



BANCO CENTRAL DE RESERVA DEL PERÚ

An Empirical Analysis of the Credit-Output Relationship: Evidence from Peru

Erick Lahura*

* Central Bank of Peru.

DT. N° 2011-018
Serie de Documentos de Trabajo
Working Paper series
Diciembre 2011

Los puntos de vista expresados en este documento de trabajo corresponden al autor y no reflejan necesariamente la posición del Banco Central de Reserva del Perú.

The views expressed in this paper are those of the author and do not reflect necessarily the position of the Central Reserve Bank of Peru.

AN EMPIRICAL ANALYSIS OF THE CREDIT-OUTPUT RELATIONSHIP: EVIDENCE FROM PERU¹

ERICK LAHURA*

Abstract

This paper investigates the empirical relationship between credit and output in Peru. The analysis is based on the estimation of vector error correction models and the identification of structural shocks. The models considered include real output, real credit growth (in domestic currency, foreign currency and both), and terms of trade. Using quarterly data for the period 1994-2011, the results suggest that real credit growth contain useful information to understand the evolution of the non-deterministic component of real output. In particular, the results show that: (i) there exist a stable long-run relationship between real credit growth, output and terms of trade, (ii) real credit growth is useful in forecasting output in the long-run, and (iii) a structural permanent shock in real credit has positive permanent effects on output. Therefore, credit aggregates could be useful as indicator variables for policymakers.

Key Words : *Credit growth, output growth, vector error
: correction models, structural shocks.*
JEL Classification : E51, C32.

1 Introduction

The recent international financial crisis has revived the debate about the role of quantities in the economy, with particular emphasis on money and credit, as recently emphasized by Sargent and Surico (2011): “For most of the last 25 years, the quantity theory of money has been sleeping, but during the last year, unprecedented growth in leading central banks’ balance sheets has prompted some of us to worry because the quantity theory has slept before, only to reawaken”. The question of monitoring credit market conditions and, in particular, credit aggregates as a means of explaining/predicting future output downturns and financial crises has become increasingly relevant for policymakers. For most central banks, credit and money aggregates are important variables in terms of both availability and reliability, which makes them potentially good candidates

¹The views expressed in this paper are those of the author and do not necessarily reflect the official position of the Central Bank of Peru. I am grateful to Anthony Garratt, Fabrizio Orrego, Tanja Sturm, Silvana Tenreyro, and Marco Vega for their invaluable comments on earlier drafts. All remaining errors are my own. For superb research assistance, I thank María Paula Vargas.

*Senior Economist, Research Department, Central Bank of Peru. (e-mail: erick.lahura@bcrp.gob.pe)

as information variables for macroeconomic policy. Thus, a critical question from a policymaker's point of view is whether credit or money aggregates contain any systematic information that can be useful to understand the evolution of key macroeconomic variables, such as output, inflation, employment, among others.

This paper investigates whether credit aggregates contain any systematic information that can be useful to understand the evolution of output. In order to provide a quantitative answer to this question, we perform an empirical analysis of the relationship between credit and output in Peru, trying to keep the empirical model as simple as possible in terms of both functional form and variables included. We focus on a quantitative answer because our main concern is to provide, if possible, a practical and simple result for policymakers; furthermore, the empirical results might be used as input for the construction of a DSGE model that is intended to incorporate credit variables.

Using quarterly data for Peru between 1994 and 2011, the empirical analysis is based on a structural vector error correction (VEC) model that includes output, credit growth, and terms of trade. The inclusion of terms of trade in the possible long-run relationship is justified by the fact that Peru is a small-open and partially dollarized economy that depends importantly on the evolution of international commodity prices, as shown in Castillo and Salas (2008). The results show that (i) there exist a stable long-run relationship between real credit growth, output and terms of trade, (ii) real credit growth is useful in forecasting output in the long-run, and (iii) a structural permanent shock in real credit has positive permanent effects on output. Therefore, credit aggregates could be useful as indicator variables for policymakers.

The paper is divided into 5 sections. Section 2 contains a brief literature review that further motivates the renovated interest in analysing the empirical relationship between credit and output. Section 3 describes the data used in the empirical model, and presents the results from unit root tests performed based on recursive samples. Section 4 describes the econometric methodology and presents the results. Finally, section 5 presents the main conclusions.

2 Credit and output relationship

The literature on credit and output is wide and varied. However, there is little consensus about the nature of the relationship between these variables, the causal direction and its theoretical underpinning. Recently, the literature on credit and output has focused on the ability of some measure of credit to predict/explain output and/or financial crises. Helbling et al. (2011) study the importance of credit market shocks in driving global business cycles over the period 1988 -2009, estimating common components in various macroeconomic and financial variables of the G-7 countries and then evaluating the role played

by credit market shocks using a series of VAR models. They find that these shocks have been important in explaining global activity during the latest global recession, and that credit shocks originating in the United States also have a significant impact on the evolution of world growth during global recessions. Meeks (2009) examines the role of credit shocks in explaining U.S. business cycles using a VAR model, and finds that credit shocks do play an important role during financial crises, but they have a lesser role during “normal” business cycles. Perri and Quadrini (2010) find that the latest recession and its global effect can be explained by credit market shocks in a DSGE model.

In terms of ability to predict output, the main idea is that economic activity forecasts can be improved using financial data, in particular credit spreads. Gilchrist and Zakrajsek (2011), analyse the relationship between credit spreads and economic activity, using data of corporate bonds traded in the secondary market. In particular, they show that credit spreads are good predictors of economic activity (as in Faust et al. (2011)), and that the predictive content of credit spreads is due primarily to movements in the excess bond premium. On the other hand, Schularick and Taylor (2009), and Jorda et al. (2010) show that credit growth is an important predictor of financial instability and crises; whereas Christiano et al. (2007), illustrate through an example that credit may still be useful in monetary policy.

Another branch of the literature on the relationship between credit and output focuses on the fact that economic activity may recover without a recovery of credit, an approach that have recently gained importance. This point was first made by Calvo et al. (2006a), Calvo et al. (2006b) in the context of emerging markets; recently Claessens et al. (2009) observed a similar phenomenon in the business cycle of industrialised countries. This theory of “recovery without credit” underlies Biggs et al. (2009) who point out that the principal reason why previous research had not found a relationship between credit and output during economic recovery was due to an incorrect comparison between levels (of credit) and flows (of output). As an alternative, these authors suggest analysing the relationship between these two variables using the concept of “credit impulse” defined as the change in the flow of credit. In particular, the work of Biggs et al. (2009) examines the relationship between the rate of growth of output, the flow of credit and credit impulse during a series of financial crises in different countries. They find that credit impulse follows closely the rate of growth of output both during the downturn phase and during economic recovery.

