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

Documento de Trabajo 2013-02

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(Documento de Trabajo 2013-02)

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Resumen

El presente estudio provee evidencia sobre la relación entre el crédito y la actividad real en Centro América y la República Dominicana (RD). Se investiga el vínculo entre crédito y actividad real para el caso de un grupo de países en vías de desarrollo con mercados financieros limitados, donde el crédito bancario es la principal fuente externa de financiamiento del sector privado.

Se compila información sobre el crédito al sector privado y el nivel de actividad económica para Costa Rica, El Salvador, Honduras, Guatemala, Nicaragua y la RD. La información es analizada mediante técnicas estadísticas convencionales (contrastos de causalidad de Granger y análisis espectral) para identificar hechos estilizados relacionados con la relación entre crédito y actividad.

Se encuentra una relación positiva entre el crédito al sector privado y el nivel de actividad económica para Costa Rica, El Salvador, Honduras, Guatemala, Nicaragua y la RD. La relación crédito-actividad en ciclos de 10 a más años de duración es relevante en Costa Rica y la RD. Existe evidencia que sugiere que el crédito precede la actividad económica en frecuencias de ciclo económico en Costa Rica, El Salvador, Honduras, Nicaragua y la RD. Excluyendo Nicaragua, este patrón es observado en ciclos de 8 años para las economías mencionadas. En el caso de Guatemala no se encuentra evidencia estadística de la precedencia del crédito a la actividad económica.

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

(Documento de Trabajo 2013-02)

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Abstract

This study provides evidence of the relationship between credit and real activity in Central America and the Dominican Republic. 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.

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 relationship.

We find a positive relationship between credit and real activity in frequencies associated to business cycles for all countries. The credit - economic relationship 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 8 years for mentioned economies. In case of Guatemala there is no evidence of statistical precedence of credit to economic activity.

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

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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 credit in different periods of expansion and recession generally associated to business cycle frequencies in advanced economies¹ and emerging economies and recently in Latin America².

The purpose of this study is to provide evidence of the relationship 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 analyzing 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.

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¹Helbling, et. al. (2010), Zhu (2011), Busch (2012), Chen, et. al. (2012) and Claessens, et. al. (2012)

²Gómez-González, et. al. (2013)

To reach that goal, we compile information credit directed 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 to identify stylized facts on the credit-activity relationship. First, we rely on cross correlations and Granger causality tests to learn about the statistical relationship between these time series and how the facts fit with conventional theories of credit-output linkages. In a second stage, spectral analysis decomposition techniques are used to explore the link between credit and activity in different frequencies. That is, we estimate and classify by the order of importance the type of cycles that best characterize each time series and inquire on which frequency the relationship 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, Gertler and Gilchrist, 1999; among others), meaning that credit and economic activity data must show a high level of covariance in these frequencies.

In terms of the results, the study has mixed findings for the countries under analysis. First, we find a positive relationship 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 relationship 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 8 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 the 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 interest on the role of credit cycles on economic fluctuations is long-standing. Different theories compete on what kind of relationship 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 5 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 ISLM model, and show that credit and asset price shocks are relevant sources of business cycle fluctuations.

Contemporary macroeconomic theories of credit address the relationship 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, Gertler and Gilchrist (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 Cespedes, Chang and Velasco (2004) and Caballero and Krishnamurthy (1998).

2.2 Empirical literature

Recent empirical literature on the relationship 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.

For the G-7 economies Helbling et. al. (2010) analyze the role of credit shocks on global business cycles. Using a VAR methodology they conclude that in business cycle frequencies credit has as much of an impact as productivity in explaining economic activity for this specific group of economies, that put together, account for almost 40% of the global economy.

Claessensa, Kose and Terrones (2012) 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, specifically by some $1\frac{1}{2}$ 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 4 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 persistence 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 relationship distinguishing types of frequency cycles has been explored for the US 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 both 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 relationship 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 8 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 on 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 DR as well as the macroeconomic database of the Monetary Council of Central America (CMCA, for its acronym in spanish).

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 we 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 co-variation 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, nearly 1.3 times in the case of Honduras, and they are relatively equivalent in Nicaragua and El Salvador.

