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The Interdependence between Credit and Real Business Cycles in Latin American Economies¹

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Abstract

In this document we estimate credit and GDP cycles for three Latin-American economies and study their relation in the time and frequency domains. Cycles are estimated in order to analyze their medium and short-term frequencies. We find that short-term cycles are usually more volatile than medium-term cycles for credit and GDP in Chile, Colombia and Peru. We also find that credit-cycle peaks in the middle 1990s and middle 2000s precede notable GDP recessions 2 or 3 years later in these countries. Additionally, credit cycles in Latin-American economies tend to cause later movements in economic activity. This effect can be decomposed into two components: first, a negative effect in the case of business-cycle frequencies, and a positive effect in the case of medium-term GDP fluctuations.

JEL Classification: E32; E44; C32

Keywords: Short and Medium-Term Cycles, Frequency Domain, Granger Causality, Credit Booms and Crunches, Recession

¹ May 2013. Disclaimer: The findings, recommendations, interpretations and conclusions expressed in this paper are those of the authors and do not necessarily reflect the view of the Banco de la República or its Board of Directors.

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1. Introduction

The real business cycle has been widely studied in macroeconomics (see, for instance, Kydland and Prescott, 1982; Lucas, 1987; King, Plosser and Rebelo, 1988; Rotemberg and Woodford, 1991; Christiano and Eichenbaum, 1995). The recent international financial crisis has motivated increasing attention on the behavior of financial indicators and the identification of financial cycles. This new focus is important according to recent literature that has pointed out the shortcomings of real business cycle (RBC) models since they exclude financial variables. This new trend calls also for studying the interdependence between financial and real business cycles (Goodhart and Hofmann, 2008; and, Drehmann, Borio and Tsatsaronis, 2012; among others).

Studies in this strand have focused on developed economies. An import exception is Claessens, Kose and Terrones (2012), who study the interaction between the short-run financial and real business cycles in a group of 44 countries, among which some emerging economies are included.

In this study, we identify macroeconomic and credit cycles for three emerging, commodity-producing economies using data for the last three decades. We estimate short and medium-term credit and GDP cycles and measure their degree of interdependence.

Therefore, the contributions of this document to macroeconomic cycles' literature are twofolded. First, we focus on three Latin American countries, namely Chile, Colombia and Peru. Studying cycles in these economies is of major interest because of the unique features that characterize them. Trade reforms and financial liberalization processes were implemented in these economies during the late 1980s and early 1990s. These processes led to greater economic integration with the rest of the world, and therefore to greater vulnerability to international shocks. While other emerging countries undertook similar structural reforms at the same time, our set of countries has the important characteristic of being commodity producers and, therefore, being subject to commodity price volatilities. Recent studies have shown that commodity price shocks have a significant impact on output and investment dynamics in commodity-producing economies. There is also

evidence that the impact of those shocks on investment is asymmetric, being larger for economies with under-developed financial markets, (Céspedes and Velasco, 2012).

Second, while most existing studies deal only with short-term cycles, in this paper we characterize both short-run and medium-run cycles for our set of countries. Drehmann, Borio and Tsatsaronis (DBT) do a similar exercise but only for developed economies, with particular emphasis on the United States. Our work allows making a comparison with their results. Interesting lessons can be derived from this comparison, as some of our results diverge importantly from theirs.

DBT find that, in developed economies, the medium-term cycles of financial indicators are more volatile than the corresponding short-run cycles. Furthermore, the peaks of financial cycles are identified as good predictors of financial crises. Finally, these authors show that GDP recessions become more severe if they coincide with a decreasing phase of the credit cycle.

This study finds that, in contrast to DBT, financial and GDP cycles in Chile, Colombia and Peru are usually more volatile at short-term than at medium-term horizons. The only exception is in the case of the credit cycle in Colombia. In line with DBT, we identify peaks in medium-term financial cycles in all three countries both during the mid-1990s and during the mid-2000s, a few quarters before important downturns of economic activity.

An additional methodological improvement in this study is that we use frequency-domain statistics in order to analyze cyclical movements in financial and economic activity indicators and their interdependence.

The remainder of this paper is organized as follows. Section 2 presents a brief review of related literature. In Section 3 we describe the methodology employed for identifying and characterizing short-run and medium-run cycles. Section 4 briefly describes the data used for our empirical analysis. In Section 5, we present our results for Chile, Colombia and Peru. Conclusions are presented in Section 6.

2. Literature Review

The recent international financial crisis has renewed academic interest for studying the interdependence between financial and real variables along cycles. A strand of this literature has centered in the dynamic interactions among financial variables, real activity, monetary aggregates and asset prices. For instance, Goodhart and Hoffman (2008) use a sample of 17 industrialized economies for the period 1970 – 2006, and estimate the multi-dimensional links between money, credit, house prices and economic activity. They find a strong link between house prices and monetary variables post–1985. They also find that the macroeconomic effects of monetary and credit shocks are stronger when house prices are booming.

A few papers have studied these relations from a historical perspective. Schularick and Taylor (2012) evaluate the behavior of financial, monetary and macroeconomic indicators for a set of 14 countries with data starting back in 1870. A key finding of this paper is that exuberant credit growth usually anticipates financial crisis. Similar results have been obtained by Alessi and Detken (2011), Borio and Drehmann (2009) and by Tenjo and López (2010) who construct early warning models of financial crises for alternative groups of countries.

Other strand of the literature deals with the predictive power of financial indicators on economic crises. Ng (2011) uses three alternative financial measures to evaluate their capacity of forecasting business cycles. He finds that only measures related to financial stress have important short-run predictive power.

Some recent papers study the interaction between real and financial cycles. Aikman et al (2011), construct a model of the banking industry where credit cycles emerge as a consequence of coordination failure among banks. These authors estimate medium-term cycles both for GDP and credit for 12 countries using Schularick and Taylor's (2012) database. They find evidence favoring the existence of financial cycles and their predictive power of banking crises. Additionally, these cycles are found to be different from the business cycle in frequency and amplitude.