There is also a branch of the literature in which credit plays the role of a nonlinear propagator of shocks as in Bernanke and Gertler (1989), Blinder (1987), Azariadis and Smith (1998). In this context, a nonlinear relationship between credit and economic activity emerges due to either regime switching or asymmetric responses to shocks, as in Balke (2000). Bernanke and Gertler (1989) construct a model in which negative credit shocks are likely to have

a greater effect than positive shocks, which originates in the balance-sheet of firms. Blinder (1987) develops a model in which monetary shocks have different effects when the economy is in a credit-rationing regime than at other times. Balke (2000) uses a threshold vector autoregression that changes “structure” if credit market conditions cross a critical threshold. Using nonlinear impulse-response analysis, he finds that shocks during a “tight” credit regime have a larger effect on output than do shocks in the “normal” regime.

For the case of Peru, credit aggregates has been excluded from forecasting models intended for policy-making, which is partly explained by the recent global dominance of DSGE models that use relative prices rather than quantities. However, the recent economic growth that Peru has experienced since 2002 at annual rates above 5% -closely related to the improvement of terms of trade-together with an upward trend in credit growth, constitute a situation where prudential policies must be considered in order to avoid any economic downturn. In particular, the recent financial crisis has shown that credit disruptions are closely related to output contraction, and that some measure of credit can help to forecast output. Even though policy makers in Peru have not entirely lost sight of credit as a variable with predictive power as to the evolution of output in the short- and medium-term, a formal econometric analysis is required to identify the relevance of credit - and other financial variables - for forecasting models, at least for the Peruvian economy.

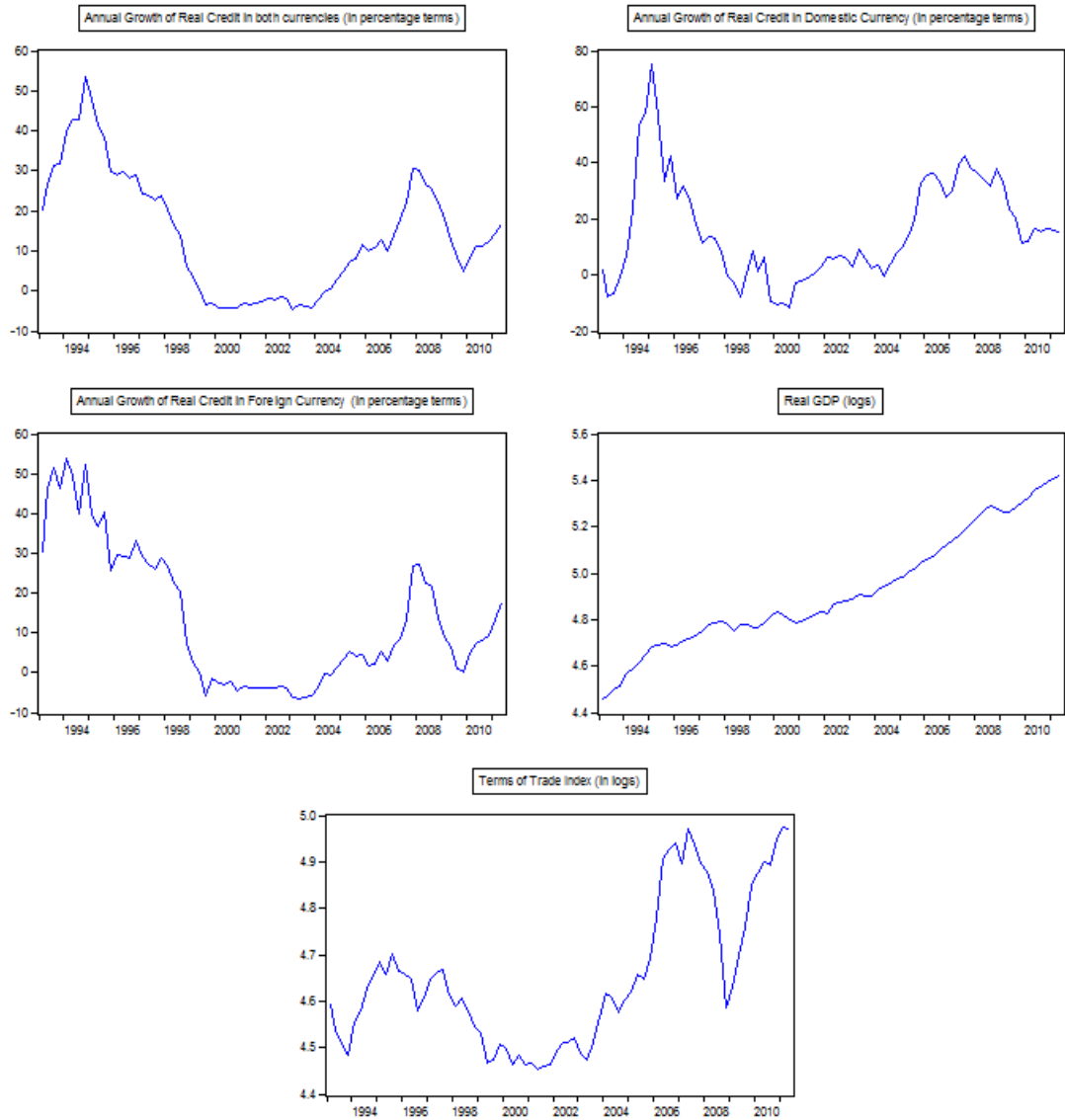
This paper extends in several dimensions the analysis performed by Lahura and Vega (2011), a first recent attempt to analyse the relationship of credit and output in Peru: (i) terms of trade is considered as an additional variable in the analysis of cointegration, which allows testing alternative specifications and contributes to get more stable parameters, (ii) a structural decomposition of the residuals is performed in order to provide economic interpretation of the shocks, (iii) the presence of unit roots is extended by using additional tests, and (iv) the sample is extended from 2009 up to the second quarter of 2011.

3 Data analysis

Figure 1 shows the evolution of the main variables for the period 1993Q1-2011Q2: log of seasonally-adjusted real GDP (LGDP), annual growth of real credit in domestic currency (CGDC), annual growth of real credit in foreign currency (CGFC), annual growth of real credit in both currencies (TCG), and the terms of trade index expressed in logs, (LTOT).²

²Macro-level studies of the Peruvian economy usually take 1994 as the starting point in order to exclude the effects of the hyperinflation (1988-1999) and the stabilization period (1990-1993).

