BANCO CENTRAL DE RESERVA DEL PERÚ

Dynamic Relationship between Credit and Economic Growth

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DT. N°. 2025-011

Serie de Documentos de Trabajo

Working Paper Series

December 2025

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September, 2025

Abstract

This article empirically examines the relationship between credit and economic activity. The literature suggests that credit indicators can help explain and predict the evolution of economic activity. Using granular data, we test several specifications to capture the impact of credit growth on GDP growth. Our findings show a positive and statistically significant, though moderate, effect of credit on GDP when controlling for heterogeneity across economic sectors and regions. Moreover, this impact becomes more pronounced the greater the dependence of real activity on the credit market.

Keywords: credit, GDP, economic sector, region.

1 Introduction

Credit is an important macroeconomic variable that can contribute to economic growth. Several authors indicate that there is a significant relationship between credit and economic activity. As discussed in the literature review, credit indicators are suggested to help explain the evolution of economic activity. In Figure 1, for the 2012 - 2019 period we can observe a positive relationship between these two variables in their year-on-year growth rates for the Peruvian economy.

*The views expressed in this paper are those of the authors and do not reflect necessarily the position of the Central Reserve Bank of Peru. We thank the comments received from Sergio Serván in the 2023 Economist Meeting organized by the Central Reserve Bank of Peru.

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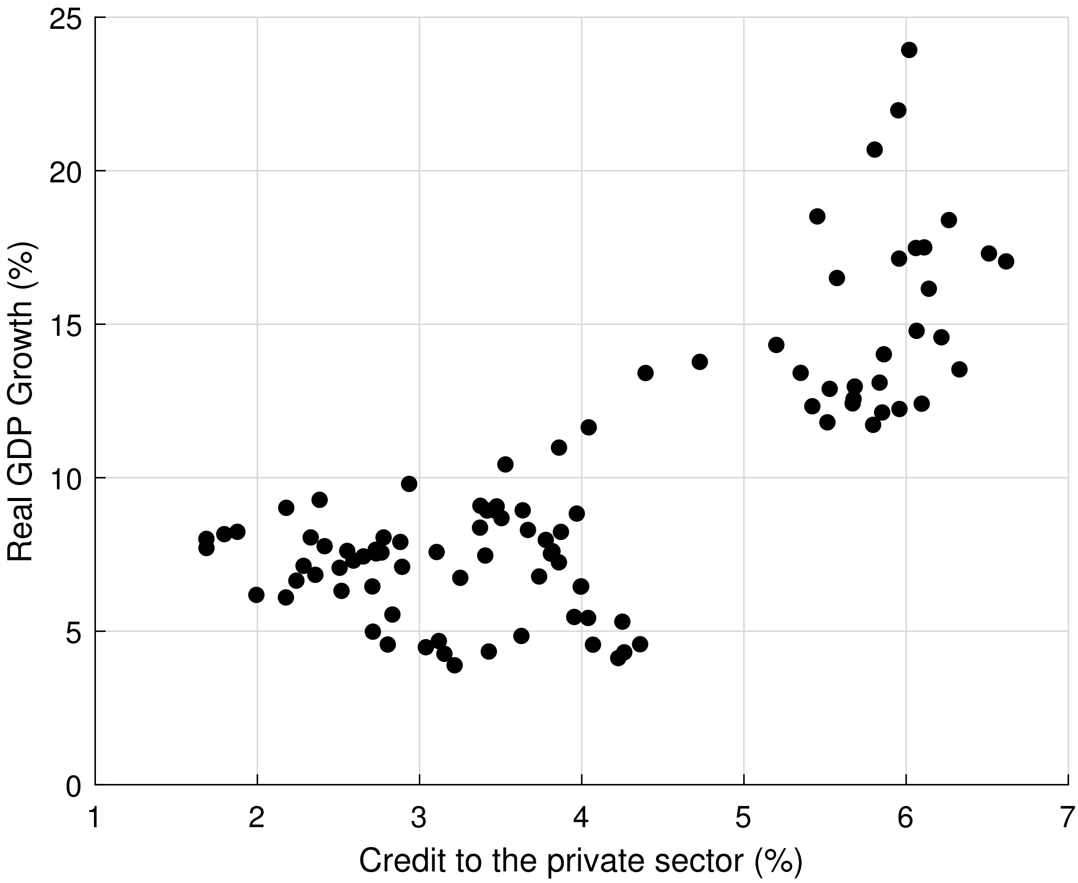

Figure 1: *Relationship between credit and GDP: 2012 - 2019*

In this paper, using granular data, we assess the impact of credit on the real economy. Specifically, we study the joint dynamics of credit and economic activity (GDP) by analyzing economic sectors and regions, in order to quantify the above-mentioned relationship.