Claessens et al (2012) measure the interdependence between business and financial cycles on short-term frequencies for a list of 44 countries over 50 years. They report evidence on strong statistical liaisons between these cycles, for instance, recessions appear to be deeper when they coincide with troughs in financial variables such as asset prices. DBT find similar evidence using fewer developed countries, but separating the cycles in their short and medium-term components. They also find that the medium-term cycle is more volatile than the short-term cycle.

3. Statistical Methodology

With the purpose of comparing the relation between output and financial cycles in the three emerging economies we use statistical methodologies which study both the time domain and the frequency domain. In the time domain, the analysis relies on traditional cross correlation analyses. Thus, the co-movement between cycles is measured through the correlation coefficients among leads and lag of the original cycles, (see for instance Comin and Gertler, 2006).

Statistical methods for studying the time domain are commonly used for the study of economic time series; see for instance, Hamilton (1994). Therefore, in the remainder of this section we focus in describing the methods used for frequency domain analysis.

The frequency domain approach is implemented by proceeding into three stages. First, we estimate the spectral function for each variable. This estimation allows comparing the shape of the spectral density with the “typical shape” identified by Granger (1966). Second, we use the Direct Filter Approach to extract short and medium-term cycles through Fourier analysis. Finally, we estimate the co-movement between cycles by using the cross spectral density function and its related measures of coherence.

This methodology is conducted on the entire frequency range from 0 to π . This approach allows estimating the proportion of the total variance determined by each periodic component, using spectral analysis. Therefore, we capture the components of credit and

output by decomposing the original series and using approximation methods based on trigonometric functions at each frequency.

The traditional econometric methods of signal extraction are based on smoothing filters (Christiano and Fitzgerald, 2003) and modeling-based procedures. However, the components of the time series give rise to spectral structures that fall within well-defined frequency bands that are isolated from each other by spectral dead spaces (Pollock 2000). Thus, the frequency domain offers a better way of implementing signal extraction methods, and filters are used to separate the components of a time series.

One of the tools in the frequency domain is the spectrum of the time series which is the Fourier transformation of its autocovariance function $\gamma(\cdot)$ and is given by the following symmetric function:

$$f(\lambda) = (2\pi)^{-1}[\gamma(0) + 2 \sum_{\tau=1}^{\infty} \gamma(\tau) \cos \lambda\tau] \quad (1)$$

Where λ is the frequency in radians in the range $[-\pi, \pi]$. The standardized function, known as spectral density, is obtained by normalizing using $\gamma(0)$. A cycle is defined as one complete period of a sine or cosine function over a time interval of length 2π .

It is important to note that the spectrum and the covariances are equivalent. However, some features of the time series, such as its serial correlation, are easier to grasp with the autocovariances, while others, such as unobserved components, are easier to analyze in the spectrum.

Values of λ near zero correspond to long-term cycles, while values of λ near π correspond to short-term cycles. Following DBT, we consider as medium-term cycles those corresponding to frequencies $\lambda \in [0.785, 0.196)$, and short-term cycles those corresponding to $\lambda \in [0.196, 1.25]$. In the time domain, these intervals correspond to cycles between 32 and 80 quarters for the medium-term case and cycles between 5 and 32 quarters for the short-term case.

The peaks observed in the spectrum indicate those periodicities which contribute the most to the variability of the series. Additionally, confidence intervals for the spectrum can be

obtained from the fact that $\hat{f}(\lambda)$ follows a χ^2 distribution with ν degrees of freedom where $\nu = \frac{3\sqrt{n}}{2}$, and n stands for the sample size.

The Direct Filter Approach (DFA) emphasizes on filter errors rather than on the one-step ahead forecasting error. Furthermore, the DFA uses an algorithm based on an optimization criterion which consists of minimizing the mean square error of the filter.

Given a stochastic process $\{Y_t\}$, the real time signal extraction is concerned with the estimation of \hat{Y}_t and \bar{Y}_t such that $E(\bar{Y}_t - \hat{Y}_t)^2$ is minimized. Where \bar{Y}_t is the result of applying a symmetric filter to the original series $\{Y_t\}$, and \hat{Y}_t the result of an asymmetric filter.

The result of this minimization is the following transfer function which can be used as a filter. One particular application which we use in this document is the filter proposed by Christiano and Fitzgerald (2003).

$$\Gamma(\lambda) = \begin{cases} 1 & 0 \leq |\lambda| \leq \pi b_p \\ \frac{\pi b_p - |\lambda|}{\pi b_s - \pi b_p} & \pi b_p < |\lambda| \leq \pi b_s \\ 0 & \pi b_s < |\lambda| \leq \pi \end{cases} \quad (2)$$

Where b_p determines the width of the pass band and b_s determines the width of the stop band (Wildi, 2008).

The cross-spectral correlation function measures the correlation between two series indexed by the frequency. The square of the value of this correlation function at every frequency λ is defined as coherence. This statistic is the analogous of the square of the correlation coefficient and takes values in the interval $[0,1]$. A value of coherence near one indicates that the two series are highly correlated at the given frequency. A value near zero describes that at this frequency the series are almost independent.

In order to test for causality between GDP and Credit cycles in the frequency domain, we use measures proposed in the framework by Geweke (1982) and Hosoya (1991) and adopted by Breitung and Candelon (2006) in a VAR system setup.

Let $Z_t = [GDP_t, CREDIT_t]$ be a two dimensional vector of time series observed for $t = 1, 2, \dots, T$, which represents the total cycle of these two variables. Thus, the VAR representation of this system can be written in the following way:

$$\Theta(L)Z_t = \varepsilon_t \quad (3)$$

And the MA representation of the system is the following:

$$Z_t = \Phi(L)\varepsilon_t = \begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} = \Psi(L)\eta_t = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix} \quad (4)$$

Where,

$$\Phi(L) = \Theta(L)^{-1} \text{ and } \Psi(L) = \Phi(L)G^{-1}$$

And G is the lower matrix of Cholesky decomposition.