Figure 1. *Annual Growth of Real Credit, Seasonal-Adjusted Real GDP and Terms of Trade: 1993Q1-2011Q2*



These variables were constructed from the database provided by the Central Bank of Peru,³ using nominal banking credit to the private sector in both domestic and foreign currency, the consumer price index with base year 2009,

³<http://www.bcrp.gob.pe/estadisticas.html>.

real GDP, nominal exchange rate of the banking sector⁴ and terms of trade.⁵

We test for the presence of unit root in each series using the procedures proposed by Elliot et al. (1996) and Ng and Perron (2001), which will be referred to as ERS and NP respectively. Using locally demeaned or detrended time series obtained through a procedure called GLS detrending, ERS propose a feasible Point Optimal P_t test and a modified version of the Dickey-Fuller t test (DF-GLS). As shown in Elliot et al. (1996), the P_t and DF-GLS tests have higher size-adjusted power than the standard Dickey-Fuller (DF) test, especially for the constant mean case. Furthermore, based on Monte Carlo experiments they conclude that the DF-GLS test, together with the Schwarz (1978) Bayesian Information Criterion for lag-length selection, has the best overall performance in terms of small sample size and power.

Ng and Perron (2001) developed a class of Modified tests or M tests (MZ_a , MZ_t , MSB , and MP_t) that have good size and power under the null of unit root compared to standard unit root tests (e.g. Augmented Dickey-Fuller and Phillip-Perron tests), especially when there are errors with a moving-average coefficient close to -1 . The MZ_a and MZ_t statistic can be viewed as modified versions of Z_a and Z_t tests from Perron (1987) and Perron (1988); MSB test is a modified version of Bhargava (1986), and MP_t is a modified version of the Elliot-Rothenberg-Stock Point Optimal test. These tests are constructed using two main ingredients: (i) GLS detrending of data as in ERS, and (ii) modified versions of Akaike and Schwarz information criteria (MAIC and MSIC, respectively) to select a truncation lag when the estimation of the residual spectrum at frequency zero is based on some autoregressive spectral density estimators. Ng and Perron (2001) conclude that the use of M tests along with MAIC provide unit root tests with desirable size and power properties. Furthermore, they find that MAIC yields important size improvements to the DF-GLS and the feasible point optimal P_t test proposed by ERS.

Table 1 shows the results from ERS and Ng-Perron unit root tests, which considered lag lengths of 0 up to 8 (two years).⁶ The feasible Point Optimal test P_t does not reject the null of unit root in any of the series at any level of

⁴We use banking credit to the private sector instead of financial system credit because statistics for the latter do not go back long enough. In the case of exchange rate, we use the monthly “ask rate”. For each series, quarterly observations are obtained as the simple average of the corresponding monthly figures.

⁵Annual credit growth in foreign currency (CGFC) was obtained from real credit in foreign currency expressed in domestic currency (RCFDC). RCFDC was constructed adding up the flows of nominal credit in foreign currency multiplied by an average real exchange rate (ARER). ARER in period “ t ” is equal to $0.5 * [(E_t/P_t) + (E_{t-1}/P_{t-1})]$, where E_t is nominal exchange rate and P_t is the CPI. Total real credit was obtained as the simple sum of real credit in domestic currency and in foreign currency.

⁶For comparison reasons, Augmented Dickey-Fuller (ADF) and Phillip-Perron (PP) unit root tests were also performed. Furthermore, in order to allow for the presence of breaks, Zivot and Andrews (1992), and Perron and Rodriguez (2003) tests were also applied. Overall, the

significance; however, the DF-GLS rejects the null at 10% for CGDC and TCG series. Although CGFC appears to be the only series that contains a negative MA term (according to simple OLS estimates), NG-Perron tests were applied to all the series analysed. In particular, the MP_t test (last column of Table 1) suggests no evidence against the null of unit root. Therefore, the results support the presence of unit root in the series considered.

Table 1. *Elliot-Rothenberg-Stock and Ng-Perron unit root tests: 1993-2011*^{1/}.

Series	Elliot-Rhothenberg-Stock 2/		Ng-Perron 2/
	DF-GLS	Pt	MPt
Real GDP	-1.34	18.99	18.80
TCG	-2.03***	7.42	4.54
CGDC	-1.73***	4.98	11.00
CGFC	-1.31	14.41	8.05
Terms of Trade	-1.34	6.43	5.88

1/ All tests include a constant in the deterministic part with the exception of LGDP, which includes both constant and trend. The symbols “*”, “**”, “***” indicate rejection of the null hypothesis of unit root at 1%, 5%, and 10% significance level, respectively. The Ng-Perron tests use autoregressive spectral density estimators based on GLS detrending.

2/ Based on Modified Akaike information criterion, as suggested by Ng and Perron(2001).

In order to assess the robustness of the unit root hypothesis to the sample length, we perform recursive unit root tests using period 1994-2004 as the starting sample and then increasing it by one period at a time until 2011Q2. Figures 2, 3 and 4 show the results of the DF-GLS test (ERS), the P_t test (ERS) and the MP_t (Ng-Perron) test applied recursively to each series, which provide evidence supporting the unit root hypothesis in all cases.⁷

results of all these tests (which are all available upon request) support the unit root hypothesis for all series considered.

⁷For the case of LTOT the unit root hypothesis is rejected at 5% in 2008Q4 with both the Pt test (Figure 2) and the MPt test (Figure 3). The tendency towards rejecting the unit root hypothesis observed since 2008Q1 and the reversion of this tendency after 2009 can be related to the global financial crisis experience since 2008Q3, which affected terms of trade.