As a preliminary analysis, we compute correlations and causality tests between credit and GDP growth. This analysis is conducted by components (region and economic sector) of both credit and GDP, using annual variations to avoid seasonality. These rates are considered in both real and nominal terms. For credit, we also differentiate by currency type (domestic and foreign). We find a greater number of significant results when comparing 12-month accumulated GDP with the year-on-year growth of credit stock. Among the most important relationships, at the sectoral level, we find a significant association between foreign currency credit and the output of manufacturing, mining, and energy industries. In contrast, domestic currency credit is significantly related to the economic activity of construction and commerce. Based on this, we propose a panel framework to estimate the impact of credit growth on GDP.

Then, we perform several econometric regressions to test the impact of credit activity on real activity. We include region–sector–time fixed effects whenever possible, in order to control for credit demand shocks and thus better capture credit supply shocks.

We find that, on average, a one percent increase in credit growth may lead to an increase of up to 0.29 percentage points in real GDP. The results are qualitatively robust. We also find that the impact of credit on economic activity is stronger the higher the dependence of real activity on the credit market, and it is particularly stronger when considering only domestic currency loans.

Finally, we perform robustness exercises that focus on the impact of credit o real activity by the different types of credit to firms. We find a relatively stronger long-term relationship between medium- and small-sized loans and GDP, and a relatively stronger short-term relationship between corporate and large-sized loans and GDP.

This paper proceeds as follows. Section 2 presents the literature review. Section 3 describes the data used. Section 4 provides a preliminary assessment of the data. Section 5 conducts the econometric analysis and presents the results. Finally, Section 6 concludes.

2 Literature review

This paper is related to the empirical and theoretical literature on the impact of credit on economic activity. Next, we discuss related studies.

Using annual data on year-on-year and bank-level growth rates for the period 1999–2016 in a country panel covering 39 European countries, Antoshin et al. (2017) find that bank credit positively, but moderately, influences economic activity. In particular, a 10 percent increase in domestic bank credit would raise real GDP by 0.6 to 1 percent, mainly through the private investment channel, which would increase by 2 to 2.5 percent. Moreover, real GDP growth is positively correlated with real credit growth, implying an important role for demand factors.

In another study for Europe, using monthly data for 10 European Monetary Union countries over the period 2003–2016, Guender (2018) compares the predictive power of different credit indicators for economic activity, distinguishing between prices (represented by interest rate spreads) and quantities (financial system size index). He finds that the spread between the cost of borrowing and the short-term money market rate is a good indicator of economic conditions in the short term, especially during periods of declining output.

In addition, Armeanu et al. (2015), using year-on-year growth rates of credit (segmented into individuals, firms, and the public sector) and GDP for Romania over the 2007–2013 period, calculate that a 1 percent increase in any of these three components has an impact of 0.17 percentage points (p.p.), 0.25 p.p., and 0.0225 p.p., respectively, on annual economic growth.

For the U.S. economy, using quarterly credit flow data instead of credit stock for the period 1954–2008, Biggs et al. (2010) show that economic recovery after a financial crisis does not typically occur without a rebound in credit. To demonstrate this, they analyze the relationship between GDP and credit flow (rather than credit stock). These variables are expressed in year-on-year terms, and they define the change in credit flow as the "credit impulse." They find that credit flow is more correlated with economic activity, with the relationship being amplified during recovery periods. Although their main objective is not to measure the impact of credit on GDP, they still find it to be significant when credit flow is used as the variable of interest.

In a VAR model for the U.S., Chatterjee (2023) finds that mortgage credit is useful in both explaining and predicting GDP. To address stationarity, he uses the year-to-year difference in the logarithm of the series. He shows that mortgage credit provides additional information, as it has a low correlation with real estate investment, which improves GDP growth estimates. Moreover, a one standard deviation shock to mortgage credit growth increases GDP growth by 0.4 p.p. He uses quarterly data for the period 1975–2019.

Clavellina (2013) employs real year-on-year credit and GDP growth rates to estimate an error correction model, finding that the impact of credit on economic activity is negative but not statistically significant. This result is attributed to specific characteristics of the Mexican financial system, namely the low credit-to-GDP ratio (scarcity), the high concentration of the credit market, and the distribution of credit across segments (with a focus on consumption and the public sector). The analysis covers the period 1995–2012 using quarterly data.

For Mexico, two additional related studies can be highlighted. First, De la Cruz y Alcántara (2011) estimate a VEC model of credit and GDP (using real year-on-year growth), disaggregated by components. They find that consumer credit and credit to the service sector have a positive and significant impact on GDP in the tertiary sector (services). In other words, the relatively small aggregate impact of credit on economic activity, when disaggregated, reveals through which channels this influence occurs. They use monthly data for Mexico from 1995 to 2010.