Using this representation, the spectral density of GDP_t , for example, can be expressed as:

$$f_{GDP}(\omega) = \frac{1}{2\pi} \left(\left(\Psi_{11}(e^{-i\omega}) \right)^2 + \left(\Psi_{12}(e^{-i\omega}) \right)^2 \right) \quad (5)$$

From which, According to Breitung and Candelon (2006), the measure of causality is defined in the following way:

$$M_{CREDIT \rightarrow GDP} = \log \left(1 + \left(\frac{\left(\Psi_{12}(e^{-i\omega}) \right)^2}{\left(\Psi_{11}(e^{-i\omega}) \right)^2} \right) \right) \quad (6)$$

This causality measure is zero if $\left(\Psi_{12}(e^{-i\omega}) \right) = 0$, which means that CREDIT does not cause GDP at frequency ω . The causality from GDP to CREDIT is built using a similar approach.

4. Data Description

We use quarterly credit and GDP data for Chile, Colombia and Peru. Data were collected for the longest available period for each country. In the case of Chile, the data comprise the period 1986Q1-2012Q2. For Colombia, we use data from 1978Q1 through 2012Q2. And for Peru, available data span the period 1994Q1-2012Q2. All information was obtained from central banks. All data are reported at constant prices using the consumer price index of the respective country.

5. Empirical Results for Chile, Colombia and Peru

5.1 Characterizing short and medium-term cycles

It is usual to identify the business cycle using macroeconomic data with cycles of less than eight years. In this work, following Drehmann, Borio and Tsatsaronis, (DBT), we focus on two different cyclical patterns. On the one hand, we estimate short-term cycles with duration between 5 and 32 quarters. On the other hand, we estimate medium-term cycles lasting between 32 and 80 quarters.

For all three countries we are able to identify the existence of both short and medium-term cycles for GDP and credit. We use the Band-Pass filter of Christiano and Fitzgerald (2003) to isolate the component of each series that corresponds to the chosen frequency interval.

Table 1 presents volatility indicators of short and medium-term cycles for GDP and credit. The short-term cycle is more volatile than the medium-term cycle except for the credit cycle in Colombia. Thus, for these variables short-term cycles are more important in shaping the behavior of the series than longer term cycles. These results contrast those of DBT for whom the medium-term cycle is more volatile for all variables and countries in the sample. Hence, for GDP and credit in these three countries, short-term cycles appear to be more important than longer term cycles on average.

Table 1: Relative volatility of short and medium-term cycles for GDP and Credit*

	Chile			Colombia			Peru		
	Short-term	Mid-term	Ratio	Short-term	Mid-term	Ratio	Short-term	Mid-term	Ratio
GDP	0.027	0.007	0.256	0.018	0.010	0.558	6.182	3.031	0.490
Credit	0.046	0.026	0.579	0.048	0.055	1.150	2.695	1.326	0.492

* Third and sixth columns refer to the ratio of the standard deviations of the medium-term cyclical component to that of the short-term component over the entire sample period. A number greater (smaller) than 1.0 means that the medium-term cyclical component is more (less) volatile than the short-term component.

Table 1 also shows that in Colombia and Chile, credit volatility is higher than GDP volatility both in short and medium-term cycles. On the contrary, in Peru GDP cycles appear to be more volatile than credit cycles. In a way similar to DBT, we find that the ratio of medium to short-term volatility is higher for credit than for GDP for all three countries.

Table 2 presents the estimated duration of the average short and medium-term cycles for GDP and credit. Regarding the total duration, credit cycles last on average longer than GDP cycles both for short and medium-term cycles for all countries except for the case of Peru in the medium-term. This result is similar to the one in DBT for the US. We also find that the longest durations correspond to Colombia for the credit cycle and to Peru for the GDP cycle.

Contractions are found to be longer than expansions in the case of short-term cycles in both variables for all countries except for GDP in Peru. In contrast, medium-term expansions seem to be longer than contractions for both variables in Chile and Peru while for Colombia contractions are longer in both variables. In contrast, DBT find that GDP and credit expansions are usually longer than contractions for both short and medium-run cycles in the US.

Table 2: Cycles Duration in Quarters for GDP and Credit

Variable		Expansion		Contraction		Cycle	
		Short	Med	Short	Med	Short	Med
Chile	GDP	4.151	17.766	4.520	15.888	8.671	31.966
	Credit	4.949	22.833	5.070	22.311	10.146	45.644
Colombia	GDP	3.269	17.588	3.946	18.937	7.215	39.055
	Credit	3.853	22.811	5.075	24.366	8.840	47.177
Peru	GDP	3.721	23.333	3.606	22.311	7.327	45.644
	Credit	4.869	22.322	6.257	21.311	10.553	43.633

Table 3: Cycles Amplitude in per cent for GDP and Credit

Variable		Expansion		Contraction	
		Short	Med	Short	Med
Chile	GDP	5.1	1.5	-4.8	-1.4
	Credit	7.7	3.5	-8.3	-8.8
Colombia	GDP	2.6	2.4	-2.5	-2.5
	Credit	8.4	9.4	-7.7	-16.3
Peru	GDP	4.9	3.8	-5.3	-4.2
	Credit	10.2	25.1	-11.7	-27.0

Table 3 describes the average amplitude of expansions and contractions for GDP and credit. An interesting feature is that expansions and contractions appear to be larger for credit than for GDP for all three countries both at medium and short terms. This stylized fact is also reported by DBT using US data. It is interesting to note that the amplitude of most cycles in Peru is larger than the corresponding cycles in both Colombia and Chile.