Figure 2. Recursive DF-GLS test (Elliot-Rothenberg-Stock): 2004Q1-2011Q2

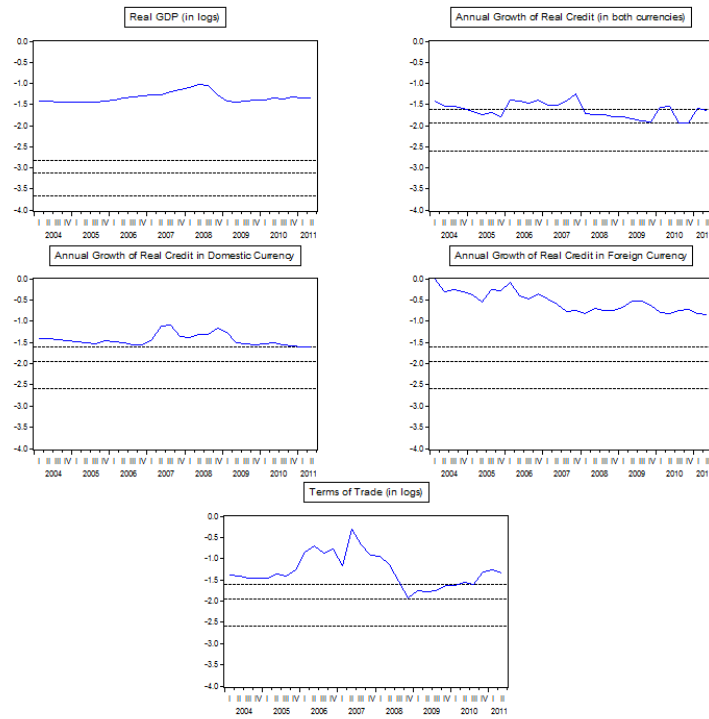


Figure 3. Recursive P_t test (Elliot-Rothenberg-Stock): 2004Q1-2011Q2

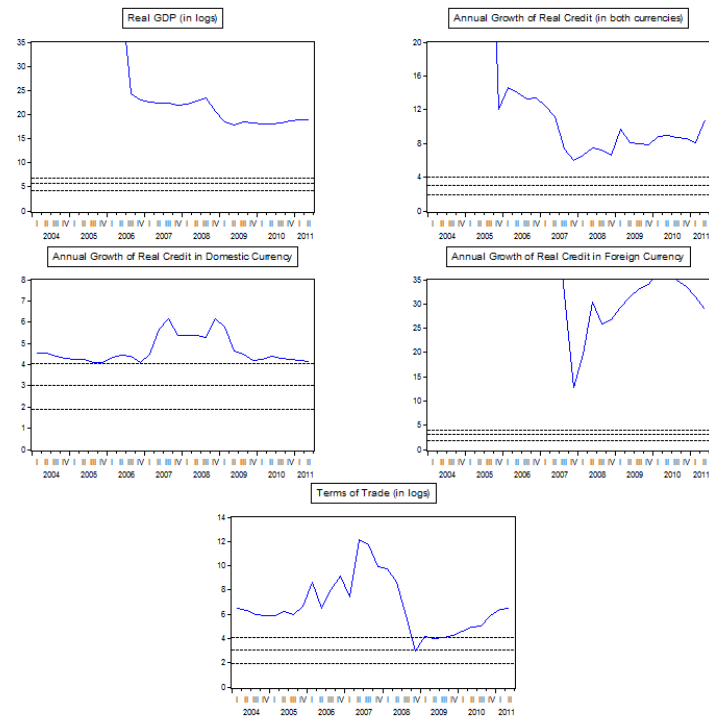
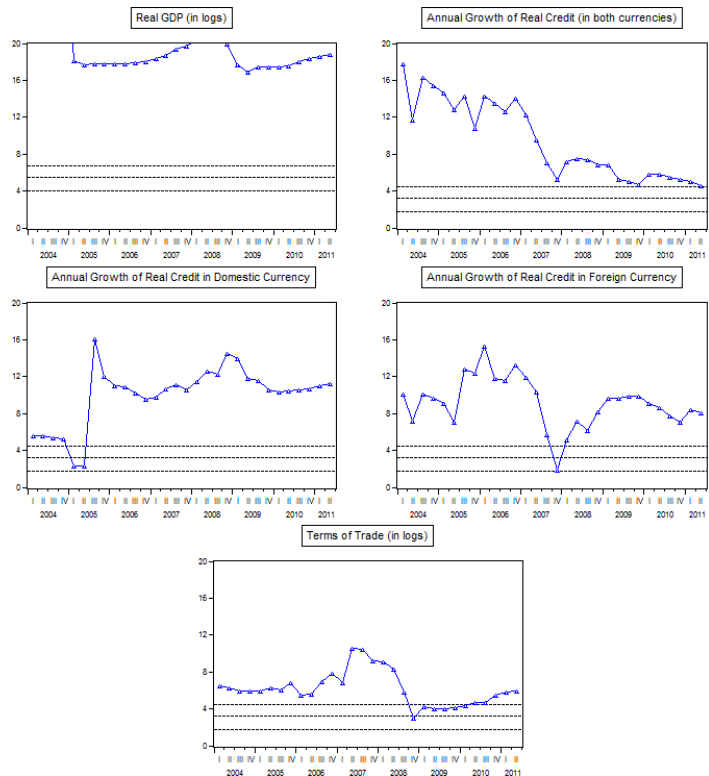


Figure 4. Recursive MP_t test (Ng-Perron): 2004Q1-2011Q2



4 Cointegration Analysis

In order to investigate the usefulness of real credit in anticipating future output movements, we estimate a dynamic system that includes credit growth (measured as TCG, CGDC, or CGFC), the non-deterministic component of seasonally-adjusted real GDP (in logs), GDP, and the log of terms of trade, LTOT.⁸ Given the evidence from previous section about the non-stationarity of the data, in this section we explore the possibility of cointegration among the series.

Let X_t be a vector of unit root series, which in our case consists of GDP, LTOT, CGDC, and CGFC. First, we estimate VAR models for X_t in order to determine the appropriate lag length of the system. The unrestricted vector autoregressive model for X_t with “ k ” lags, $VAR(k)$, can be written as:

$$X_t = \Pi_1 X_{t-1} + \dots + \Pi_k X_{t-k} + u_t$$

⁸From now on and unless otherwise stated, the non-deterministic component of the log of real GDP, which is denoted by GDP, will be referred to as “output”. See Appendix A for an explanation about the construction of the non-deterministic component of the log of real GDP.

The lag length of “ k ” is determined based on the assessment of three information criteria: the likelihood ratio test (LR), Akaike information criterion (AIC), and Schwarz information criterion (SIC). An alternative representation of (4.1) is called a vector error correction (VEC) model and is given by:⁹

$$\Delta X_t = \Pi X_{t-1} + \Gamma_1 \Delta X_{t-1} + \dots + \Gamma_k \Delta X_{t-(k-1)} + u_t$$

where the lag length is one lag less than for the VAR representation, $\Pi = -(I - \sum_{i=1}^k \Pi_i)$, and $\Gamma_i = -\sum_{j=i+1}^k \Pi_j$. Equation (4.2) combines both the levels, X_t , and first differences, ΔX_t , of the series.

