). To test the robustness whether the credit performance changed during the pandemic period, we set a dummy treatment group where the pandemic takes place three months (M+3) and six months (M+6) later than the reality. This test is conducted for data in total, data by credit decomposition and data of credit by economic sectors. The DID regression results are shown in Table 9, Table 10, and Table 11. The findings provide evidence that credit performance has significant changes during the pandemic in those two periods.

Table 9.
DID Regression Results of Credit in Total (Dummy Treatment Group)

This table reports estimating results of total credit in dummy treatment group. The Asterix sign (*) means that the coefficient has statistically significant at a 5% significance level. The data are split into two samples: Panel I (M+3) denotes the pandemic sample period (2020:04-12) and Panel II (M+6) denotes the pandemic sample period (2020:07-12). The FEM regression results indicate that credit performance has significant change during the pandemic period since (M+3) rather than (M+6) due to insignificant interaction coefficient, $T\_Covid.Credit_{it}$.

DID Regression	Panel A: (M+3)		Panel B: (M+6)	
	Pre-COVID Period	COVID Period	Pre-COVID Period	COVID Period
	Coefficient (SD)	Coefficient (SD)	Coefficient (SD)	Coefficient (SD)
Credit	1.79*	1.79*	1.79*	1.79*
	(0.04)	(0.04)	(0.04)	(0.04)
T_Covid		62.15*		41.64*
		(14.84)		(18.05)
*T_Covid*Credit*		-0.04*		-0.01
		(0.02)		(0.02)
Constant	363.87*	363.87*	364.71*	364.71*
	(24.82)	(24.82)	(23.83)	(23.83)

Table 10.
DID Regression Results of Credit Decomposition (Dummy Treatment Group)

This table reports estimating results of total credit in dummy treatment group. The Asterix sign (*) means that the coefficient has statistically significant at a 5% significance level. The data are split into two samples: Panel I (M+3) denotes the pandemic sample period (2020:04-12) and Panel II (M+6) denotes the pandemic sample period (2020:07-12). The FEM regression results indicate that credit performance by type has significant change during the pandemic period since (M+3) rather than (M+6) due to insignificant interaction coefficient, $T\_Covid.Credit_{it}$, except for investment and consumers credit.

DID Regression	Panel A: (M+3)		Panel B: (M+6)	
	Pre-COVID Period	COVID Period	Pre-COVID Period	COVID Period
Working Capital	1.79*	1.75*	3.22*	3.24
Investment	4.40*	4.05*	4.38*	4.06*
Consumers	6.64*	6.89	6.95*	7.06
SMEs	9.70*	10.28*	9.95*	10.37
Constant (1)	386.87*	449.02*	456.93*	507.31*
Constant (2)	770.69*	896.62*	778.78*	886.45*
Constant (3)	431.67*	478.96	392.93*	444.49
Constant (4)	490.58*	460.08	470.52*	443.07

Table 11.
DID Regression Results of Credit by Economic Sectors (Dummy Treatment Group)

This table reports estimating results of total credit in dummy treatment group. The Asterix sign (*) means that the coefficient has statistically significant at a 5% significance level. The data are split into two samples: Panel I (M+3) denotes the pandemic sample period (2020:04-12) and Panel II (M+6) denotes the pandemic sample period (2020:07-12). The FEM regression results indicate that credit performance by economic sectors has changed during the pandemic period (M+3) and (M+6) due to significant interaction coefficient, $T\_Covid.Credit_{it}$, except credit for industrial sector.

DID Regression	Panel A: (M+3)		Panel B: (M+6)	
	Pre-COVID Period	COVID Period	Pre-COVID Period	COVID Period
Trade	9.49*	10.86*	9.93*	11.5*
Industry	4.24*	4.40	4.48*	4.52
Agriculture	31.25*	28.15*	31.75*	28.10*
Construction	7.58*	7.03*	7.70*	7.08*
Constant (1)	361.04*	295.71*	319.47*	222.08*
Constant (2)	800.89*	918.46*	776.23*	898.15*
Constant (3)	584.79*	720.88*	576.40*	706.99*
Constant (4)	781.93*	894.37*	777.67*	875.43*

C. Policy Impact

Our findings on regional level highlight a critical piece of information for policy makers. In order to recover the economy, it is necessary to marry the financial sectors and the real sectors. During the pandemic, several prospective and safe sectors have been identified in terms of their prospects and risks, such as information & communications, financial services, and agriculture sectors, see the matrix in Figure 2. The matrix is developed from the category of pandemic spread risks and an annual 2020 growth of each economic sector. The most prospective and safe sectors are in the low risks raw and prospect column in terms of growth performance. Those economic sectors may be the impetus for recovery. Pro priority sector policies have already been highlighted in other developing countries, like India (Ahmed, 2010).

These policies aim to increase the public purchasing power to raise the real sectors while simultaneously supporting bank liquidity and decreasing credit risk to improve the bank intermediary function.

Figure 2.
Matrix of Prospective and Safe Economic Sectors

This matrix horizontally consists of economic sectors categorized in a three level of risks derived from The Indonesia COVID Handling Task Force. The prospect of each economic sectors, vertically clustered by the annual growth from Bank Indonesia. The matrix shows that infomation & communication sector is the most prospect and low risks.

	UNPROSPECT	MIDDLE	PROSPECT
LOW RISKS		Finn. Services Agriculture Mining Public Admin.	Info&Comm
MEDIUM RISKS	Trade Electricity Transportation	Real Estate Business Services Manufacturing Construction	Water Supply
HIGH RISK	Accomodation	Education	Health & Social Services

-15%	-5%	5%	15%

Source: Indonesia COVID Handling Task Force & Bank Indonesia

IV. CONCLUDING REMARKS

In this paper we investigated whether the credit performance changed during the pandemic in regional Java as well as investigating the phenomena at sectoral level. Our findings suggest that credit performance declined during the COVID-19 pandemic in the Java region. These findings augment the earlier work of Ariani *et al.* (2019) by employing regional data to focus on credit performance in pre and pandemic phase.

The main contribution of our research is the pandemic impact evaluation in the regional context. Our DID result reveals that the COVID-19 outbreak has impacted the banking sector through the decline of credit delivery to the real sectors. Our findings suggest that delivery of all credit types (credit decomposition) have been affected except the working capital which might be related to resilient industries during the pandemic, such as food & beverages, health devices, and pharmaceuticals. By economic sectors, the ultimate sectors (trade, industry, agriculture, construction) are all significantly influenced by the pandemic.

These findings lead to insights for policy makers on identification of prospect and risk mapping for policy orientation. However, we realize that the proposal is good only at the concept level.

The research has implemented the DID as a quasi-experiment method to assess the impact evaluation on regional credit performance in the post-COVID period. While our results are robust we nee to highlight that a primary assumption of parallel trends is taken. Future research is recommended to further focus on policy level impacts and methodological refinements to address the issue.

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