Figure 1: Short-term Cycles for GDP and Credit

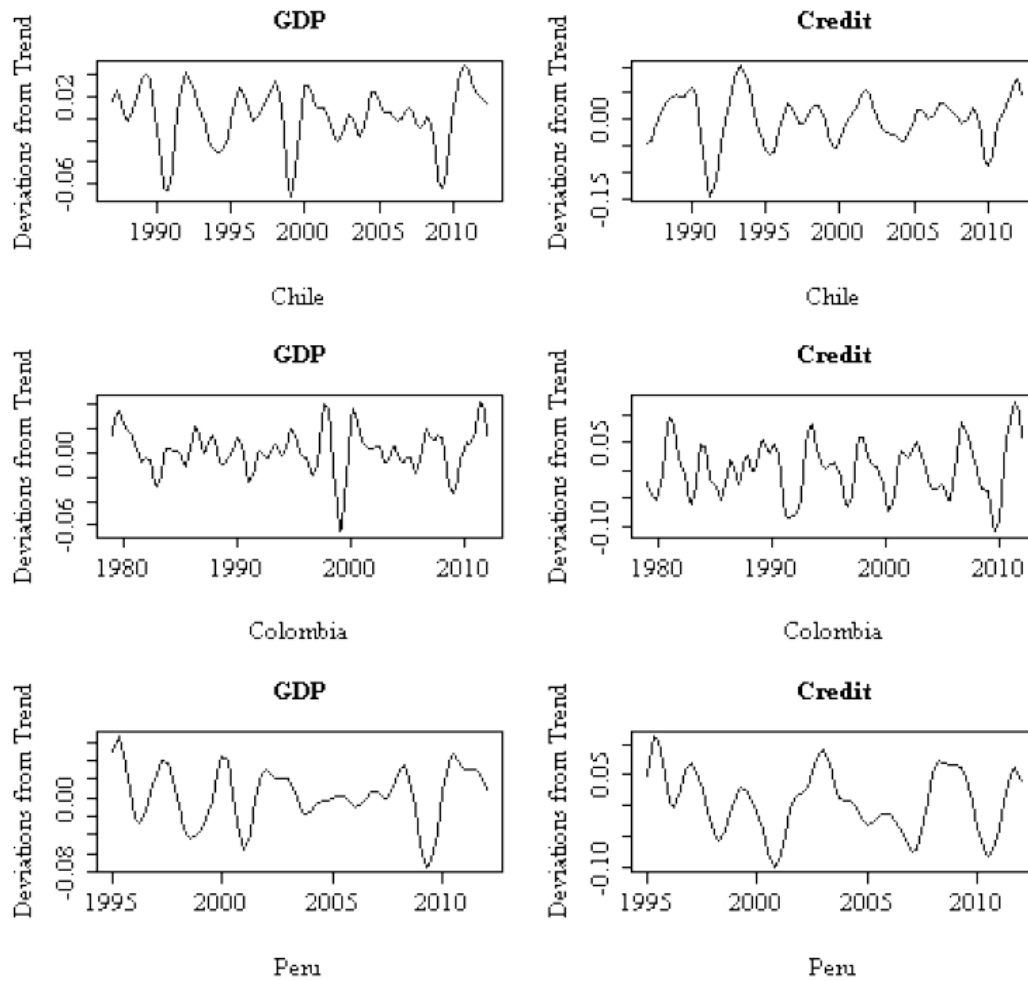


Figure 1 presents short-term cycles for GDP and credit. Although these cycles span different time periods, it is possible to observe some common features. First, around 2010 there is a trough in all six graphs. This trough can be associated to the effect of the international financial crisis on macroeconomic and financial variables in the three economies considered. Second, there are other troughs around 2000 in all six graphs which are possibly associated to the effect of the Asian, Brazilian and Russian financial crises of the late 1990s.

