The Relation Between Credit and Business Cycles in Central America and the Dominican Republic

Francisco Ramírez

Abstract

This study provides evidence of the relation between credit and real activity in Central America and the Dominican Republic (DR). The link between credit and real activity is addressed for the case of a group of developing countries with limited financial markets where bank credit is the main source of external finance for the private sector. We compile information of credit to the private sector and the aggregate economic activity for Costa Rica, El Salvador, Honduras, Guatemala, Nicaragua and the DR. The data is analyzed using simple statistical tools (Granger causality tests and spectral analysis) to identify stylized facts on the credit-activity relation. We find a positive relation between credit and real activity in frequencies associated to business cycles for all countries. The credit-economic relation in cycles lasting 10 or more years seems relevant in Costa Rica and the DR. There is evidence suggesting that credit precedes economic activity at business cycles frequencies in Costa Rica, El Salvador, Honduras, Nicaragua and the DR. Excluding Nicaragua, this pattern is observed also in cycles over eight years for mentioned economies. In case of Guatemala there is no evidence of statistical precedence of credit to economic activity.

Keywords: credit cycle, banking credit, business cycle, developing countries, Central America, Dominican Republic.

JEL classification: C32; E32; E51.

F. Ramírez <f.ramirez@bancentral.gov.do>, Banco Central de la República Dominicana. I thank the excellent assistance and suggestions of Fernando Casanova. The views expressed in this chapter are my own, and do not reflect the view of the Banco Central de la República Dominicana.

1. INTRODUCTION

Since the beginning of the international financial crisis in 2007-2009 there has been a renewed interest on the linkages of financial markets and the real economy, as well as its implications towards the design of monetary policy. In particular, there is a surge in macroeconomic literature relating credit and business cycles and the role of credit shocks on economic dynamics, both theoretical and empirical.

On the empirical side, new evidence has been collected on the role of the credit in different periods of expansion and recession generally associated to business cycle frequencies in advanced economies (Helbling et al., 2010; Zhu, 2011; Busch, 2012; Chen et al., 2012; and Claessens et al., 2011), emerging economies, and recently in Latin America (Gómez-González et al., 2013).

The purpose of this study is to provide evidence of the relation between credit and real activity in Central America and the Dominican Republic (hereafter DR). We address the empirics of the link between credit and real activity for the case of a group of developing countries with limited financial markets where bank credit is the main source of external finance for the private sector. There has been a rise on empirical literature analizing this phenomena in developed and emerging countries, but with little attention to small developing economies. This paper seeks to fill that void in the literature.

To reach that goal, I compile information on credit to private sector and from aggregate economic activity for Costa Rica, El Salvador, Honduras, Guatemala, Nicaragua and the DR. The data is analyzed using simple statistical tools to identify stylized facts on the credit-activity relation. First, I rely on cross correlations and Granger causality tests to learn about the statistical relation between these time series and how the facts fit with conventional theories of credit-ouput linkages. In a second stage, spectral analysis decomposition techniques are used to explore the link between credit and activity in different frequencies. That is, I estimate and classify by the order of importance the type of cycles that best characterize each time series and inquire on which frequency the relation is verified. This is relevant because, according to macroeconomic theory, credit has an important role on real fluctuations at business cycles frequencies (Kiyotaky and Moore, 1997; Bernanke et al., 1999; among others), meaning that credit and economic activity data must show a high covariance in these frequencies.

In terms of the results, the study has mixed findings for the countries under analysis. First, I find a positive relation between credit and real activity in frequencies associated to business cycles (that is, cycles between 1.5 and 8 years) for all countries. Second, the credit and economic relation in cycles lasting 10 or more years seems relevant in Costa Rica and the DR. Third, there is evidence suggesting that credit precedes economic activity at business cycles frequencies in Costa Rica, El Salvador, Honduras, Nicaragua and the DR. Excluding Nicaragua, this pattern is observed also in cycles over eight years for mentioned economies. In case of Guatemala there is no evidence of statistical precedence of credit to economic activity.

The rest of the document is organized as follows. Section 2 resumes the main theories of credit cycles and its implications for real economic activity; it also discusses related empirical literature. Section 3 provides a description of data and the empirical analysis. Section 4 states concluding remarks.

2. LITERATURE REVIEW

2.1 Theory

The research's interest on the role of credit cycles on economic fluctuations is long-standing. Different theories compete on what kind of relation exists and if credit plays a passive or active role in the generation of real cycles. For example, Hayek (1929) stated that recessions are the result of credit cycles. A credit boom reduces interest rates and increases investment relative to savings. The increase in aggregate demand, given the higher levels of consumption and investment pushes up consumer prices, making consumer goods more profitable than producer goods, and in consequence, shifts investment from producer goods to consumer goods, and eventually leading to recession.

Another author who places credit in the core of economic fluctuations is Minsky (1982). He has a theory associated with large business cycles (more than five years) and relates financial innovation to periods of steady growth that encourage risk taking. In other words, changes in financial markets are responsible for the economic conditions in the medium term. The mechanism implies that an overheating economy will induce a tightening of monetary policy and will eventually cause a recession.

Recent research highlights the relevance of the linkages between credit and assets prices. Brunner and Meztler (1990) incorporate the credit market to the IS-LM model, and show that credit and asset price shocks are relevant sources of business cycle fluctuations.

Contemporary macroeconomic theories of credit address the relation between financial markets and the real economy at business cycle frequencies, highlighting market imperfections such as asymmetric information between agents as well as other financial frictions. According to this approach, the credit market play the role of a propagation mechanism of business cycles when the economy is affected by shocks (Kiyotaki,1998; Kocherlakota, 2000). In other words, in this literature the credit and financial markets have a peripherally role that, given financial frictions, they are amplifying mechanisms of macroeconomic fluctuations. The most popular mechanism of this type is the financial accelerator developed by Bernanke et al. (1999) who establish that, due to imperfect information in credit markets, fluctuations in asset prices affect agent's net worth and therefore influences on its borrowing, investing and consuming capacities, bringing more volatility to the economy. This mechanism has been applied to open economies and emerging markets by Céspedes et al. (2004), and Caballero and Krishnamurthy (1998).