Table 1: Descriptive Statistics (Annual Growth Rates)

Country		CR	ES	HN	GT	NI	DR
Ec.Act. Index	Average	4.7%	1.3%	5.2%	3.3%	3.2%	5.9%
	S.D.	3.8%	4.3%	4.4%	3.1%	4.4%	3.9%
Real Loans	Average	9.7%	1.0%	6.9%	7.1%	3.5%	9.2%
	S.D.	10.5%	3.7%	7.8%	6.5%	10.1%	14.7%
Sample		Jan. 1992	Dec. 2002	Dec. 2002	Jan. 1996	Jan. 2007	Jan. 1992
		Dec. 2012	Dec. 2012	Dec. 2012	Dec. 2012	Dec. 2012	Dec. 2012

CR: Costa Rica; ES: El Salvador; HN: Honduras; GT: Guatemala; NI: Nicaragua; DR: Dominican Republic

When we 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 we analyze the relationship 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:

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

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

Where $\gamma_{xy}(k)$ is the cross covariance between X and Y, and $\gamma_{xx}(0)$ ($\gamma_{yy}(0)$) 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 the large correlation is observed with the k-th lag of X, that is $corr(x_{t-k}, y_t)$, 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, we conclude that X lags Y.

The computation of cross correlation coefficients assumes that the series are stationary, so we compute the coefficients using the annual rates of growth of real loans and economic activity. In addition, we 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 varies between them.

Table 2. Cross Correlations			
Maximum Correlation (number of months leading(+) of 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 2 to 6 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 3 month lag. In other countries loans lag economic activity by 5 months, and they are coincidental in Guatemala and Nicaragua.

In conclusion, cross correlation analysis suggests a relationship 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 relationship between real credit and activity, we 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.

Countries	Ho	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*
Honduras	Cr \nrightarrow Y	2.05	3.00**	1.99**	2.08**	1.64*
	Y \nrightarrow Cr	4.50**	2.20*	1.50	1.62*	1.81**
Guatemala	Cr \nrightarrow Y	2.04	0.81	0.69	1.77*	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*	
	Y \nrightarrow Cr	0.48	0.39	0.93	1.38	
Dominican Republic	Cr \nrightarrow Y	14.10***	10.45***	5.95*	5.13***	2.25***
	Y \nrightarrow Cr	4.09**	1.80	1.63	1.67*	1.16

\nrightarrow does not Granger cause

3.2.2 Credit and activity in the frequency domain

In this section we analyze the relationship using spectral analysis. There are different theories regarding the relationship of credit and economic activity depending of the horizon on which the

relationship 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 on 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 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, we visually explore if the distribution of variance across frequencies of each series shows any type of correspondency. Next, we formally 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:

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

Where T is the sample size, and $\omega_j = \frac{2\pi j}{T}$ denotes the frequency j and each frequency is associated to a specific period $\frac{2\pi}{\omega_j} = \frac{T}{j}$. The number of cycle components (j) is bounded by 0 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 DR 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 6 years.

For all countries, most part of the variance of both series is concentrated at frequencies of 18-month cycles or more. Neglecting Nicaragua, not 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 dominates the distribution. This pattern is present on all countries, except in Guatemala, where great part of the variance of economic activity growth is in frequencies of 2-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 does 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.

3.2.4 Bivariate analysis

Similar to cross correlation analysis, we can compute a measure of the bivariate relationship 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:

$$s_{xy}(\omega_j) = \frac{1}{2\pi} \sum_{k=-T+1}^{T-1} \hat{\gamma}_{xy}^{(k)} e^{-i\omega k} \quad (4)$$

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

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

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:

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

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

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

The co-spectrum gives an idea of the relationship 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, we 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:

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

Assuming that s_{yy} and s_{xx} are different from zero, and the series under analysis are stationary, the coherence is bounded by 0 and 1.

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 relationship is high (over 0.5) for El Salvador, the DR 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 than business cycles frequencies. Finally, although the series were seasonally adjusted, correlation on frequencies below 1.5 years were found to be important.

Particular attention is given to what coherence are showing in frequencies associated to business cycles, for it implication in terms of monetary and macroprudencial policy implications. 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 4 to 5 years, while for Guatemala, the DR and Honduras, for business cycles lasting nearly 10 years.