Figure 2: Medium-term Cycles for GDP and Credit

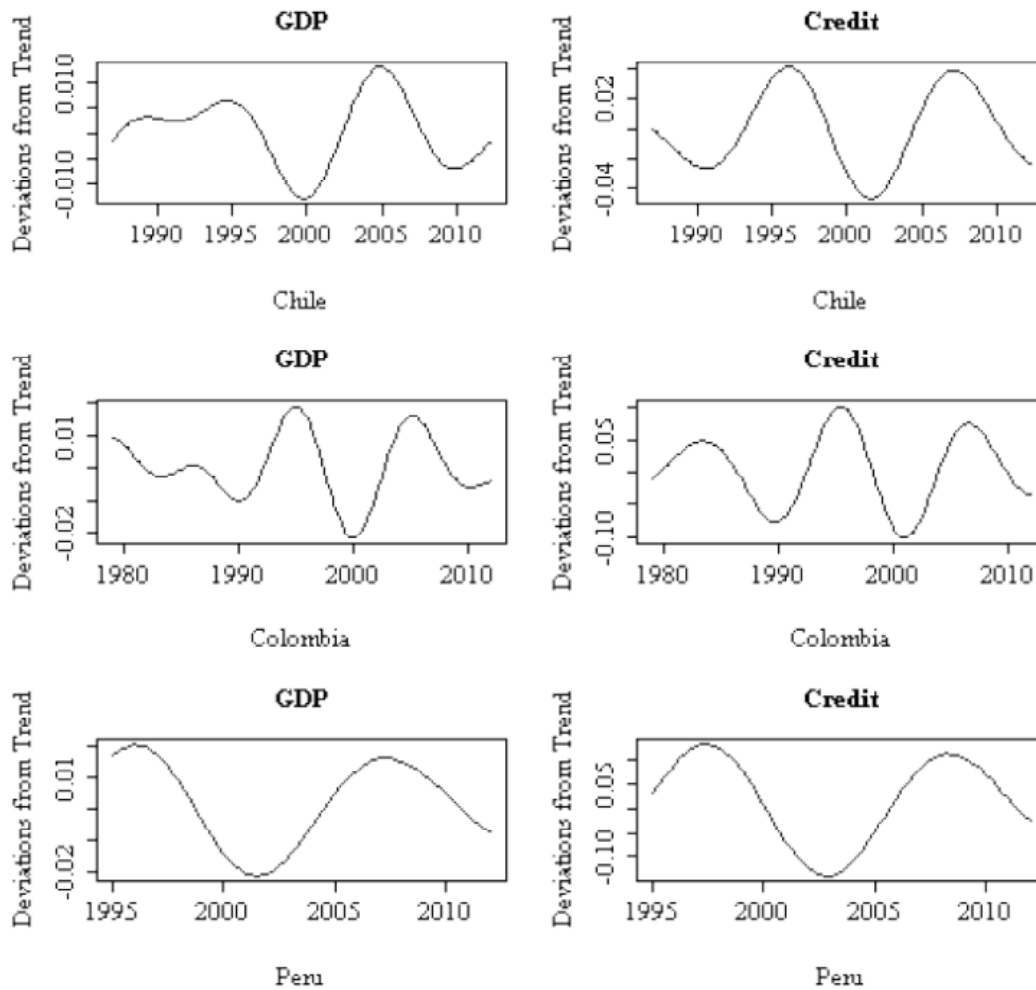
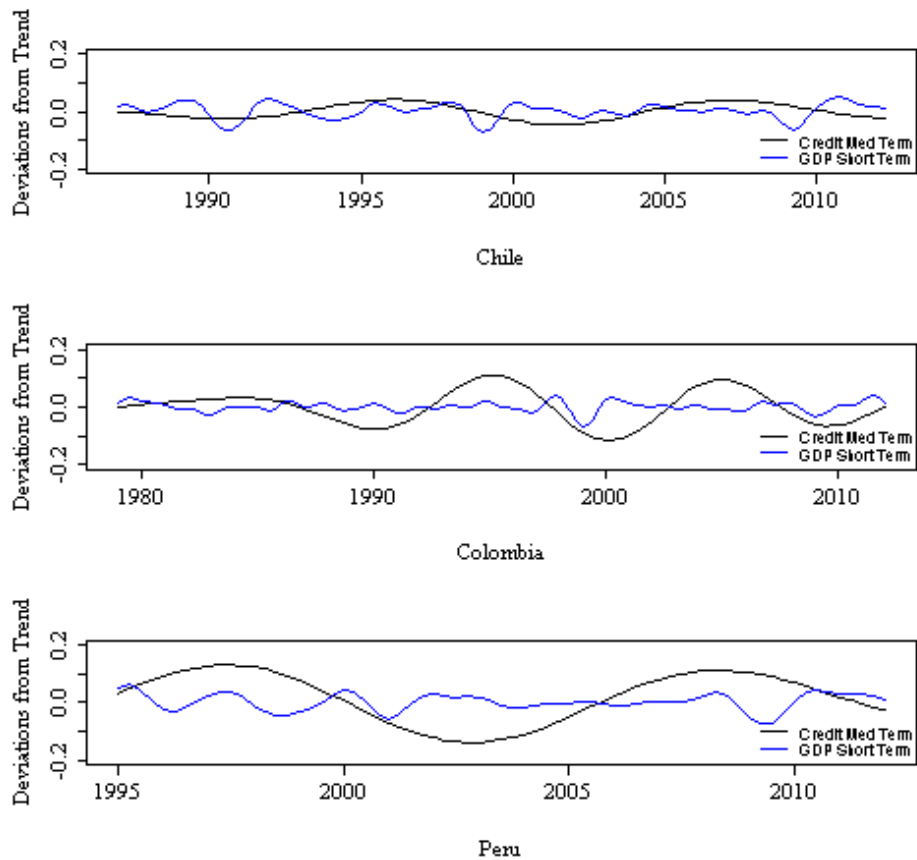


Figure 2 shows medium-term cycles for GDP and credit. For Colombia and Chile, there are troughs in GDP around 2000 and troughs in credit a couple of years later. Similar troughs are observed in Peru a few years later. It is also worth pointing out that the most recent peak in both credit and GDP occurred right before the financial crisis of 2007-2008.

Following DBT, we compare the medium-term financial cycle with the short-term GDP cycle in each country. This exercise allows examining whether peaks in the financial cycle are associated with severe recessions a few quarters later during the decreasing phase of these cycles.

Figure 3: Comparing Financial and Business cycles

The financial (Medium term) and real business (Short term)cycles

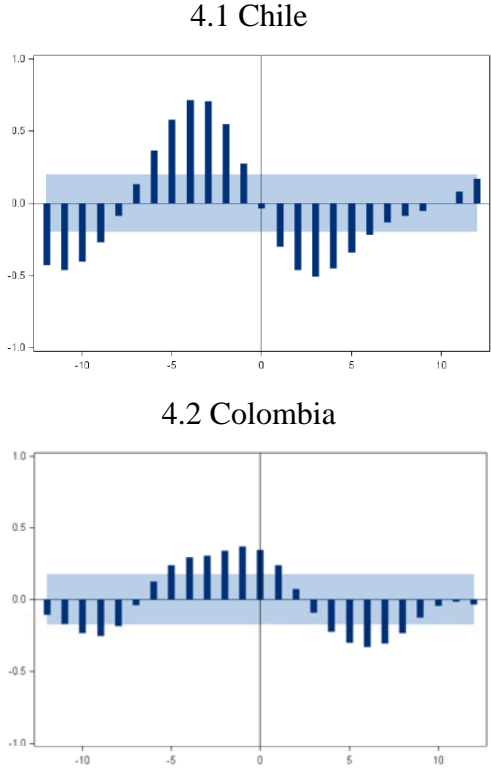


It is possible to observe in Figure 3 that there are peaks in medium-term credit cycles in all three countries during two key periods: mid-1990s and mid-2000s. The credit-cycle peak observed around 1997 can be associated with posterior important economic downturns observed a few years later especially in Chile and Colombia. Meanwhile, the peak observed around 2007 in all three countries can be associated with the posterior downturn observed a couple of years later especially in Chile and Peru. However, it is clear that an important cause of this recent downturn is the international financial crisis which started in the US in September 2008.