2.2 Empirical Literature

Recent empirical literature on the relation between credit and economic activity focuses on the role and weight that financial shocks have played on the Great Recession for developed countries, their importance explaining global business cycles and lessons from emerging markets experience dealing with real effects from financial crisis.

Helbling et al. (2010) analyze the role of credit shocks on global business cycles for the G7 economies. Using a VAR methodology they conclude that in business cycle frequencies, credit has much impact as productivity in explaining economic activity for this specific group of economies, that put together, account for almost 40% of the global economy.

Claessens et al. (2011) study in detail the interaction between business and financial cycles using a database of 44 countries for a period that spans 50 years. They enumerate several interesting findings about recessions. First, financial cycles are often more pronounced than business cycles, with deeper and more intense downturns than recessions. Second, recessions accompanied with financial disruptions tend to be longer and deeper than other recessions. In particular, recessions associated with house price busts last significantly longer than recessions without such disruptions, especifically by some 1.5 quarters on average. Third, recessions with credit crunches and house price busts result in significantly larger drops in output and correspondingly greater cumulative output losses (more than four percentage points in case of house price busts) relative to those without such episodes. Recessions accompanied with equity busts are also associated with significantly larger output declines than recessions without the busts, although the typical cumulative loss in such a recession is somewhat smaller than in those recessions accompanied with a credit crunch or a house price bust.

Similar to how financial disruptions are associated with longer and deeper recessions, so are recoveries associated with credit or house price booms shorter and associated with stronger output growth. The speed of recovery is also faster for those episodes associated with financial booms. Recoveries with financial booms are not necessarily accompanied with rapid growth on financial variables, reflecting the persistance of financial downturns during recoveries. These results indicate that changes in asset prices tend to play a critical role in determining the duration and the cost of recessions as well as on the strength of recoveries.

The study of credit-output relation distinguishing types of frequency cycles has been explored for the United States and euro area economies. Chen et al. (2012) use a multivariate unobserved components model with phase shifts to analyze the interactions of financial variables and output. They find that longer-run and business output cycles are correlated with assets prices, interest rates and credit. However, Zhu (2011), using time and frequency-domain methods, examines the credit-output link and concludes that the cyclical relation between the two variables is weak in the United States, relatively weak in Japan, and strong in the euro area. For Latin America, Reyes et al. (2013) analyze the problem of interest and find that credit and activity cycles with duration between 1.25 to less eight years are more volatile than medium size cycles (8 to 20 years) in Colombia, Chile and Peru. In terms of causation, they document that credit precedes activity, being negative in the case of short term cycles and positive in medium term GDP fluctuations.

3. DATA AND EMPIRICAL ANALYSIS

3.1 Data

This study uses monthly data to loans to the private sector by the banking system as a measure of aggregate credit, and uses production and economic activity indexes as an indicator of GDP or real economic activity. Data sources include the central banks of Central America and the Dominican Republic as well as the macroeconomic database of the Consejo Monetario Centroamericano.

The choice of these datasets is based on two reasons. First, since the financial sector in these countries is basically the banking system, and there is no data available on internal finance or corporate bond markets, the analysis restricts the definition of credit solely to loans to the private sector. Second, monthly data is used because GDP time series in some of the countries are not available with enough observations (Nicaragua) or exist only on an annual basis (Honduras); but for each of these countries there is a monthly measure of production or economic activity that I use for convenience. However, despite our gains from using this data, the sample sizes are not the same for all countries.

Finally, all series are seasonally adjusted and deflated by the CPI of each country. Figure 1 displays the evolution of logs of real private sector loans and real economic activity.The first prominent feature is the substantial covariation between real loans and economic activity for all countries despite the differences in variability around trend behavior. Except for the DR and Nicaragua, where loan series show sharp trend movements relative to real activity, all other countries show a loan trend behavior similar to the trend of the real activity.

Table 1 analyzes more closely the statistic regularities between both series. It provides some statistics for the series of annual growth of real loans and economic activity indexes.

Overall, real loans tend to grow at higher average annual rates and displays more volatility than economic activity, with the exception of El Salvador. Real loans grow at rates that double the growth of economic activity in Costa Rica, Guatemala and the Dominican Republic; are nearly 1.3 times in the case of Honduras; and are relatively equivalent in Nicaragua and El Salvador.