Second, Ermisoglu et al. (2013) employ the concepts of credit flow and credit impulse to improve both estimation and forecasting of economic activity, since these variables expressed in flows provide timelier information. Given that credit data and the production index are published with only a one-week delay, this speed is useful for making GDP predictions. They conclude that including these credit indicators (credit flow as the change in credit stock and credit impulse as the change in credit flow) indeed improves results. Their analysis covers Turkey from 2006 to 2012 with quarterly data.

In Kishor and Koenig (2014), the authors test whether GDP and employment growth projections improve when credit indicators are incorporated as explanatory variables. These indicators capture credit market profitability, the cost of credit, and banks' willingness to lend. The latter (obtained from a Fed survey) proves to be the most relevant for improving quarterly projections of GDP and employment. Using a VAR, they show that an increase in willingness to lend strengthens GDP and employment growth. Their dataset covers U.S. quarterly data from 1985 to 2011.

For the Peruvian economy, Lahura y Vega (2011) use a VEC model to include credit impulse (defined as the first difference of the real year-on-year credit growth rate) in forecasting real GDP growth. Using quarterly data, they find that in the short run credit impulse contains relevant information for predicting output growth. They recommend differentiating credit impulse by currency, since a 1 p.p. increase in the growth rate of credit in dollars raises GDP by 0.12 percent, while a 1 p.p. increase in credit growth in soles raises GDP by 0.5 percent. Their analysis covers 1992–2009.

Wachtel (2018) highlights the importance of the relationship between the financial system and the real sector by reviewing the nexus between financial depth (credit growth) and economic growth. He documents the efforts of different authors that corroborate the existence of a strong relationship between these variables. On the other hand, he stresses the dual nature of credit booms: some support GDP growth, while others lead to financial crises, pointing out this as an important area for further research.

Finally, when using granular data at the sectoral or regional level, panel models with fixed effects present clear advantages over traditional VAR models. They allow to control for unobserved heterogeneity across economic units (regions or sectors), which reduces estimation bias by capturing time-invariant characteristics such as size, productivity, or productive structure (Hsiao (2014); Baltagi (2008)). Additionally, by exploiting the combined variation in the cross-sectional and temporal dimensions, panel models are more parsimonious and require fewer degrees of freedom than VARs, whose dimensionality increases rapidly with the number of variables and lags (Canova and Ciccarelli (2013)). Moreover, panels allow for the inclusion of different fixed-effects structures (region, sector, or region-sector-time), which facilitates isolating demand shocks and improves the identification of credit supply shocks or other phenomena of interest (Hsiao (2014)). In addition, panel models are better suited to capturing heterogeneity in the dynamic responses of different sectors or regions, whereas a VAR tends to impose aggregate average dynamics. Thus, the interpretation of coefficients in a structured panel framework is more straightforward in causal terms, while VAR models tend to capture dynamic correlations without a clear identification strategy (Stock and Watson (2016)).

3 Data Description

A credit database was constructed using data from the Peruvian Credit Registry (RCC), with dimensions of time (monthly frequency), lending entity, region of the borrowing entity, economic sector of the borrowing entity, credit segment, and currency.[1] By segment (or credit type), credit can be classified as credit to the public sector, credit to firms, and credit to financial entities. Public sector credit is not available across regions (i.e., it is only reported for Lima, the capital region) and focuses on the services sector. Credit to individuals is mainly available across regions, while credit to financial entities is reported only for Lima and the services sector.

For the region and sector dimensions, information is obtained from alternative sources such as SUNAT's RUC registry and the BSI's RUC registry.[2] To this credit database, we add information on GDP by economic sector (provided by the Economic Activity Indicators Department), both at a monthly frequency and accumulated over the last 12 months. Likewise, regional GDP is incorporated, obtained from the National Institute of Statistics (INEI), as well as GDP with both regional and sectoral dimensions, also from INEI.

Additionally, information on the regional CPI (provided by the Price Statistics Department) and on Credit Conditions Indices—covering both supply and demand, for the current situation as well as expectations—is incorporated. These indices are obtained from the survey conducted by the Monetary Statistics Department.

Table 1 summarizes the main statistics of the variables used in the econometric regressions in section 5. Given the availability of granular data, the period of analysis spans from January 2012 to December 2019, thus excluding the pandemic years, which were characterized by several shocks. At the region–economic sector–year level, the average annual growth of real GDP (RGDPGrst^{aa}) is 3.6%, while the annual growth of nominal credit (CREGrst^{a}) is 12.9%.[3] As expected, credit is more volatile. Average annual inflation (INFrt) stands at 0.3%. At the economic sector–month level, monthly growth of real GDP (RGDPGst^{mm}) averages 1.3%, while monthly growth of credit (CREGst^{m}) averages 0.7%. In this case, GDP is more volatile, mainly due to its relatively higher seasonality as a flow variable. Finally, at the economic sector–month level, annual growth of real GDP (RGDPGst^{aa}) averages 3.8%, while annual growth of credit (CREG$_{st}^{a}$) averages 8.6%. In this case, credit is more volatile.