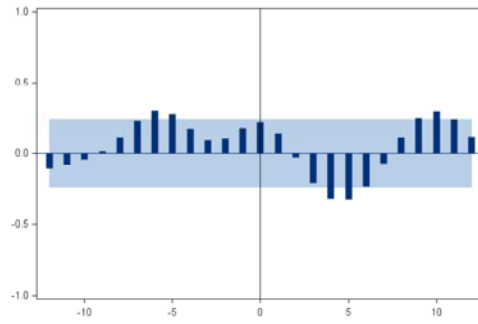
5.2 Interdependence between credit and GDP cycles

Figure 4 presents cross-correlations in the time domain between credit and GDP short-term cycles. These correlograms are computed with the following equation: $corr(GDP_{i,t}, credit_{i,t-k})$, where $i = \{Chile, Colombia, Peru\}$ and k stands for the order of the lag of credit.

Figure 4: Cross-Correlations in the Time Domain between Short-Term Cycles: Credit versus GDP



4.3 Peru

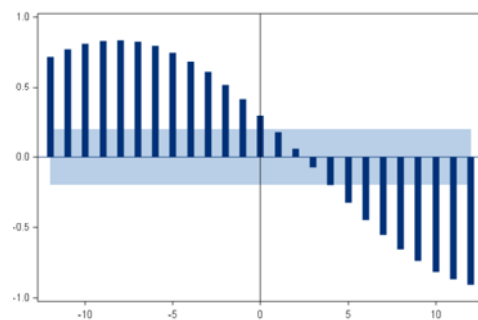


From the figures above, it is possible to infer that the maximum correlation between contemporaneous credit and lagged GDP is positive for all three countries. The lag order in which this maximum occurs is different across countries. Namely, it is 4 quarters in Chile, 1 quarter in Colombia and 6 quarters in Peru. In general terms current credit is positively correlated with the first few lags of GDP. This correlation turns negative as higher lags of GDP are considered.⁶ However, in Peru most of these correlations are not statistically different from zero at conventional significance levels.

Figure 4 also shows that the correlations of contemporaneous GDP with lagged credit are all negative for the three countries. The maximum correlations occur at the 4th, 6th and 5th lags for Chile, Colombia and Peru, respectively. In a way similar to DBT, this result suggests that peaks in credit are associated with later troughs in GDP.

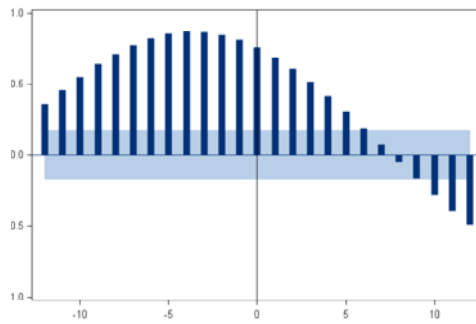
Figure 5: Cross-Correlations between Medium-Term Cycles: Credit versus GDP

5.1 Chile



⁶ For example, in the case of Chile, this result suggests that peaks in GDP are associated with peaks in credit a year later and troughs in credit two years later.

5.2 Colombia



5.3 Peru

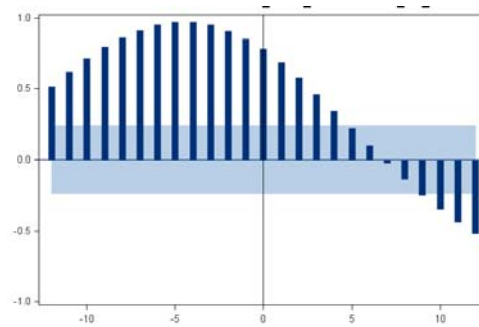
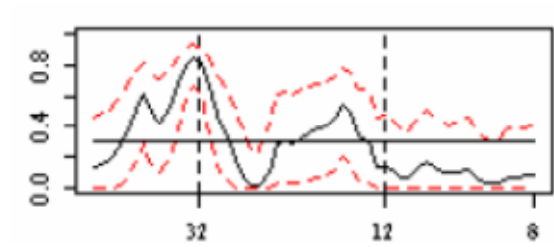


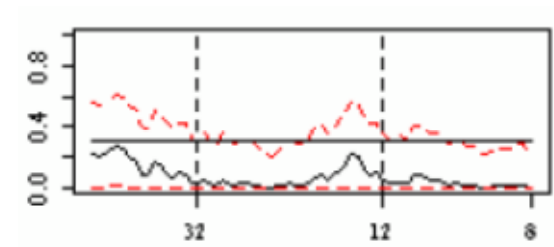
Figure 5 presents cross-correlations for medium-term cycles between GDP and credit. The correlations of contemporaneous credit with lagged GDP are found to be positive for all three countries. Meanwhile, the correlations of contemporaneous GDP with lagged credit are initially positive but then become negative for Colombia and Peru, while for Chile these correlations are all negative. This also shows that the medium-term credit booms usually do not lead to medium-term GDP recessions in these countries.