Figure 1

REAL LOANS AND ECONOMIC ACTIVITY INDEX
In logs

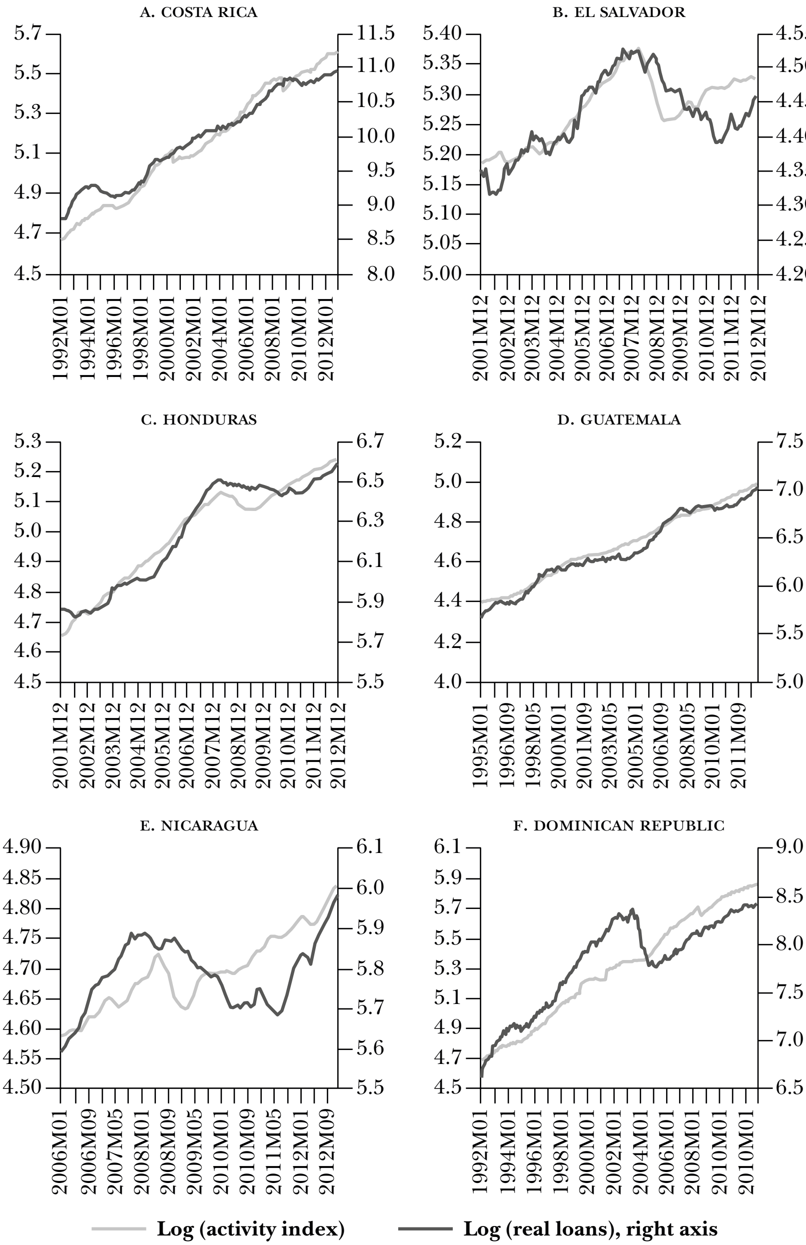


Table 1

DESCRIPTIVE STATISTICS OF ANNUAL GROWTH RATES
Percentages

	Economic activity index		*Real loans*		
Countries	*Average*	*Standard deviation*	*Average*	*Standard deviation*	*Sample*
Costa Rica	4.7	3.8	9.7	10.5	Jan. 1992 – Dec. 2012
El Salvador	1.3	4.3	1.0	3.7	Dec. 2002 – Dec. 2012
Honduras	5.2	4.4	6.9	7.8	Dec. 2002 – Dec. 2012
Guatemala	3.3	3.1	7.1	6.5	Jan. 1996 – Dec. 2012
Nicaragua	3.2	4.4	3.5	10.1	Jan. 2007 – Dec. 2012
Dominican Republic	5.9	3.9	9.2	14.7	Jan. 1992 – Dec. 2012

When I examine a common sample, 2007-2012, the period including the international financial turmoil, excluding Guatemala and the DR, there are no substantial changes in the behavior of observed series. In the case of Guatemala, real loans become more volatile relative to activity and the DR shows the opposite behavior.

3.2 Empirical Analysis

3.2.1 Cross Correlation in the Time Domain

In this section I analize the relation between real loans and economic activity using cross correlation analysis. Cross correlation is a common tool of empirical analysis in macroeconomics, and consists of estimating the correlation coefficients of an X variable with leads and lags of a Y variable. That is, the sample cross correlation coefficient of order k between X and Y is:

1
$$\rho(k) = \frac{\gamma_{xy}(k)}{\sqrt{\gamma_{xx}(0)}\sqrt{\gamma_{yy}(0)}},$$

2 $$\gamma_{xy}(k)=\begin{cases}\sum_{t=1}^{T-k}\left((x_t-\overline{x})(y_{t+k}-\overline{y})\right)/T & k=0,1,2,\ldots\\ \sum_{t=1}^{T-k}\left((y_t-\overline{y})(x_{t+k}-\overline{x})\right)/T & k=0,-1,-2,\ldots\end{cases},$$

where $\gamma_{xy}(k)$ is the cross covariance between X and Y, and $\gamma_{xx}(0)$ $\left(\gamma_{yy}(0)\right)$ is the variance of $X(Y)$.

If the coefficient of cross correlation is positive, it is said that X and Y are procyclical, and if it is negative they are countercyclical. Also, if a large correlation is observed with the k-th lag of X, that is $\mathrm{corr}(x_{t-k}, y_t)$, then it is said that X leads Y, or that the past values of X give information of present values of Y. On the other hand, if the maximum correlation is verified with the k-th lead of X, I conclude that X lags Y.

The computation of cross-correlation coefficients assumes that the series are stationary, so I compute the coefficients using the annual rates of growth of real loans and economic activity. In addition, I report the results when the cross correlations are computed using Hodrick-Prescott filtered series. Table 2 shows the results for each country specifying how sample sizes vary between them.

Table 2

CROSS CORRELATIONS
Maximum correlation, number of months leading(+) or lagging(−) real loans

Country	*Growth rate*	*HP filtered*	*Sample*
Costa Rica	0.33(+11)	0.31(−3)	Jan. 1992 – Dec. 2012
El Salvador	0.56(+5)	0.39(+5)	Dec. 2002 – Dec. 2012
Honduras	0.52(+2)	0.36(+5)	Dec. 2002 – Dec. 2012
Guatemala	0.26(0)	0.17(0)	Jan. 1996 – Dec. 2012
Nicaragua	0.45(+10)	0.30(0)	Jan. 2007 – Dec. 2012
Dominican Republic	0.44(+6)	0.45(+2)	Jan. 1992 – Dec. 2012

According to Table 2, real loans evolve procyclically with economic activity; however, it does not seem to be a variable that leads the economic activity. When correlations are calculated using the rates of growth, loans lags economic activity almost one year in the case of Costa Rica and Nicaragua, and between two to six months in El Salvador, Honduras, and the DR. On the other hand, in Guatemala it seems to be a coincident variable, but with a low coefficient.

Results do not change when filtered variables are used instead of the rates of growth. Only in Costa Rica past values of loans give information on present values of real activity, it does so with a three month lag. In other countries loans lag economic activity by five months, and they are coincidental in Guatemala and Nicaragua.

In conclusion, cross correlation analysis suggests a relation between the variables, but evidence indicates that real loans is a variable driven by economic activity. Nevertheless, one characteristic of our loan data is that it is composed of both new loans and also amortization, implying that the growth does not reflect exclusively the granting of new loans.

To further clarify the relation between real credit and activity, I perform an analysis of statistical precedence. Table 3 shows Granger causality tests among real loans and activity annual growth rates with different lags. Granger test points out that real loans *precede* the behavior of activity in the DR, Guatemala and Nicaragua, and shows mixed results in the case of Honduras. No evidence of Granger causality is found in Costa Rica and El Salvador.