[1] We consider total credit issued by the main financial entities: banks, *cajas*, and financial firms.

[2] SUNAT: National Tax Authority; BSI: Institutional Sectoral Balance Sheet.

[3] Credit is disaggregated into eight economic sectors: agriculture, commerce, construction, energy, manufacturing, mining, fisheries, and services. Total credit is defined as the sum of domestic and foreign currency credit, valued at the current exchange rate.

Table 1: *Summary Statistics*

	Obs.	Mean	SD.	Min	Max
Observations at region-economic sector-year level					
$RGDPG^{aa}_{rst}$ (%)	1 291	3.684	9.488	-28.390	49.015
$CREG^{a}_{rst}$ (%)	1 291	12.967	34.524	-109.738	148.027
INF_{rt} (%)	1 291	0.330	0.515	-1.133	3.173
Observations at economic sector-month level					
$RGDPG^{mm}_{st}$ (%)	693	1.388	7.909	-19.941	29.984
$CREG^{m}_{st}$ (%)	693	0.654	3.020	-13.214	14.227
$RGDPG^{aa}_{st}$ (%)	731	3.851	4.835	-15.117	24.519
$CREG^{a}_{st}$ (%)	731	8.572	12.992	-55.830	50.552

SD: Standard deviations. Sources: RCC, INEI. We remove outliers or extreme values.

Table 2 reports the credit-to-GDP ratios for each sector. All ratios increased over the years until December 2019, except for the fisheries and energy sectors.

As of December 2020, all sectors had increased their credit-to-GDP ratios as a consequence of the Reactiva Peru Program. By March 2023, all sectors maintained a higher ratio than before the pandemic, except for the construction sector.

Likewise, the mining sector has the lowest credit-to-output ratio, which suggests that it is primarily financed through investment from parent companies. By contrast, the manufacturing, commerce, and agriculture sectors have considerably increased their credit as a share of GDP, indicating that firms in these sectors are relying more on this source of financing for their economic activities.

Table 2: *Credit to GDP Ratios*

	2012	2019	2020	2022	Mar-23
By Sector					
Agriculture (%)	13.3	26.2	33.1	37.9	35.8
Fisheries (%)	45.5	37.1	54.8	63.8	54.9
Mining (%)	6.9	11.3	15.7	14.3	13.9
Manufacturing (%)	32.6	59.1	73.0	70.6	70.3
Energy (%)	83.8	63.6	83.9	88.8	84.6
Construction (%)	10.8	15.7	27.9	16.3	15.5
Commerce (%)	39.7	60.0	98.1	81.0	77.7
Services (%)	14.8	20.8	30.1	22.9	22.7

Sources: BCRP.

4 Preliminary assessment: Correlations and Causality Tests

Table 3 reports the correlation coefficients between annual domestic currency credit growth and annual real GDP growth by economic sector. The results suggest that credit activity may serve as a leading indicator in the agricultural, construction, commerce, and services sectors. For the agricultural sector, credit appears to predict real activity one year ahead. For the other sectors, credit growth is highly correlated with contemporaneous, three-month, and one-year-ahead real GDP growth.

We also find that a greater number of correlation coefficients are statistically significant; however, most of them are negative, suggesting a countercyclical relationship. This indicates the need for further analysis and the computation of conditional correlations in order to control for other shocks in the real economy. It is worth noting that the results (not reported here) obtained when using foreign currency credit are not statistically significant.

Table 3: *Correlation between Credit (t) and GDP (t +/- k)*

	t-12	t-3	t	t+3	t+12
By Sector					
Agriculture (%)	-0.66**	-0.20*	0.00	0.12	0.25**
Fisheries (%)	-0.25**	-0.34**	-0.18	0.02	0.02
Mining (%)	0.18	-0.18**	-0.18	-0.22**	-0.30**
Manufacturing (%)	-0.60**	-0.21**	-0.24**	-0.28**	0.11
Energy (%)	0.56**	0.44**	0.13	-0.17	-0.30**
Construction (%)	-0.04	0.13	0.21**	0.30**	0.54**
Commerce (%)	0.21**	0.55**	0.61**	0.58**	0.55**
Services (%)	-0.15	0.16	0.22**	0.32**	0.59**

Variables are expressed in real annual growth. Only credit in domestic currency is considered. Data is at monthly frequency. Period of study: October 2012 - February 2020. Sources: Central Reserve Bank of Peru (BCRP), National Institute of Statistics (INEI). Own elaboration.