A VEC model like (4.2) with well-behaved residuals (i.e. residual with no autocorrelation, no heteroskedasticity and normally distributed), is the framework suggested by Johansen (1995) to test for cointegration. Johansen’s procedure is based on determining the rank of Π (i.e. the number of non-zero eigenvalues of Π), which defines the number of cointegrating vectors.¹⁰

4.1 Testing for cointegration between credit and output

We consider four different sets of cointegrating variables: $X^1=(\text{GDP,LTOT})$, $X^2=(\text{GDP,LTOT,GTC})$, $X^3=(\text{GDP,LTOT,GCDC})$, $X^4=(\text{GDP,LTOT,GCFC})$ and $X^5=(\text{GDP,LTOT,GCDC,GCFC})$. Following Johansen (1995), the nature of the data suggests the use of a VEC model with no deterministic trends and allowing for an intercept in the cointegrating vector. The estimation results from cointegration tests for these specifications (Models 1 to 5) and the corresponding estimated cointegrating vectors (normalised with respect to GDP) are shown in Table 2. Lag lengths for each model were chosen together with well-behaved residuals (non-autocorrelated, homoskedastic and normally distributed).

The first row of Table 2 indicates that the number of cointegrating vectors suggested by both λ_{trace} and λ_{Max} statistics (which results are not reported here). For the case of Models 1, 2, 3, and 4 the sign of the long-run coefficients are all positive as expected: higher output (GDP) is associated with higher terms of trade (LTOT) and higher real credit growth (TCG, CGDC, CGFC). However, Model 5 implies that real credit growth in domestic currency (CGDC) has a negative (although not significant) relationship with output (GDP). Model 5-R is a restricted version of Model 5 in which it is tested whether GCDC and GCFC have the same coefficient; the null hypothesis of equal coefficients cannot be rejected (probability of 0.20) using a Likelihood Ratio test (LR), both coefficients being positive and equal to 0.16. The long run coefficient of terms of trade (LTOT) is statistically significant in all specifications; however, the estimate

⁹See Hamilton (1994) pp. 580.

¹⁰Let X_t be a vector with “ n ” variables. Then, any of the following situations are possible:(i) if $Rank(\Pi) = 0$, then Π is a null matrix and there is no cointegrating vector, (ii) if $Rank(\Pi) = n$, then Π has full rank and there are “ n ” cointegrating vectors, meaning that all series are stationary, (iii) $Rank(\Pi) = r < n$, then Π does not have full rank and there are “ r ” cointegrating vectors.

reduces after the inclusion of credit aggregates, ranging from 0.67 (Model 1) to 0.27 (Models 2 and 3), which seems to indicate that Model 1 is misspecified due to the omission of credit.

Table 2. *Estimated Cointegrating Vectors (normalised with respect to GDP): 1994:Q1-2011:Q2*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 5-R
Number of cointegrating vectors	1	1	1	1	1	1
Terms of Trade (in logs)	0.67* 5.19	0.27* 4.58	0.27 1.69	0.34* 6.51	0.34* 4.95	0.34* 3.70
Growth of Real Credit		0.29* 4.45				
Real Credit Growth in Domestic			0.43* 3.05		-0.02 -0.19	0.16* 2.98
Real Credit Growth in Foreign Currency				0.25* 5.06	0.26* 3.52	0.16* 2.98
LR test(prob)						0.20
Lag length	6	6	6	6	6	6

Note: The symbols “*”, “*” and “***” represent 1%, 5% and 10% significance level, respectively.

4.2 Stability of cointegrating relationships

In order to test the stability of the estimated cointegrating vectors in each model, we analyse the evolution of the λ_{Trace} statistic and the estimated coefficients for recursive samples. The results are illustrated in Figure 5 and 6.

Figure 5 shows the evolution of the recursive λ_{Trace} since 2005¹¹ for Models 1, 2, 3, 4, and 5; where each line represents the λ_{Trace} associated with different null hypotheses. The horizontal lines represent the 5% critical values for each null hypothesis considered. For example, in the case of Model 4 the null of no cointegrating vectors is rejected in all periods because the recursive trace statistic is always above the 5% critical value (represented in the graph by first straight line starting from above), whereas the null of one cointegrating vector is not rejected in all periods because the recursive trace statistic is always below the 5% critical value (represented by the second straight line); thus, the

¹¹This is the first observation in the recursion due to data limitations.

cointegrating vector estimated in Model 4 seems to be stable. Overall, Figure 5 suggests that the estimated cointegrating vectors are reasonably stable for all models with the exception of Model 5, which seems to be stable only after 2008.