Figure 6: Coherence in the frequency domain: Credit versus GDP

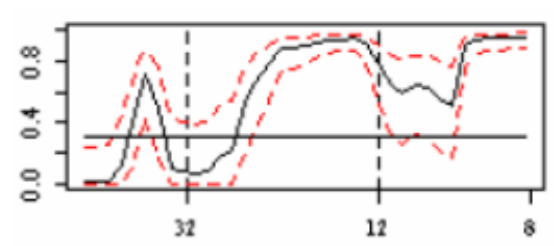
6.1 Chile



6.2 Colombia



6.3 Peru



We also perform analyses using methods that work on the frequency domain of the series. Figure 6 shows the results of computing coherence statistics between credit and GDP for all three countries. If coherence takes a value near 1 at some frequency, it means that there is a high correlation between GDP and credit cycles near this particular frequency. Results in Figure 6 shows that credit and GDP cycles appear to have greater correlation at medium-term frequencies in Chile and short-term frequencies in Peru. In the case of Colombia, this analysis shows that coherence between credit and GDP cycles is much lower than for the other two countries.

Figure 7: Cross-Correlations in the frequency domain: Credit versus GDP

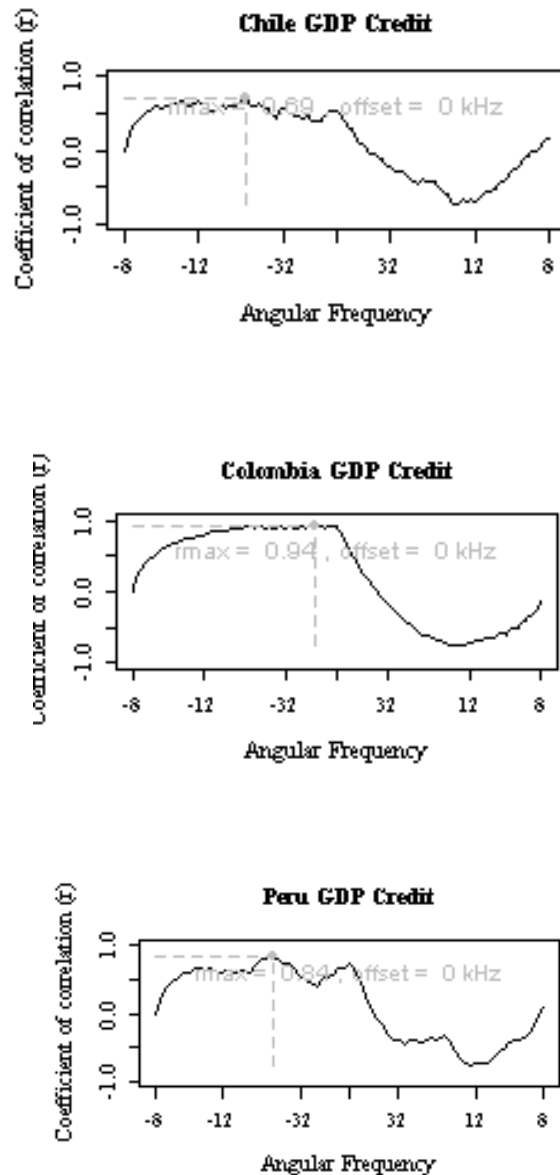
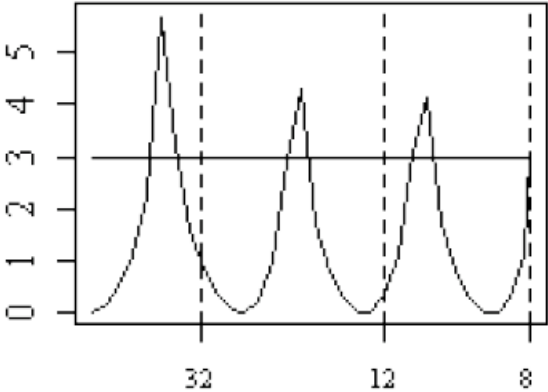


Figure 7 shows results for the cross-correlation between credit and GDP in the frequency domain. For all three countries, the maximum cross-correlations lie at the negative side of the domain indicating that there is evidence of a positive relation between lags in credit cycles and GDP cycles. Furthermore, this relation is higher approximately at medium-term frequencies. The maximum correlations are 94%, 84% and 69% in the case of Colombia, Peru and Chile, respectively.

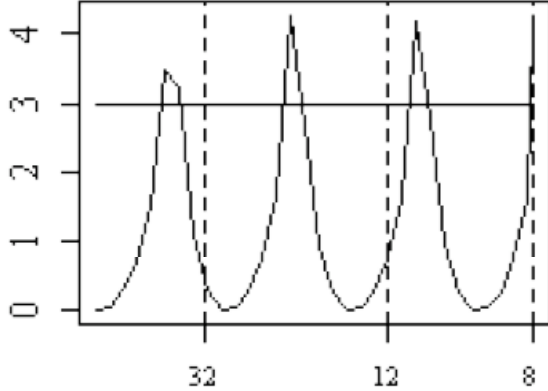
Figure 8 shows the results of performing a causality test between credit and GDP at the frequency domain. This procedure is based on Breitung and Candelon (2006) and allows testing for Granger-type of causality between any two variables across all different points of the frequency domain. These tests are calculated for the three countries and the two directions of causality, therefore Figure 8 consists of 6 graphs. The horizontal line around 3 represents the critical value of the test at the 95 % significance level. All data are de-trended before performing this multiple test.