3.2.2 Credit and Activity in the Frequency Domain

In this section I analyze the Relation using spectral analysis. There are different theories regarding the relation of credit and economic activity depending of the horizon on which the relation is analyzed. For example, as mentioned in the section 2, Misky (1982) establishes that financial innovations lead to relative large cycles of steady growth and induce risk taking, delivering a spiral of credit that ends in a recession. In this case, one must expect that credit and economic activity are tightly correlated in frequencies associated to cycles with a duration of 5 to 10 years.

Frequency or spectral analysis consist in the decomposition of variability (in case of one variable) or covariability (in case of two or more variables) in different frequencies. This approach would shed

Table 3

GRANGER CAUSALITY TEST

Countries	H_0	Lags 2	4	8	12	24
Costa Rica	Cr $\nrightarrow$ Y	0.66	0.38	1.17	1.23	1.18
	$Y \nrightarrow$ Cr	0.07	0.85	1.49	1.31	1.12
El Salvador	Cr $\nrightarrow$ Y	0.48	0.34	0.89	0.91	1.39
	$Y \nrightarrow$ Cr	2.12	1.12	1.23	1.26	1.66[a]
Honduras	Cr $\nrightarrow$ Y	2.05	3.00[b]	1.99[b]	2.08[b]	1.64[a]
	$Y \nrightarrow$ Cr	4.50[b]	2.20[a]	1.50	1.62[a]	1.81[b]
Guatemala	Cr $\nrightarrow$ Y	2.04	0.81	0.69	1.77[a]	1.15
	$Y \nrightarrow$ Cr	0.09	0.39	0.86	0.82	1.33
Nicaragua	Cr $\nrightarrow$ Y	0.54	1.02	1.70	1.82[a]	
	$Y \nrightarrow$ Cr	0.48	0.39	0.93	1.38	
Dominican Republic	Cr $\nrightarrow$ Y	14.10[c]	10.45[c]	5.95[a]	5.13[c]	2.25[c]
	$Y \nrightarrow$ Cr	4.09[b]	1.80	1.63	1.67[a]	1.16

Note: $\nrightarrow$ does not Granger cause. H_0 is rejected at [a] 1%, [b] 5%, and [c] 10 percent.

light on the idea of whether the evidence of correlation between the two variables happens solely because of the duration of the cycle that it is analyzed on.

We first proceed showing an univariate analysis through the estimation of the periodogram, which is a tool that describes how much variation of the series is accounted by the frequencies related with each cycle. With this information, I visually explore if the distribution of variance across frequencies of each series shows any type of correspondency. Next, I formaly analyze the covariability of both series using bivariate analysis in frequency domain, through the computing of the coespectrum, the quadrature and the coherence, each one gives an idea of the comovement of both series by frequency. Finally, Granger causality test in frequency domain is done by the test proposed in Breitung and Candelon (2006).

3.2.3 Univariate Analysis

Following Hamilton (1994), the sample periodogram or estimated spectral density can be expressed as:

$$\hat{s}_y(\omega_j) = \frac{1}{2\pi T}\left\{\left[\sum_{t=1}^{T} y_t \cos\left[\omega_j(t-1)\right]\right]^2 \left[\sum_{t=1}^{T} y_t \sin\left[\omega_j(t-1)\right]\right]^2\right\}, \tag{3}$$

where T is the sample size, and $\omega_j = 2\pi j/T$ denotes the frequency j, and each frequency is associated to a specific period $2\pi j/\omega_j = T/j$. The number of cycle components *(j)* is bounded by cero and $T/2$. Figure 2 shows the periodogram of the annual rate of growth real loans and economic for each country. The number of cycles is limited by the sample available. For Costa Rica and the Dominican Republic the longer cycle last almost 21 years, while in Guatemala, El Salvador and Honduras last 17 and around 10 years, respectively. Finally, Nicaragua has the shortest sample (2007-2012), then its longer cycle last six years.

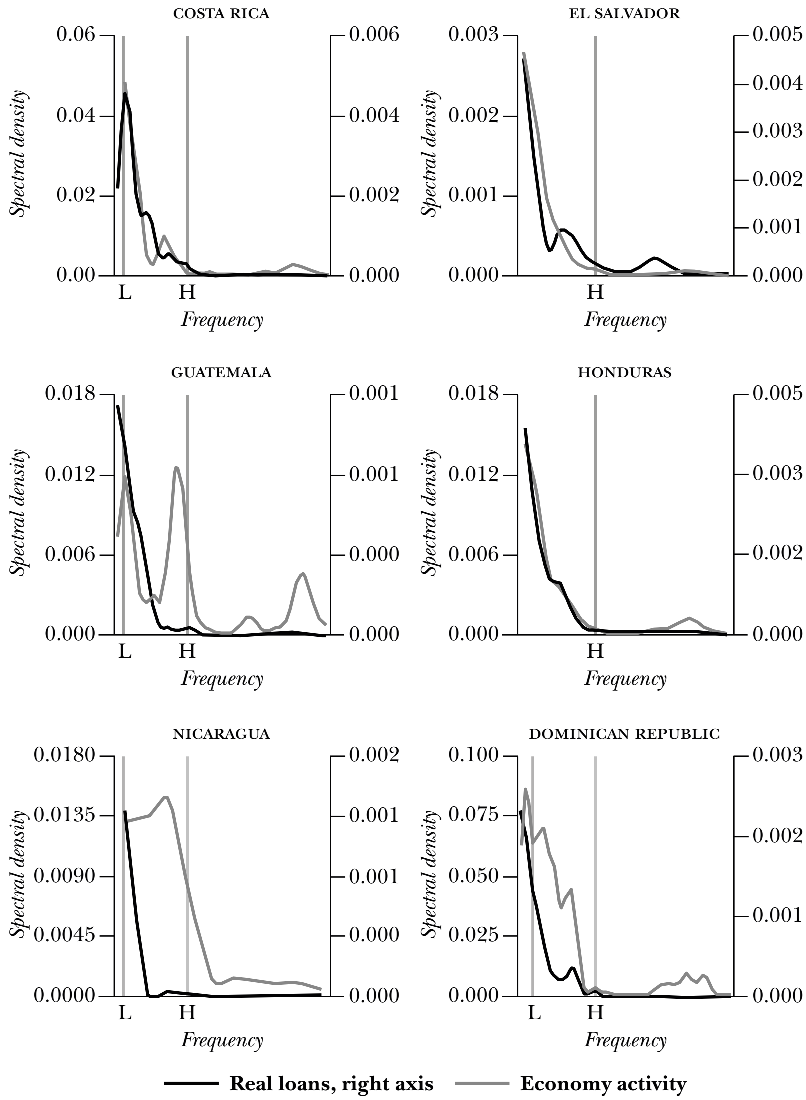
For all countries, most part of the variance of both series is concentrated at frequencies of 18-month cycles or more. Neglecting Nicaragua, no negligible proportions of the variance of real loans and activity is verified to be in frequencies over 96 months. Another regularity for these countries is that the distribution of cycles inside the range classified as business cycle frequencies is far from symetric. In fact, relative large business cycles with at least 3.5 years of duration dominate the distribution. This pattern is present on all countries, except in Guatemala, where a great part of the variance of economic activity growth is in frequencies of two-year cycles.