Figure 5. *Recursive Trace Statistic for Models 1 to 5*

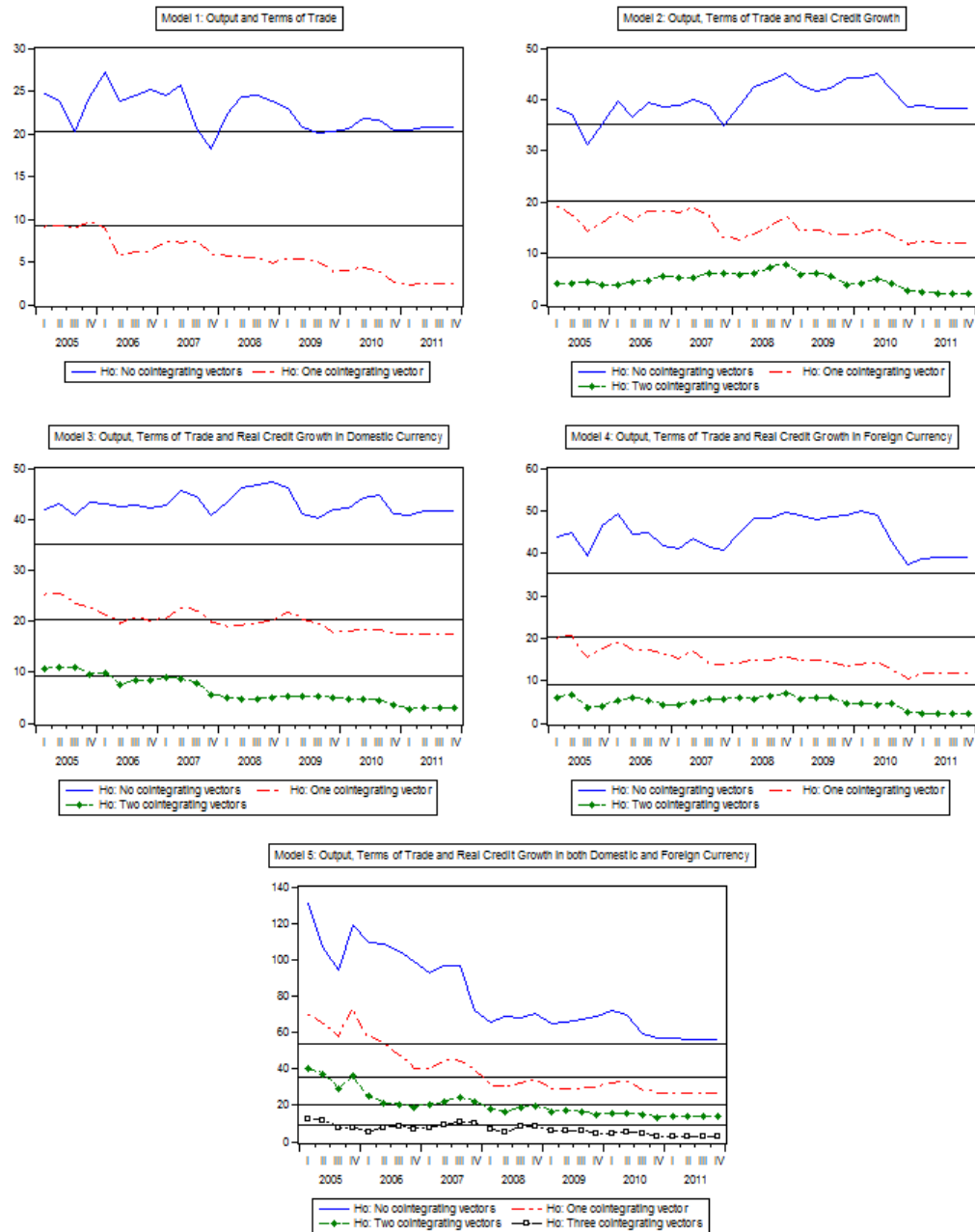
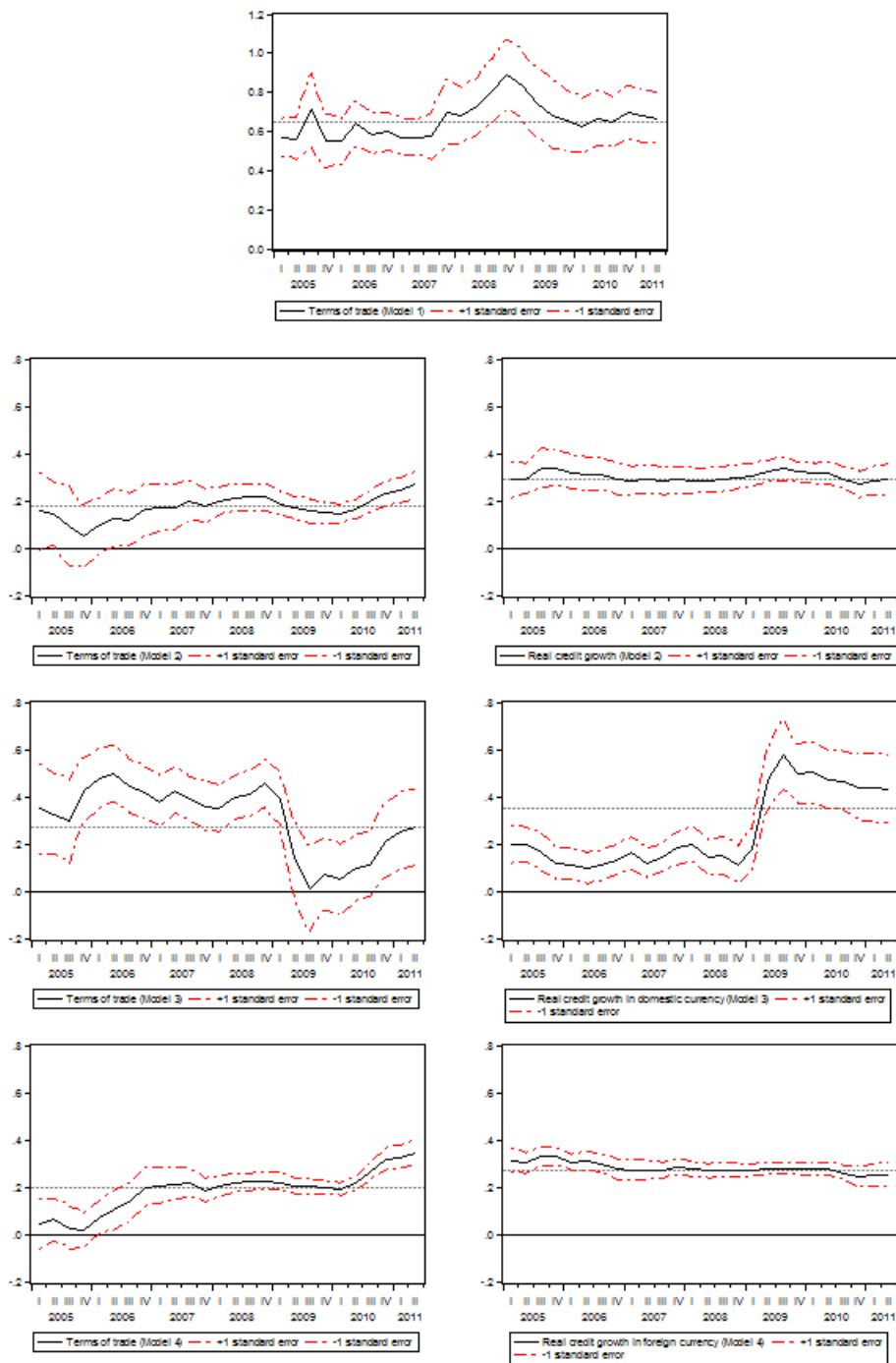


Figure 6 shows the evolution of recursively estimated long-run coefficients for LTOT and CGT in Model 2, LTOT and CGME in Model 3, and for LTOT and CGFC in Model 4. Overall, the parameters do not show drastic changes along the sample analysed, which suggest they are stability.