3.2.5 Granger Causality Test in Frequency Domain

In section 2 we shows 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, we analyze the statistical precedence by frequency through the Granger test version of Breitung and Candelon (2006). The methodology consist 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,

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

Where $Y_t = [activity_t, credit_t]$ is a two dimensional vector with credit and economic activity, $\Theta(L) = I - \Theta_1 L - \dots - \Theta_p L^p$ is a lag polinomial of order 2X2, and ε_t is a vector or 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 MA representation is given by:

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

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:

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

Based on (12), the spectral density of activity is :

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

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

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

Where the null hypotesis is that $\Phi_{12}(e^{-i\omega}) = 0$, meaning that credit does not cause activity at frequency ω . 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 8 years. Also, this pattern is observed in business cycle frequencies for the previously mentioned countries and Nicaragua. In the case of Guatemala, we 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 relative large cycles of 6-8 years. Finally, in the DR and Nicaragua credit seems to precede activity across frequencies linked to business cycles.

4 Conclusion

This paper addresses the relationship 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.

We find 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 relationship 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, who measure the correlation by frequency among credit and activity, we find that 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, we identify 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 8 years for these mentioned economies. In case of Guatemala there is no evidence of statistical precedence of credit to activity.

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A Figures

Figure 1: Real Loans and Economic Activity Index (in logs)