Furthermore, some important causal relationships are identified through the Granger causality test at the economic sector level, as reported in Table 4. In particular, we find that domestic currency credit Granger-causes GDP in the construction, energy, agriculture, and fisheries sectors, whereas foreign currency credit Granger-causes GDP in the mining, manufacturing, and services sectors.

Indeed, the results so far show that domestic currency credit is a good leading indicator of real activity in the previously listed sectors, due to the importance of credit financing (i.e., the higher credit-to-GDP ratio) in the fishing and energy sectors, and the relatively low level of credit dollarization in the construction sector (43%, Inflation Report, June 2019, BCRP). Similarly, foreign currency credit may have a positive impact on the mining sector, given its relatively high level of credit dollarization (94%, Inflation Report, June 2019, BCRP), even though the foreign currency credit-to-GDP ratio is the lowest among all sectors.

Table 4: *Causality test*

	Currency	p-value
Credit cause GDP		
Agriculture	National	0.06*
Fisheries	National	0.09*
Mining	Foreign	0.00***
Manufacturing	Foreign	0.00***
Energy	National	0.05**
Construction	National	0.01***
Commerce	National	0.18
Services	Foreign	0.00***

Variables are expressed in real annual growth. Sources: BCRP, INEI.

5 Model Description and Results

The following specification is established to evaluate the impact of credit growth on GDP growth:

$$RGDPG^{aa}_{rst} = \alpha + \beta_0 RGDPG^{aa}_{rst-1} + \beta_1 CREG^{a}_{rst} + \epsilon_{rst}, \tag{1}$$

where the subscript r refers to a region, the subscript s refers to an economic sector, and the subscript t refers to a sample year; $RGDPG^{aa}_{rst}$ denotes the annual growth rate of real annual GDP, and $CREG^{a}_{rst}$ denotes annual nominal credit growth.[4] ϵ_{rst} is a random error term that follows a normal distribution. We may include region fixed effects, sector fixed effects, or region-sector fixed effects to control for credit demand shocks, so that our variable $CREG^{a}_{rst}$ better captures credit supply shocks.

[4] In contrast to the preliminary assessment, we consider total credit (i.e., the sum of domestic and foreign currency credit evaluated at the current exchange rate).

According to Panel A in Table 5, the results suggest that, on average, a one percent increase in credit growth leads to an annual increase of 0.013–0.025 percentage points in real GDP. The results remain robust across different combinations of fixed effects, except when region-time fixed effects are included, in which case they are no longer statistically significant. In particular, the results hold even when controlling for region-sector fixed effects (columns 3 and 6), which may capture demand shocks. However, they lose statistical significance when region-time fixed effects are included (columns 4 and 8). Finally, the AR(1) term is not statistically significant.

Since credit is measured in nominal terms, one might argue that real credit growth should be used instead. To address this concern, Panel B reports the results when the annual inflation rate is included as a control variable. The findings confirm that the main results hold, and although inflation is negatively related to real GDP, the effect is not statistically significant.

In Panel C, equation (1) is extended to include the interaction between the credit-to-GDP ratio (CTG) and credit growth. As expected, the results indicate that the higher the dependence of the real sector on the credit market (captured by the credit-to-GDP ratio at the sector–region–time level), the stronger the impact of credit on GDP.

Finally, Panel D reports the results for an identical specification to Panel A (baseline), but considering only domestic currency loans. As suggested by the preliminary assessment, the impact of credit growth is generally more economically significant when focusing solely on domestic currency loans. Specifically, a one percent increase in credit growth is associated with an increase of 0.023–0.026 percent in GDP growth (excluding the results with region–time fixed effects). Interestingly, unlike in Panel A, in this case the results remain statistically significant even when region–time fixed effects are included.