Figure 6. *Recursive Coefficients from each Cointegrating Vector*



4.3 Empirical causality and forecasting

Given the existence of at least one cointegrating vector between the non-deterministic component of seasonally-adjusted real GDP (GDP), terms of trade (LTOT) and credit growth (Z_t , measured as either TCG, CGDC, or CGFC), consider the following possible normalised long-run relationship:

$$GDP_{t-1} - \beta_0 - \beta_1 LTOT - \beta_2 Z_t = \varepsilon_t$$

and the corresponding error-correction equations for each variable:

$$\begin{aligned} \Delta GDP_t &= \alpha_1 (GDP_{t-1} - \beta_0 - \beta_1 LTOT - \beta_2 Z_t) \\ &+ \sum_{i=1}^p \gamma_i \Delta GDP_{t-i} + \sum_{i=1}^p \theta_i \Delta LTOT_{t-i} \\ &+ \sum_{i=1}^p \varphi_i \Delta Z_{t-i} + u_t \end{aligned}$$

$$\begin{aligned} \Delta LTOT_t &= \alpha_2 (GDP_{t-1} - \beta_0 - \beta_1 LTOT - \beta_2 Z_t) \\ &+ \sum_{i=1}^p \gamma_i' \Delta GDP_{t-i} + \sum_{i=1}^p \theta_i' \Delta LTOT_{t-i} \\ &+ \sum_{i=1}^p \varphi_i' \Delta Z_{t-i} + u_t^2 \end{aligned}$$

$$\begin{aligned} \Delta Z_t &= \alpha_3 (GDP_{t-1} - \beta_0 - \beta_1 LTOT - \beta_2 Z_t) \\ &+ \sum_{i=1}^p \gamma_i'' \Delta GDP_{t-i} + \sum_{i=1}^p \theta_i'' \Delta LTOT_{t-i} \\ &+ \sum_{i=1}^p \varphi_i'' \Delta Z_{t-i} + u_t^3 \end{aligned}$$

where Z_t represents a measure of real credit growth, and the first difference of real credit growth, ΔZ_t , is usually called “credit impulse”. This model allows to test for empirical causality in the context of cointegration; in particular, we can test whether real credit growth is weakly and/or strongly exogenous for its long-run parameter β_2 . Weak exogeneity of Z_t implies that Z_t can be used to make inference on β_2 and conditional predictions about GDP one period ahead, whereas strong exogeneity of Z_t implies that Z_t can also be used to make conditional predictions about GDP more than one period ahead. Thus, testing for weak/strong exogeneity is equivalent to test whether real credit growth helps forecasting real output.

Following Hendry (1995), weak exogeneity of Z can be tested by assessing the statistical significance of α_3 (the speed-of-adjustment coefficient in the error correction equation of Z); thus, if $\alpha_3=0$ then Z_t is weakly exogenous. Strong exogeneity of Z requires the following two conditions to hold: (i) Z is weakly exogenous for its long-run parameter, and (ii) the first difference of GDP (real output growth) does not Granger cause real credit growth in first differences (credit impulse). If Z is weakly exogenous, then testing for strong exogeneity

is equivalent to test the validity of $\gamma_1'' = \gamma_2'' = \dots = \gamma_p'' = 0$, i.e. testing that GDP does not Granger cause Z_t .

Table 3 shows the results of weak and strong exogeneity tests for terms of trade and all credit aggregates considered in each model. The top part of the table shows the estimated speed-of-adjustment (sa) coefficients for each error-correction equation and their corresponding “t” statistics, obtained by estimating the vector error correction model (4) using maximum likelihood.

Table 3. *Analysis of weak and strong exogeneity*

Speed-of-Adjustment estimates and t-statistics

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 5-R
Error Correction equation for d(GDP)	-0.12* -4.07	-0.29* -4.68	-0.12* -4.11	-0.29* -4.74	-0.30* -4.47	-0.21* -4.53*
Error Correction equation for d(LTOT)	-0.10 -0.88	-0.06 -0.25	-0.15 -1.27	0.09 0.38	0.10 0.39	0.01 0.05
Error Correction equation for d(TCG)		-0.22 -0.16				
Error Correction equation for d(GCDC)			0.18 1.38		-0.10 -0.39	-0.01 -0.04
Error Correction equation for d(GCFC)				-0.06 -0.32	-0.03 -0.17	-0.08 -0.66

Note: The symbols “*”, “*” and “***” represent 1%, 5% and 10% significance level, respectively.

Granger Causality test in the VEC models (probabilities)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 5-R
dLTOT $\not\sim$ Granger cause dGDP	0.57	0.71	0.59	0.22	0.35	0.79
dGDP $\not\sim$ Granger cause dLTOT	0.81	0.90	0.74	0.95	0.85	0.86
dTCG $\not\sim$ Granger cause dGDP		0.13				
dGDP $\not\sim$ Granger cause dTCG		0.27				
dCGDC $\not\sim$ Granger cause dGDP			0.52		0.90	0.95
dGDP $\not\sim$ Granger cause dCGDC			0.70		0.33	0.40
dCGFC $\not\sim$ Granger cause dGDP				0.19	0.22	0.36
dGDP $\not\sim$ Granger cause dCGFC				0.76	0.74	0.72

Note: The expression “ $\not\sim$ Granger cause” means “does not Granger cause”.

In all models, the sa coefficients are negative and significant, which means that GDP adjusts when a long-run disequilibrium occurs and thus can be considered as endogenous. In Model 1, the estimated sa coefficient in the error

correction equation (ECE) for $dLTOT$ is negative (-0.10) and not significant, which means that $LTOT$ is weakly exogenous for its long-run coefficient shown in Table 4 (0.67). Furthermore, $LTOT$ is weakly exogenous in all models analysed. In Model 2, the estimated α coefficient in $dCGT$'s ECE is negative (-0.02) and not significant, meaning that TCG is weakly exogenous for its long-run coefficient shown in Table 2 (0.29). Using the same type of analysis, results for Model 3, 4 and 5-R show that $CGDC$ and $CGFC$ are weakly exogenous for their corresponding long-run coefficients shown in Table 2. In summary, only $CGDC$ (in Model 2) and $CGFC$ (in Model 3) are weakly exogenous and thus candidates to be strongly exogenous.

The lower part of Table 3 shows the results from Granger causality tests in terms of the corresponding probabilities. For the case of Model 2, the result is that output growth ($dGDP$) does not Granger cause real credit impulse in domestic currency ($dCGDC$); therefore, real credit in domestic currency is strongly exogenous for β_2 and thus helps forecasting output. The same conclusion applies to all models, meaning that both terms of trade and real credit growth are useful to make forecasts about output. Notice that the absence of Granger causality from either terms of trade or real credit impulse to output (as it can be read from the second line of each pair of variables analysed in the lower part of Table 3), implies that Granger causality in first differences and without considering we conclude that there is no evidence that real credit impulse or terms of trade do help predict output growth through.