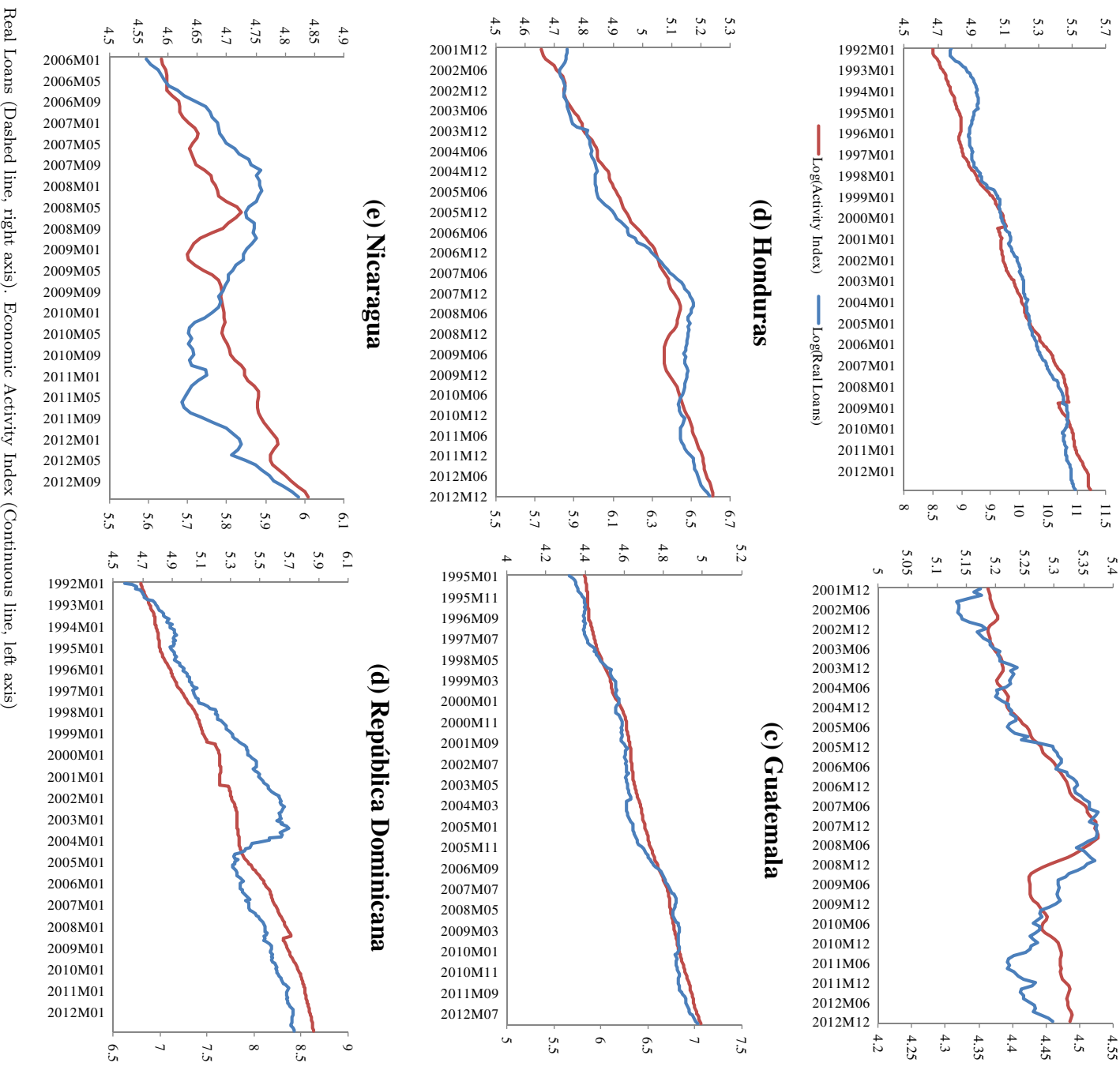
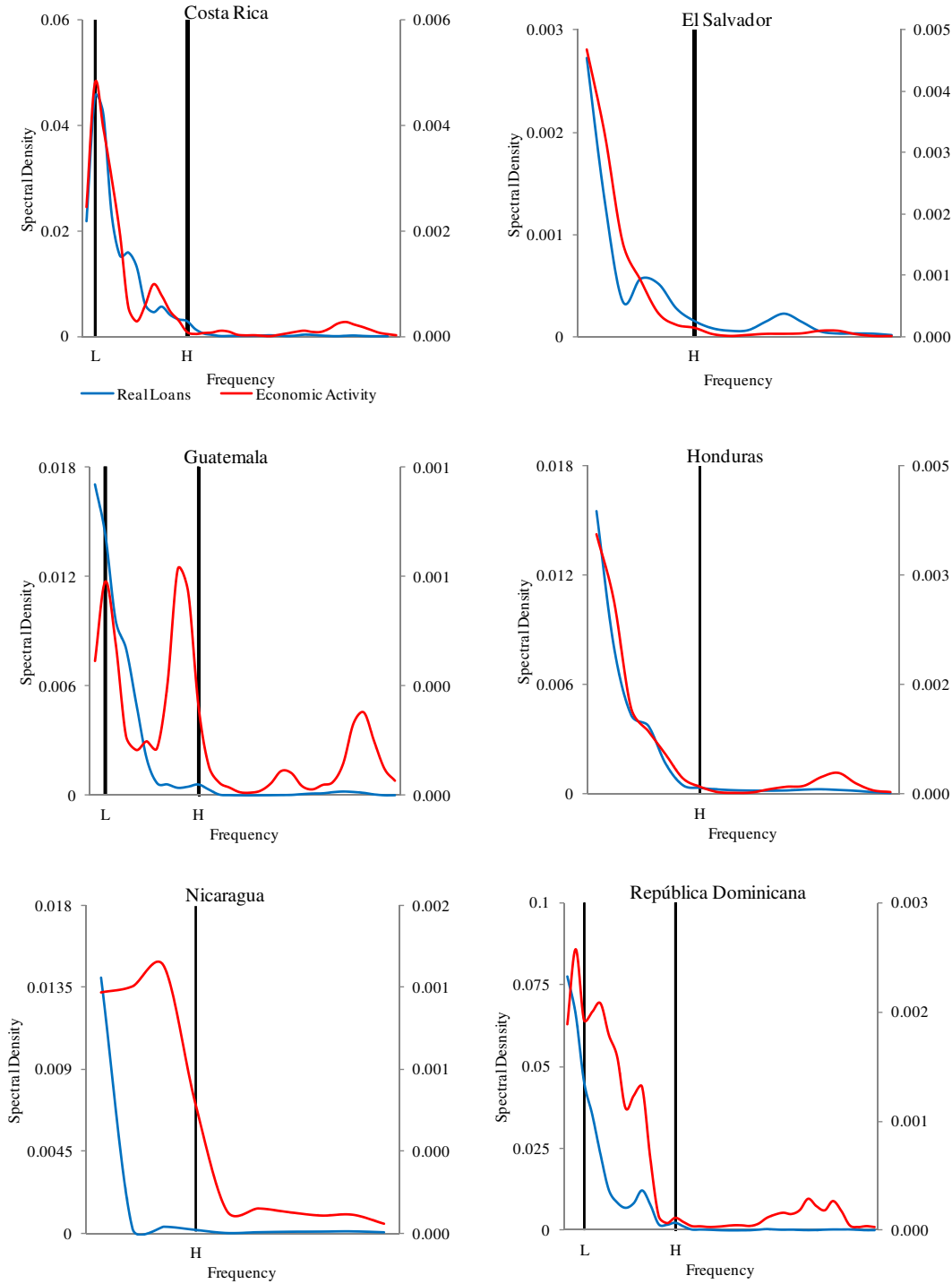