Table 5: *Regression Results*

	1	2	3	4	5	6	7	8
Panel A								
$\text{RGDPG}^{aa}_{rst-1}$					0.0111	-0.0131	-0.0761**	0.00287
CREG^{a}_{rst}	0.0152*	0.0134*	0.0181**	0.00916	0.0245***	0.0233***	0.0254***	0.0182**
Observations	1,266	1,266	1,256	1,266	1,223	1,223	1,216	1,223
R-squared	0.014	0.036	0.139	0.171	0.024	0.050	0.163	0.178
F test (ρ-value)	0.0548	0.0903	0.0345	0.280	0.00447	0.00819	0.000421	0.0848
Panel B								
$\text{RGDPG}^{aa}_{rst-1}$					0.00705	-0.0166	-0.0799***	0.000439
CREG^{a}_{rst}	0.0154*	0.0135*	0.0183**	0.00928	0.0251***	0.0237***	0.0257***	0.0185**
INF_{rt}	-0.491	-0.477	-0.696		-0.820	-0.809	-0.854	
Observations	1,259	1,259	1,249	1,259	1,217	1,217	1,211	1,217
R-squared	0.014	0.037	0.140	0.171	0.026	0.052	0.165	0.179
F test (ρ-value)	0.109	0.170	0.0512	0.280	0.00447	0.00788	0.000397	0.0831
Panel C								
$\text{RGDPG}^{aa}_{rst-1}$					0.00891	-0.0147	-0.0829***	0.00133
CREG^{a}_{rst}	0.00911	0.00720	0.0130	-0.000476	0.0202**	0.0188**	0.0244***	0.0106
CTG_{st}	-0.0101	-0.0129	-0.0787**	-0.00136	-0.00656	-0.00814	-0.0861***	0.00352
$\text{CREG}^{a}_{st}\ \text{CTG}_{st-1}$	0.000691*	0.000694*	0.000790*	0.000959**	0.000508	0.000521	0.000349	0.000738**
INF_{rt}	-0.462	-0.445	-0.636		-0.788	-0.776	-0.793	
Observations	1,259	1,259	1,249	1,259	1,217	1,217	1,211	1,217
R-squared	0.017	0.040	0.146	0.177	0.028	0.054	0.171	0.183
F test (ρ-value)	0.0852	0.119	0.00996	0.0340	0.00876	0.0137	0.000110	0.0290
Panel D: As in Panel A but only domestic currency loans								
$\text{RGDPG}^{aa}_{rst-1}$					-0.0565***	-0.0634***	-0.112***	-0.0539**
CREG^{a}_{rst}	0.0233***	0.0233***	0.0246***	0.0150*	0.0244***	0.0245***	0.0259***	0.0169**
Observations	1,257	1,257	1,246	1,257	1,243	1,243	1,235	1,243
R-squared	0.019	0.047	0.162	0.181	0.026	0.054	0.177	0.185
F test (ρ-value)	0.00180	0.00170	0.00186	0.0656	0.000169	5.68e-05	5.13e-08	0.00716
Region FE	Yes	Yes	No	No	Yes	Yes	No	No
Sector FE	No	Yes	No	No	No	Yes	No	No
Region-Sector FE	No	No	Yes	No	No	No	Yes	No
Region-Time FE	No	No	No	Yes	No	No	No	Yes

*** statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Panel D: similar to Panel A, but considering only domestic currency loans.

Given the availability of credit and sectoral GDP data at a monthly frequency, we propose an additional specification at the economic sector–time level, with the aim of assessing the implications of credit growth for GDP growth, as before:

$$RGDPG^{mm}_{st} = \alpha + \beta_0 RGDPG^{mm}_{st-1} + \beta_1 CREG^{m}_{st} + \beta_2 CREG^{m}_{st-1} + ... + \beta_{k+1} CREG^{m}_{st-k} + \epsilon_{st}, \tag{2}$$

where the t subscript refers to a sample month, $RGDPG^{mm}_{st}$ denotes the monthly growth rate of real monthly GDP, $CREG^{m}_{rst}$ denotes the monthly nominal credit growth, and ϵ_{rst} is a random error term assumed to be normally distributed. We include economic sector fixed effects.

According to Table 6, credit growth has a statistically significant impact on GDP at the contemporaneous level and up to four months lag. In particular, the contemporaneous effect is positive; however, this does not necessarily hold for the lagged variables.

Table 6: *Regression Results*

	1	2	3	4	5	6
RGDPG^{mm}_{st-1}		-0.177***	-0.173***	-0.181***	-0.186***	-0.182***
CREG^{m}_{st}	0.210**	0.273***	0.272***	0.285***	0.293***	0.289***
CREG^{m}_{st-1}			-0.0936	-0.0979	-0.0922	-0.107
CREG^{m}_{st-2}				-0.291***	-0.296***	-0.303***
CREG^{m}_{st-3}					-0.109	-0.0999
CREG^{m}_{st-4}						0.167*
Observations	693	658	658	658	658	658
R-squared	0.054	0.109	0.111	0.121	0.123	0.127
F test (ρ-value)	0.0332	2.94e-06	8.21e-06	6.92e-07	1.36e-06	1.13e-06

*** statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. All regressions include sector fixed effects.

In Table 7, we present an alternative specification to the previous one (equation 2), introducing two changes:

$$RGDPG^{aa}_{st} = \gamma_s + \alpha + \beta_0 RGDPG^{aa}_{st} + \beta_1 CREG^{a}_{st} + \beta_2 CREG^{a}_{st-1} + ...$$
$$+ \beta_{k+1} CREG^{a}_{st-k} + \beta_{k+2} CREG^{a}_{st} CTG_{st-1} + \beta_{k+3} CREG^{a}_{st} DOL_{st-1} + \beta_{k+4} X_t + \epsilon_{st} \tag{3}$$

This time, we use the annual growth of real annualized GDP and the annual growth of credit. As expected, GDP growth is both statistically and economically persistent, and the R-squared for all regressions is greater than 0.69. Moreover, the impact of credit growth on GDP is quantitatively smaller, but still statistically significant. In this exercise, we also include the interaction between credit growth and the credit-to-GDP ratio, as well as the interaction between credit growth and the dollarization ratio. Finally, X_t includes both the dollarization ratio and the credit-to-GDP ratio.

The different quantitative results in tables 6 and 7 can be explained by the fact that, in 6, we capture the impact of short-term credit movements on short-term production, which shows a stronger contemporaneous correlation. By contrast, the impact is smaller when considering the effect of annual credit growth on the annual growth of annualized GDP. Moreover, according to table 7, as expected, the impact of lagged credit growth is statistically significant, although not necessarily as economically significant as the contemporaneous impact.

In addition, according to table 7, the greater the dependence of an economic sector on credit (i.e., the higher its credit-to-GDP ratio), the stronger the impact of credit. Furthermore, the higher the degree of credit dollarization, the more positive the impact of credit growth tends to be, although this effect is not always statistically significant.

Table 7: *Regression Results*

	1	2	3	4	5	6	7	8
RGDPG^{aa}_{st-1}	0.849***	0.868***	0.870***	0.870***	0.827***	0.847***	0.849***	0.848***
CREG^{a}_{st}	0.0310***	0.140***	0.138***	0.140***	-0.0647*	0.0438	0.0413	0.0405
CREG^{a}_{st-1}		-0.117***	-0.0741**	-0.0747**		-0.111***	-0.0727**	-0.0735**
CREG^{a}_{st-2}			-0.0716**	-0.0716**			-0.0713**	-0.0715**
CREG^{a}_{st-3}			0.0303	0.0155			0.0345	0.0172
CREG^{a}_{st-4}				0.0144				0.0170
CTG_{st-1}	-0.0183	-0.00603	-0.00538	-0.00590	-0.0306*	-0.0179	-0.0172	-0.0182
DOL_{st-1}	-0.00732	-0.00460	-0.00502	-0.00504	-0.00202	0.000130	-0.000160	-0.000274
CREG^{a}_{st} CTG_{st-1}					0.00120***	0.00110***	0.00109***	0.00110***
CREG^{a}_{st} DOL_{st-1}					0.000715	0.000689	0.000705	0.000747*
Observations	724	724	724	717	724	724	724	717
R-squared	0.749	0.760	0.762	0.761	0.757	0.767	0.769	0.768
F test (ρ-value)	0	0	0	0	0	0	0	0

*** statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. All regressions include region fixed effects.

5.1 Robustness Exercise: An analysis within the credit to firms

Similar to Armeanu et al. (2015), we investigate the impact of credit by segment, but focus only on credit to firms due to data availability. Within this segment, we distinguish the following types: corporate, big-sized firms, mid-sized firms, small-sized firms, and micro-sized firms.

In particular, we estimate the specification presented in equation 1 for each type of credit to firms. According to Panel A in table 8, credit to big-sized, mid-sized, and small-sized firms has a positive impact on GDP. The effect is quantitatively larger for credit to mid-sized firms, whereas the impact of corporate loans and micro-sized loans is not statistically significant.

Since the market share of micro-sized loans is relatively low, their impact on GDP is expected to be small. However, these micro-sized firms are relevant because they can later grow into small- and mid-sized firms and thus have a positive effect on the aggregate economy.

In contrast to micro-sized loans, the share of credit to corporate firms is relatively large. We argue that the lack of significance of corporate loans on GDP can be explained as follows. Since we control for region-sector fixed effects, the estimated impact of credit growth is intended to capture a positive credit supply shock. However, in the corporate loan market, such a shock is not binding (as it may be for other types of credit), because loan volumes are mainly determined by demand, which comes from large companies with strong credit records. Corporate firms, moreover, have greater access to alternative funding sources, such as capital markets. Thus, in favorable periods, corporate firms may prefer to obtain financing from capital markets rather than bank credit.