Judging for the amplitude of periodograms, credit cycles are more volatile and persistent than economic activity cycles, a pattern that is observed mainly at very low frequencies. Finally, credit cycles do not show important cycles at frequencies higher than business cycles, that means cycles in frequencies below 18 months.

Summarizing, the analysis of individual periodograms suggest that both series concentrate high levels of variability in frequencies associated to business cycles, and the distribution of the variability inside this type of cycles varies significantly across frequencies.

Figure 2

PERIODGRAMS OF REAL LOAN AND ECONOMIC ACTIVITY INDEX, BY COUNTRY



Notes: Periodgrams are computed using the annual rates of growth of both variables and conditional to the sample available for each country. The area between bars shows frequencies asociated with business cycles (cycles of 18 to 96 months or 1.5 to 8 years), where the upper limit is given by L (cycles of 96 months) and the lower limit is given by H (cycles of 18 months).

3.2.4 Bivariate Analysis

Similar to cross correlation analysis, I can compute a measure of the bivariate relation between real loans and economic activity rates of growth by frequency, and identify the cycles where these variables are most related to each other, if they indeed are. Following Hamilton (1994), the equivalent in spectral analysis of cross correlation is the cross spectrum which, in the case of two variables, can be defined by:

4 $$s_{xy}\left(\omega_j\right)=\frac{1}{2\pi}\sum_{k=-T+1}^{T-1}\hat{\gamma}_{xy}^{(k)}e^{-iwk},$$

where $i=\sqrt{-1}$ and $\hat{\gamma}_{xy}^{(k)}$ is the covariance function at lag k, which is given by:

5 $$\hat{\gamma}_{xy}^{(k)}=\hat{\gamma}_{xy}^{(-k)}=E\left(x_{t+h}-E(x)\right)\left(y_t-E(y)\right).$$

The cross spectrum can be rewritten in terms of two important measures: the co-spectrum and the quadrature that are expressed in equations 7 and 8 as:

6 $$s_{xy}(\omega)=c_{xy}(\omega)+i.q_{xy}(\omega),$$

7 $$c_{xy}(\omega)=\frac{1}{2\pi}\sum_{k=-T+1}^{T-1}\hat{\gamma}_{xy}^{(k)}\cos(\omega k),$$

8 $$q_{xy}(\omega)=\frac{1}{2\pi}\sum_{k=-T+1}^{T-1}\hat{\gamma}_{xy}^{(k)}\sin(\omega k).$$

The cospectrum gives an idea of the relation of x and y in a phase, that is, the covariation in a determined type of cycle. Quadrature, meanwhile, provides information on the linkages out of phase. With these measures, I can construct the coherence that summarizes the strength of correlation between two time series at selected frequencies. In other words, coherence indicates the percentage share of the variance between two time series at a particular frequency. Equation 9 shows how to compute this indicator:

$$h_{xy}(\omega) = \frac{\left[c_{xy}(\omega)\right]^2 + \left[q_{xy}(\omega)\right]^2}{s_{yy}(\omega)s_{xx}(\omega)}. \tag{9}$$

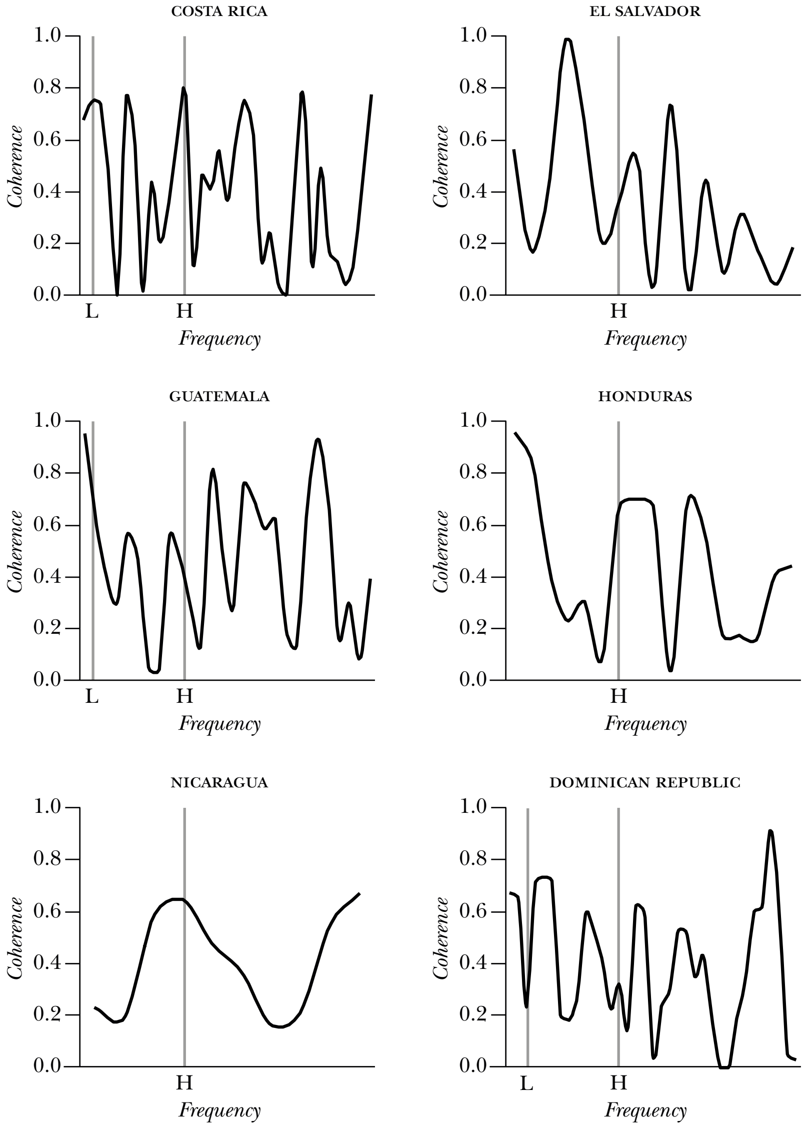
Asuming that s_{yy} and s_{xx} are different from zero, and the series under analysis are stationary, the coherence is bounded by zero and one.