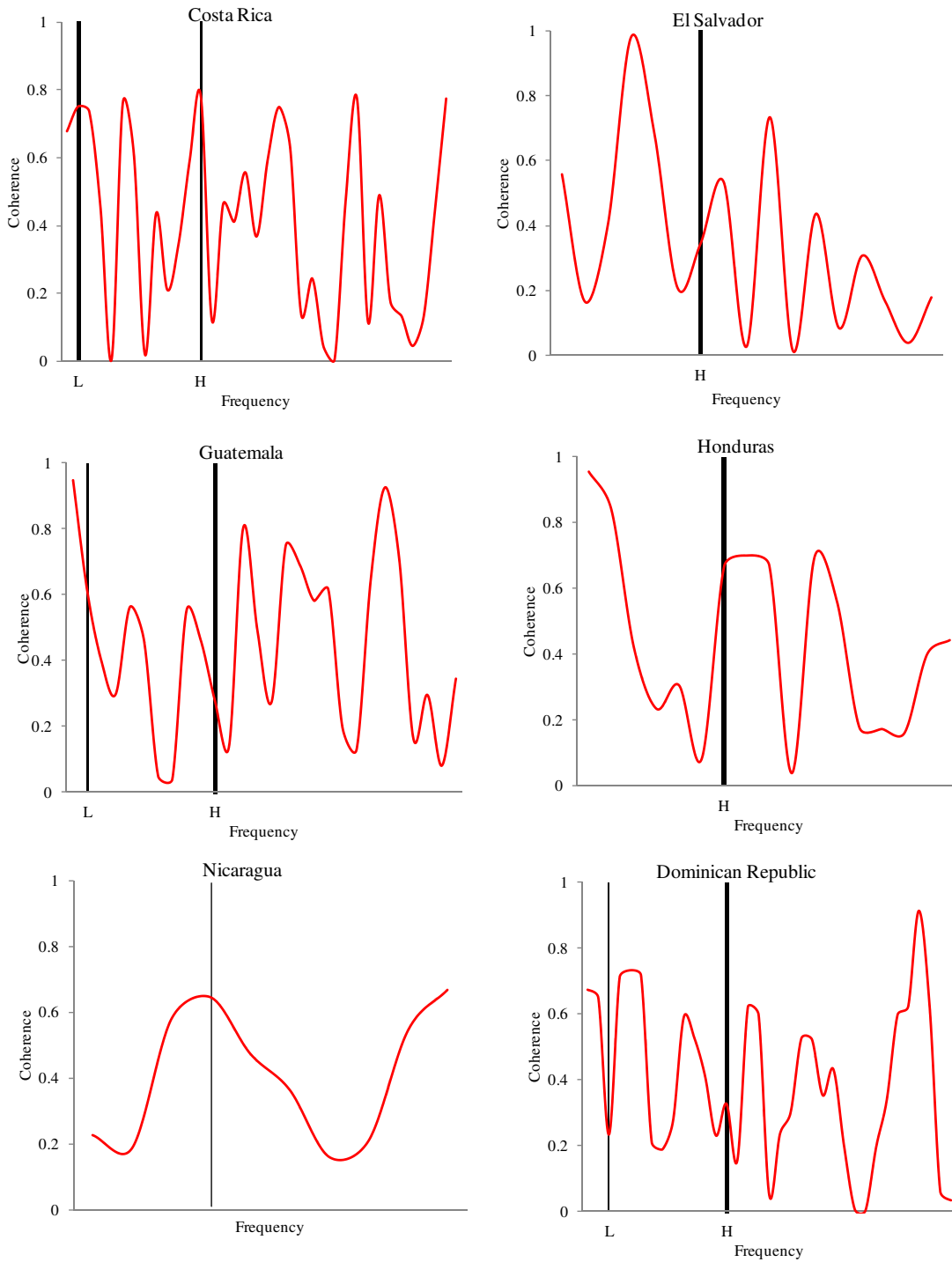