When performing the regressions by type of currency, Panels B and C in table 8 show that the impact of credit is relatively stronger for domestic currency across all types of credit. These results may be explained by the asymmetric effects of domestic monetary policy on domestic versus foreign currency loans, as well as by the natural constraints on obtaining foreign currency funding. Consequently, the relationship between domestic currency credit and GDP is quantitatively more relevant, given the more direct influence of domestic monetary policy on domestic currency lending rates. It is also worth noting that, although the Peruvian banking system is exposed to foreign monetary policy shocks, regulatory measures (e.g., higher reserve requirements on short-term foreign deposits in banks, limits on foreign currency lending, etc.) mitigate the exposure of the domestic credit market to such shocks.

Table 8: *Regression Results*

	Corporate	Big	Mid	Small	Micro
Panel A: Total currency					
$\text{RGDPG}^{aa}_{rst-1}$	-0.269***	-0.206***	-0.0602*	-0.0736**	-0.0192
CREG^{a}_{rst}	-0.00829	0.0143**	0.0307***	0.0232***	-0.00274
Observations	144	511	1,036	1,132	823
R-squared	0.213	0.224	0.188	0.187	0.167
F test (ρ-value)	0.0122	1.81e-05	9.81e-05	0.000359	0.744
Panel B: Domestic currency					
$\text{RGDPG}^{aa}_{rst-1}$	-0.241***	-0.183***	-0.101***	-0.0809***	-0.00395
CREG^{a}_{rst}	0.0154	0.0181***	0.0291***	0.0184**	4.67e-05
Observations	132	419	989	1,128	829
R-squared	0.260	0.326	0.205	0.192	0.198
F test (ρ-value)	0.0155	1.92e-06	7.46e-06	0.00126	0.993
Panel C: Foreign currency					
$\text{RGDPG}^{aa}_{rst-1}$	-0.211**	-0.184***	-0.131***	-0.104***	-0.0363
CREG^{a}_{rst}	-0.0267*	0.00933	0.0113*	0.0111**	-0.00364
Observations	120	458	841	778	311
R-squared	0.161	0.249	0.172	0.192	0.442
F test (ρ-value)	0.0269	0.000359	0.000260	0.00423	0.697

*** statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. All regressions include region-sector fixed effects.

With the same spirit as before, we estimate table 7, which uses monthly information at the sector–month level, for each type of credit to firms. According to table 9, this time we find evidence of a positive impact of corporate credit on GDP. This may be because in this exercise we are not fully controlling for credit demand shocks, since we only include economic sector fixed effects. Moreover, in contrast to the results in table 7, we find a non-statistically significant impact of mid-sized and small-sized credit on GDP growth. As before, the explanation could be that we are not adequately controlling for credit demand shocks.

In general, the AR(1) coefficient is positive and close to one, which suggests that GDP growth is highly persistent at the monthly frequency, as expected. This leaves relatively less room for credit growth to explain GDP dynamics across all types of credit, except for corporate and big-sized loans.

Table 9: *Regression Results*

	Corporate	Big	Mid	Small	Micro
$RGDPG^{aa}_{st-1}$	0.925***	0.834***	0.843***	0.860***	0.826***
$CREG^{a}_{st}$	0.0294***	0.0268***	-0.00350	-0.00181	-0.00116
$CREG^{a}_{st-1}$	-0.0191***	-0.0102	0.00671	0.000240	0.00109
$CREG^{a}_{st-2}$	-0.0137**	-0.0122	-0.00392	-0.00152	0.00552**
$CREG^{a}_{st-3}$	-0.00318	0.00711	-0.00233	0.00479	-0.000689
$CREG^{a}_{st-4}$	0.0135***	0.00798	-0.00126	-0.00228	0.00435**
CTG_{st-1}	0.00848	0.00651	-0.159***	-2.232***	8.629***
DOL_{st-1}	0.00205	0.0162	-0.00136	0.0168**	-0.0112
Observations	697	717	717	706	655
R-squared	0.840	0.750	0.746	0.745	0.754
F test (ρ-value)	0	0	0	0	0

*** statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. All regressions include economic sector effects.

6 Conclusions

In this paper, we study the relationship between credit and GDP. We find a positive impact of annual credit growth on economic activity. As expected, the greater the dependence of the economy on credit, the stronger the effect. These results remain robust even after controlling for heterogeneity across regions and economic sectors. We also find that the impact of credit growth is stronger when considering only domestic currency loans.

Using monthly data, we find a positive impact of credit growth on GDP, both contemporaneously and with lags of up to four months. When considering annual credit growth, the impact on GDP is also positive, both contemporaneously and with lags of up to three to four months.

Finally, we perform an analysis by type of credit to firms. The results suggest a relatively stronger long-term relationship between mid- and small-sized loans and GDP, and a relatively stronger short-term relationship between corporate and big-sized loans and GDP.

In consequence, the econometric regressions confirm that credit dynamics can help explain, and therefore predict, GDP dynamics when using information at the sectoral and regional levels.

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