Figure 3 shows the estimated coherence for each countries. According to the coherence, the correlation varies significantly across frequency. In business cycle frequencies (between 1.5 to 8 years) the credit-economic activity relation is high (over 0.5) for El Salvador, the Dominican Republic, and Costa Rica in less degree in Guatemala and Honduras, and not relevant in the case of Nicaragua. For Guatemala and Honduras, credit-activity relation seems to be important in cycles over 10 years, a pattern also observed in the DR and Costa Rica; however, it is not different from business cycles frequencies. Finally, although the series were seasonally adjusted, correlation on frequencies below 1.5 years was found to be important.

Particular attention is given to what coherence is shown in frequencies associated to business cycles, for its implication in terms of monetary and macroprudencial policy issues. We can identify that correlations are important in cycles between 1.5 to 3 years of length, linked to what is known as a monetary policy horizon, for Costa Rica, Honduras, Guatemala, Nicaragua, and the DR. On the other hand, Costa Rica and El Salvador display high covariability of the mentioned variables for cycles lasting four to five years, while for Guatemala, the DR, and Honduras, for business cycles lasting nearly 10 years.

Figure 3

COHERENCE



Notes: The coherence is computed using the annual rates of growth of both variables and conditional to the sample available for each country. The area between bars shows frequencies asociated with business cycles (cycles of 18 to 96 months or 1.5 to 8 years), where the upper limit is given by L (cycles of 96 months) and the lower limit is given by H (cycles of 18 months).

3.2.5 Granger Causality Test in Frequency Domain

In section 2 I showed the results of the statistical precedence test between credit and activity, finding evidence for the DR, Guatemala, and Nicaragua and in lesser extent for Honduras. Now, I analyze the statistical precedence by frequency through the Granger test version of Breitung and Candelon (2006). The methodology consists in estimate a bivariate VAR using credit and economic activity index, where the order of the lag is obtained by the AIC criteria. That is,

10
$$\Theta(L)Y_t = \varepsilon_t,$$

where Y_t= [*activity*$_t$, *credit*$_t$] is a two dimensional vector with credit and economic activity; $\Theta(L) = I - \Theta_1 L - \ldots - \Theta_p L^p$ is a lag polinominal of order 2×2, and ε_t is a vector of structural innovations with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_t') = \Sigma$ as the positive definite variance-covariance matrix. Assuming the stationarity of the bivariate process, the moving-average representation is given by:

11
$$Y_t = \Phi(L)\eta_t,$$

where $\eta_t = B\varepsilon_t$ is the vector of reduced form residuals and B is a lower diagonal matrix of the Cholesky decomposition $B'B = \Sigma^{-1}$. $\Phi(L) = \Theta(L)^{-1} B^{-1}$ represents the reduce form coefficients that can be partitioned as:

12
$$\begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{bmatrix}.$$

Based on 12, the spectral density of activity is:

13
$$f_{activity} = \frac{1}{2\pi}\left\{\left|\Phi_{11}\left(e^{-i\omega}\right)\right|^2 + \left|\Phi_{12}\left(e^{-i\omega}\right)\right|^2\right\}.$$

From 13, Breitung and Candelon (2006) proposed the following measure of Granger causality:

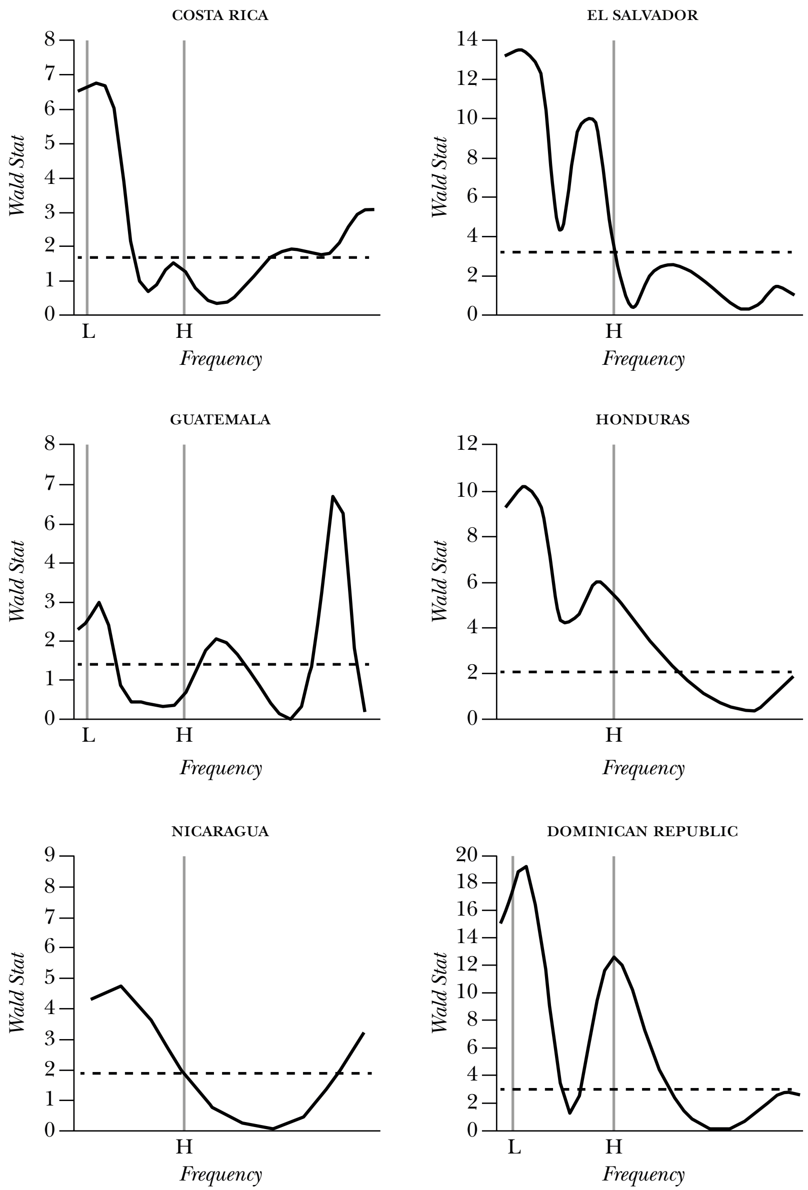
14 $$M_{credit \rightarrow activity}(\omega) = \log\left[1 + \frac{\left|\Phi_{12}\left(e^{-i\omega}\right)\right|}{\left|\Phi_{11}\left(e^{-i\omega}\right)\right|}\right],$$