Figure 8: Granger Causality Test in the Frequency Domain: Credit Cycles versus GDP Cycles

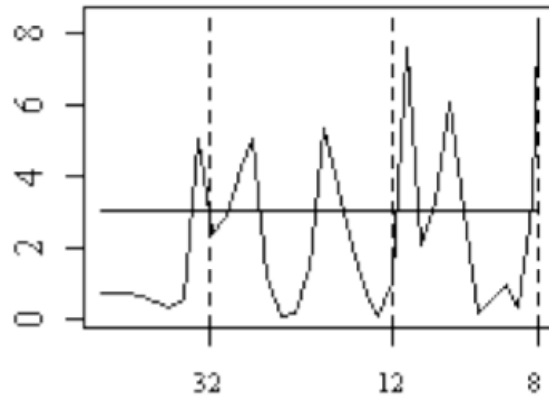
8.1 Chile: Credit to GDP



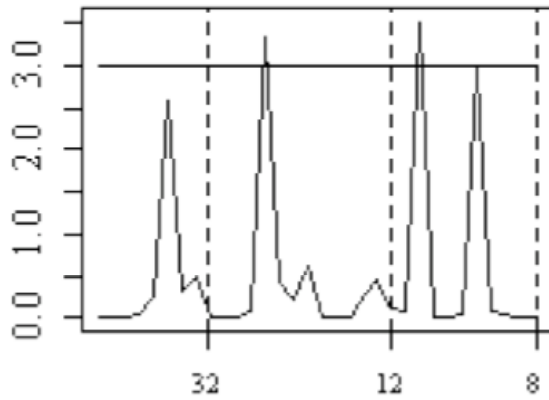
8.2 Chile: GDP to Credit



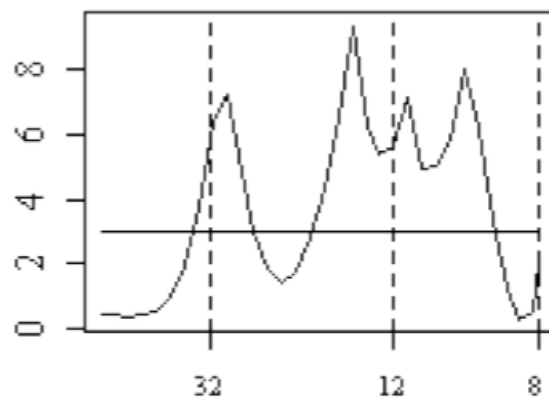
8.3 Colombia: Credit to GDP



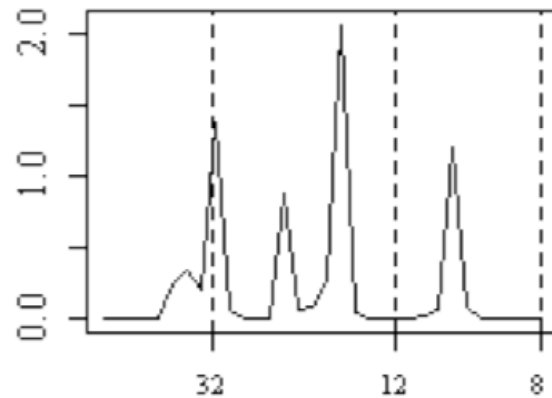
8.4 Colombia: GDP to Credit



8.5 Peru: Credit to GDP



8.6 Peru: GDP to Credit



The results for Chile indicate causality in both directions for frequencies associated with short, medium and long –term cycles. In the case of Colombia, causality shows stronger from credit to GDP in almost all frequencies. Particularly, there appears to be no causality from GDP to credit in the long-run. Finally, in the case of Peru, causality runs only from credit to GDP at all frequencies.

According to these results, there is evidence supporting the hypothesis that credit cycles influence GDP cycles in all three countries. In concrete, the credit cycle Granger-causes the business cycle at different frequencies. Although with this test it is not possible to identify the sign of this causality, the results of Figure 5 indicates that these correlations are positive in the medium term, showing that peaks in the credit cycle cause later peaks in the business cycle. Meanwhile, Figure 4 indicates that these correlations are negative in the short run.

Overall, our findings illustrate that GDP and credit cycles are not perfectly synchronized. An interesting policy implication for monetary policy is that it is difficult to target both financial and real variables using just one instrument. Moreover, these results show that credit should not be ignored when the objective is to stabilize the economy, as credit cycles exert important influence over the business cycle.

Another implication of these findings is that business cycles can be smoothed if credit cycles are smoothed. One possibility is the implementation of macroprudential policies oriented towards reducing the amplitude of the credit cycle.

6. Conclusions

In this document we estimate credit and GDP cycles for three Latin-American economies using Christiano and Fitzgerald's Band-Pass Filter, and study the interrelation between these cycles in the time and frequency domains. Cycles are estimated in order to analyze separately medium and short-term frequencies. While short-term frequencies correspond to traditional business cycle computations, medium-term frequencies are chosen following DBT in order to include fluctuations related to the leverage cycle of modern economies.

Opposite to the findings of DBT for developed economies, in this document we find that short-term cycles are usually more volatile than medium-term cycles for credit and GDP in Chile, Colombia and Peru. However, in line with DBT, the average duration of cycles is found to be longer in medium than for short-term cycles in all variables and countries.

DBT shows that peaks in medium-term cycles are seemingly associated with later financial crisis. In this document, we find an analogous result since credit-cycle peaks in the middle 1990s and middle 2000s precede notable GDP recessions 2 or 3 years later in all three countries. This result is confirmed by analyzing the cross-correlations between short-term cycles of GDP and lagged credit cycles which are usually negative.

We go further DBT's approach by employing statistical methods which focus on the frequency domain. An advantage of these methods is that they do not need any previous assumption on the particular frequency to look at in the data. Our results for all three countries show that it is important to study the high correlation between lagged credit and contemporaneous GDP at medium term frequencies. This relationship is confirmed by Granger causality tests.

Summing up, this document finds that credit cycles in Latin-American economies tend to cause later movements in economic activity. This effect can be decomposed in two; first, a

negative effect in the case of business-cycle frequencies, and a positive effect in the case of medium-term GDP fluctuations. Frequency-based statistics show that both effects are of similar importance for the dynamics of economic activity.

These results have interesting policy implications. First, regarding monetary policy the evidence suggests that it is difficult to target financial and real variables simultaneously using just one instrument. Second, macro-prudential policies which moderate the amplitude of the credit cycle can also be useful for the stabilization of economic activity in Latin-American economies.

7. References

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