Figure 2: Periodograms of Real Loan and Economic Activity Index, by Country



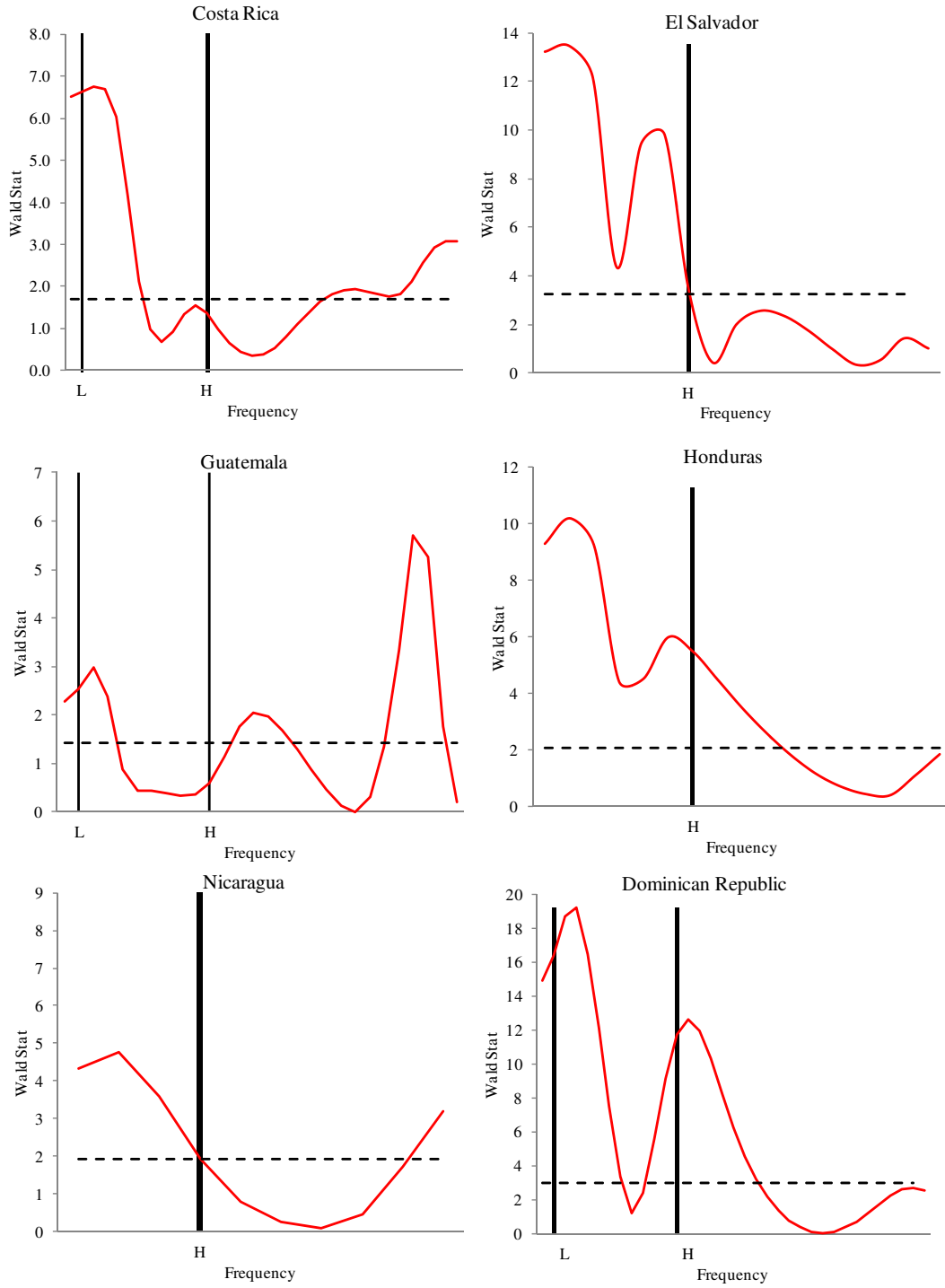
Notes: Real loans (right axis). Periodograms are computed using the annual rates of growth of both variables and conditional to the sample available for each country. The area between bars shows frequencies associated with business cycles (cycles of 18 to 96 months or 1.5 to 8 years), where the upper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

Figure 3: Coherence



Note: 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 associated 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).

Figure 4: Granger Causality Test



B Replication Codes

B.1 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')

```

B.2 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 & B. Candelon.

```
%INPUT: Y T x k 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

```