where the null hypotesis is that $\Phi_{12}\left(e^{-i\omega}\right) = 0,$ meaning that credit does not cause activity at frequency $\omega.$ The evaluation of the proposed hypotesis is based on a Wald test for each frequency. Figure 4 display the results with the Wald statistic critical value for each frequency represented by the dotted horizontal line.

Granger test results suggest that the relation of causation from credit to activity is restricted to certain types of cycles. For Costa Rica, El Salvador, Honduras, Guatemala and the DR there is evidence that credit granger causes activity in cycles over eight years. Also, this pattern is observed in business cycle frequencies for the previously mentioned countries and Nicaragua. In the case of Guatemala, I do not find evidence of granger causation in frequencies associated with cycles between 1 and 4 years. In Honduras and El Salvador credit is relevant to explain future values of activity, both in short cycles between 1.5 to 3 years and relatively large cycles of 6 to 8 years. Finally, in the DR and Nicaragua credit seems to precede activity across frequencies linked to business cycles.

Figure 4

GRANGER CAUSALITY TEST



4. CONCLUSION

This study addresses the relation between credit and economic activity in Central America and the Dominican Republic. Using time and frequency domain techniques, it explores the linkages between the credit cycles and economic activity cycles. As a proxy of credit, this paper uses aggregate loans to the private sector in real terms and as a proxy of economic activity the economic activity index, both variables in monthly frequency.

I found that real loans and economic activity display different types of cycles, standing out those known as business cycles (1.5 to 8 years) and low frequency cycles. There is evidence of a positive relation between credit and real activity growth in frequencies associated to business cycles for all countries with the exception of Nicaragua with correlation coefficients below 0.5.

According to the coherence, which measures the correlation by frequency among credit and activity, I foundthat for Costa Rica and the DR this correlation is important in frequencies with cycles lasting 10 or more years.

Using a frequency version of Granger test, I identified evidence suggesting that credit precedes economic activity business cycles frequencies in Costa Rica, El Salvador, Honduras, Nicaragua and the DR. Excluding Nicaragua, this pattern is observed also in cycles lasting over eight years for these mentioned economies. In case of Guatemala there is no evidence of statistical precedence of credit to activity.

ANNEX

Replication Codes

Matlab Procedure to Compute Periodograms and Coherence based on Hamilton (1994) Chapters 6 and 10.

```
clear all; close all; clc;
DATOS;
x=x−mean(x);
y=y−mean(y);
T=length(x);
t=(1:T)';
```

```
j = (1:T/2);
w = 2*pi*j/T;
alpha = zeros(1,length(j));
delta = zeros(1,length(j));
a = zeros(1,length(j));
d = zeros(1,length(j));
for j = 1:length(j)
    alpha(j) = (2/T)*(sum(y.*cos(w(j)*(t−1))));
    delta(j) = (2/T)*(sum(y.*sin(w(j)*(t−1))));
    a(j) = (2/T)*(sum(x.*cos(w(j)*(t−1))));
    d(j) = (2/T)*(sum(x.*sin(w(j)*(t−1))));
%Periodogramas
    sy(j) = (T/(8*pi))*(alpha(j)^2 + delta(j)^2);
    sx(j) = (T/(8*pi))*(a(j)^2 + d(j)^2);
%Coespectro
    cxy(j) = (T/(8*pi))*(a(j)*alpha(j) + d(j)*delta(j));
%Cuadratura
    qxy(j) = (T/(8*pi))*(d(j)*alpha(j) + a(j)*delta(j));
end
h = 1;
m = (−h:h);
k = ((h + 1−abs(m))/(h + 1)^2);
sy = sy'; sx = sx'; cxy = cxy'; qxy = qxy';
syr = zeros(1,length(w));
sxr = zeros(1,length(w));
cxyr = zeros(1,length(w));
qxyr = zeros(1,length(w));
for r = h:length(w)−(h + 1);
    syr(r) = k*sy(r−(h−1):r + (h + 1),1);
    sxr(r) = k*sx(r−(h−1):r + (h + 1),1);
    cxyr(r) = k*cxy(r−(h−1):r + (h + 1),1);
    qxyr(r) = k*qxy(r−(h−1):r + (h + 1),1); end
for j = 1:length(w)
%Coherencia
    hxy(j) = (cxyr(j)^2 + qxyr(j)^2)/(syr(j)*sxr(j));
%Gain
    R(j) = (cxyr(j)^2 + qxyr(j)^2)^0.5;
%Phase
    Q(j) = (−atan(qxyr(j)/cxyr(j)))/w(j);
end
```

```
result = [sxr' syr' cxyr' qxyr' hxy' R' Q' w'];
figure
    subplot(2,2,1), plot(w,sxr);
    title('Spectrum X')
    subplot(2,2,2), plot(w,syr);
    title('Spectrum Y') subplot(2,2,3),
    plot(w,cxyr);
    title('Co-spectrum XY')
    subplot(2,2,4), plot(w,qxyr);
    title('Cudrature XY')
figure
    subplot(3,1,1),
    plot(w,hxy);
    title('Coherence XY')
    subplot(3,1,2), plot(w,R);
title('Gain XY')
subplot(3,1,3), plot(w,Q);
title('Phase XY')
```

Matlab Functions for Granger Causality Test by Frequency based on Breitung and Candelon (2006)'s Gauss codes (Modified to consider specific types of cycles according to sample size)

Important: This function is a Matlab version of Breitung and Candelon (2006) 's Gauss codes availables on their websites. Copyright J. Breitung and B. Candelon.

```
%INPUT: Y Txk matrix of data.
%1st column: Target variable
%2nd column: Causing variable
%p number of lags
%OUTPUT: G 314 x 2 matrix where the 1st column contains
%frequencies and 2nd column: Wald test statistics
%This function compute the test function [wald] = granger(y,p,w)
    [n,k] = size(y);
    xstar = y(3:n,2)-2*cos(w)*y(2:n-1,2) + y(1:n-2,2);
    x = horzcat(y(p:n-1,:),y(p-1:n-2,:));
    if p>2;
         i = 1;
```

```
            while i<p−2;
                x = horzcat(x,y(p−1−i:n−2−i,1));
                if k>2;
                x = horzcat(x,y(p−1−i:n−2−i,3:k));
                end
                i = i + 1;
            end
        end
    i = 1;
    while i< = p−2;
        x = horzcat(x,xstar(p−1−i:n−2−i));
        i = i + 1;
    end
    x = horzcat(x,ones(n−p,1));
    [e1,e2] = size(x);
    depvar = y(p + 1:n,1);
    b = inv(x'*x)*x'*depvar; u = depvar-x*b; sig2 = u'*u; sig2 = sig2/
(n-p-e2); varb = sig2*inv(x'*x); ind = vertcat(2,(k + 2));
    wald = b(ind)'*inv(varb(ind,ind))*b(ind);
end
%This function uses the previous function
%to calculate the test for multiple frequencies.
function [wald,wstar] = tfreq(y,p)
T = length(y); t = (1:T)';
j = (1:T/2);
wstar = 2*pi*j/T;
    wald = zeros(314,2);
        wstar = 0.01;
        j = 1;
            while wstar<3.14;
                wald(j,1) = wstar;
                wald(j,2) = granger(y,p,wstar);
                wstar = wstar + 0.01;
                j = j + 1;
            end
end
```

References

Bernanke, B., M. Gertler, and S. Gilchrist (1999), "The Financial Accelerator in a Quantitive Business Cycle Framework," in J. B. Taylor and M. Woodford (eds.), *Handbook of Macroeconomics*, Vol. 1 , part C, chapter 21, Elsevier, pp. 1341- 1393, <https://doi.org/10.1016/S1574-0048(99)10034-X>.

Breitung, J., and B. Candelon (2006). " Testing for Short- and Long-Run Causality: A Frequency-Domain Approach," *Journal of Econometrics*, Vol. 132. issue 2, June, pp. 363-378, <https://doi.org/10.1016/j.jeconom.2005.02.004>.

Brunner, K., and A. H. Meltzer (1990), "Money supply," in B. M. Friedman and F. H. Hahn (eds.), *Handbook in Monetary Economics*, Vol. 1, chapter 9, Elsevier, pp. 357-398, <https://doi.org/10.1016/S1573-4498(05)80012-8>.

Busch, U. (2012), *Credit Cycles and Business Cycles in Germany: A Comovement Analysis*, mimeo., February, <http://dx.doi.org/10.2139/ssrn.2015976>.

Caballero, R., and A. Krishnamurthy (1998), *Emerging Market Crises: An Asset Markets Perspective*, Working Papers, No. 98-18, MIT.

Céspedes, L. F., R. Chang, and A. Velasco (2004), "Balance Sheets and Exchange Rate Policy," *American Economy Review* , Vol. 94, No. 4, September, pp. 1183-1193.

Chen, X., A. Kontonikas, and A. Montagnoli (2012), "Asset Prices, Credit and the Business Cycle," *Economics Letters*, Vol. 117, No. 3, pp. 857-861, <doi:10.1016/j.econlet.2012.08.040>.

Claessens, S., M. A. Kose, and M. E. Terrones (2011), *How do Business and Financial Cycles Interact?*, CEPR Discussion Paper, No. DP8396.

Gómez-González, J., J. Ojeda-Joya, F. Tenjo-Galarza, and H. Zárate (2013), *The Interdependence Between Credit and Business Cycles in Latin America Economies*, Borradores de Economía, No. 768.

Hamilton, J. (1994), *Time Series Analysis,* Princeton University Press.

Hayek, F. (1929), *Monetary Theory and the Trade Cycle*, Jonathan Cape, London.

Helbling, T., R. Huidrom, M. A. Kose, and C. Otrok (2010), *Do Credit Shocks Matter? A Global Perspective*, IMF Working Paper, No. WP/10/261.

Kiyotaki, N., and J. Moore (1997), "Credit Cycles," *Journal of Political Economy*, Vol. 105, No. 2, pp. 211-248, <http://dx.doi.org/10.1086/262072>.

Kiyotaki, N. (1998), "Credit and Business Cycles," *Japanese Economic Review*, Vol. 49, issue 1, pp. 18-35, <https://doi.org/10.1111/1468-5876.00069>.

Kocherlakota, N. R. (2000), "Creating Business Cycles Through Credit Constraints," *Quarterly Review*, Federal Reserve Bank of Minneapolis, Vol. 24, No. 3, Summer, pp. 2-10.

Minsky, H. (1982), "The Financial-Instability Hypothesis: Capitalist Processes and the Behavior of the Economy," in C. P. Kindleberger, and J. Laffargue, *Financial Crises*, chapter 2, University Press.

Reyes, N. R., J. E. Gómez-González, and J. Ojeda-Joya (2013), *Bank Lending, Risk Taking, and the Transmission of Monetary Policy: New Evidence for Colombia*, Borradores de Economía, No. 772.

Zhu, F., (2011), *Credit and Business Cycles: Some Stylized Facts*, mimeo., BIS.