4.4 A Structural VEC model.

In order to determine the qualitative and quantitative effect of an exogenous change in real credit, we propose a structural identification of shocks from the moving average representation of the estimated cointegrated VAR model. Given the existence of " $r = 1$ " cointegrating vector between output, terms of trade and credit (Models 2 and 3), the structural errors can be grouped into " $r = 1$ " transitory and " $n - r = 2$ " permanent shocks, the latter being related to the existence of " $n - r = 2$ " common stochastic trends.¹²

The identification of the estimated VEC models (with one cointegrating vector) requires only one identifying restriction related to the permanent shocks. For this purpose we assume that the first permanent shock (shock 1) has a lasting effect on terms of trade and thus we identify the first permanent shock as the accumulated disturbances in terms of trade's equation. The second permanent shock can be identified as the part of the disturbances in dZ_t which is not explained by the first permanent shock.

¹²It is possible to interpret it as a long-run equilibrium relationship which can be distorted temporarily by forces that create the nonstationary property of the data. These forces are called in the literature the "common stochastic trends".

Based on this identification procedure, Table 4 shows the impulse-response function of output using the structural estimates of Model 2, 3, and 4. The top part of the table contains the normalised (to 1) long-run effect of every permanent shock on real output. Permanent shock 1 (a shock in terms of trade) has a long-run impact on output of almost half of the shock (0.46), whereas Permanent shock 2 has a smaller long-run impact (0.28). In relative terms, a permanent shock in real credit growth in the models considered have a relatively lower effect on real output compared to a permanent shock in terms of trade. The second and last parts of Table 4 describe the transitional dynamics of the permanent shocks without normalisations. For example, a positive permanent shock 2 in Model 2 (an increase of 1.82 percentage points in total credit growth), the contemporaneous impact on output is positive (0.07), achieving a long-run impact of 1.08. Similar results are obtained for Models 3 and 4.¹³

Table 4. *Response of Real Output to Structural Shocks.*

	Model 2	Model 3	Model 4
Long-run effect(normalised)			
Permanent Shock 1	0.46	0.25	0.50
Permanent Shock 2	0.28	-0.15	0.23
Contemporaneous effect			
Permanent Shock 1	-0.10	-0.30	-0.06
Permanent Shock 2	0.07	1.03	0.12
Long-run effect			
Permanent Shock 1	2.48	1.48	2.52
Permanent Shock 2	1.08	0.76	1.07

In summary, the empirical results show evidence of a stable long-run relationship between output (GDP), terms of trade (LTOT) and real credit growth, measure either in domestic currency (CGDC), foreign currency (CGFC) or the sum (TCG). Furthermore, these measures of credit growth appear to be weakly and strongly exogenous for its parameter in the long-run relationship normalised to output, leading to the conclusion that credit helps to forecast real output in the long run. Finally, identifying structural shocks for each VEC model, it is found evidence that a permanent shock in real credit growth has a positive effect on output, with this effect being relatively less important compared to the effect of a permanent shock to terms of trade on output.

¹³Impulse-response functions are shown in (Appendix B).

5 Conclusions

The recent international financial crisis has brought to the fore the debate about the role of quantities in the economy, especially money and credit fluctuations. The relationship between credit and economic growth has been of special interest; in particular, the question of monitoring credit aggregates as a means of predicting, for example, future output downturns and financial crises has become increasingly relevant for policymakers.

This paper investigates whether credit aggregates contain any systematic information that can be useful to understand the evolution of output. We use quarterly data for Peru between 1993 and 2011, and the empirical analysis is based on a structural vector error correction (VEC) model that includes output, credit growth, and terms of trade.

The results show that (i) there exist a stable long-run relationship between real credit growth, output and terms of trade, (ii) real credit growth is useful in forecasting output in the long-run, and (iii) a structural permanent shock in real credit has positive permanent effects on output. Therefore, credit aggregates could be useful as indicator variables for policymakers.

References

- Azariadis, C. and B. Smith (1998), “Financial Intermediation and Regime Switching in Business Cycles”, *American Economic Review*, Vol. 88, No. 3, June. pp. 516-536.
- Balke, Nathan (2000), “Credit and Economic Activity: Credit Regimes and Nonlinear Propagation of Shocks”, *The Review of Economics and Statistics*, Vol. 82, No. 2, May. pp. 344-349.
- Bhargava, Alok (1986), “On the Theory of Testing for Unit Roots in Observed Time Series”, *Review of Economics Studies*, Vol. 53, No. 3, July. pp. 369-84.
- Bernanke, B. and M. Gertler (1989), “Agency Costs, Net Worth, and Business Fluctuations”, *American Economic Review*, Vol. 79, No. 1, March. pp. 14-31.
- Biggs, M., T. Mayer and A. Pick (2009), “Credit and economic recovery”, *DNB Working Paper* No. 218.
- Blinder, Alan (1987), “Credit Rationing and Effective Supply Failures”, *Economic Journal* Vol. 97, No. 386, June. pp. 327-352.
- Bordo, M. and J. Haubrich (2009), “Credit Crises, Money and Contractions: A Historical View”, *NBER Working Paper*, No. 15389, September.
- Calvo, G., A. Izquierdo, and E. Talvi (2006a), “Phoenix miracles in emerging markets: Recovering without credit from systemic financial crises”, *NBER Working Paper*, No. 12101, August.
- Calvo, G., A. Izquierdo, and E. Talvi (2006b), “Sudden stops and Phoenix miracles in emerging markets” *American Economic Review*, Vol. 96, No. 2, May. pp. 405-410.
- Castillo, P. and J. Salas (2008), “Choques de términos de intercambio y fluctuaciones económicas en economías en desarrollo pequeñas y abiertas: un análisis de tendencias comunes”, *Central Bank of Peru XXVII Economist Annual Meeting*, Noviembre. pp. 2-33.
- Claessens, Stijn, M. Khose and E. Terrones (2009), “A recovery without credit. Possible, but ”, [www.voxeu.org /index.php?q=node/3600](http://www.voxeu.org/index.php?q=node/3600), Mayo 22.
- Christiano, L., R. Motto, and M. Rostagno (2007), “Two Reasons Why Money and Credit May be Useful in Monetary Policy”. *NBER Working Paper* No. 13502, October. pp. 1-43.
- DeJong, D. N., J. C. Nankervis, N. E. Savin, and C. H. Whiteman (1992), “The Power Problem of Unit Root Tests in Time Series with Autoregressive Errors”, *Journal of Econometrics*, Vol. 53, No. 1-3, July-September. pp 323-343.
- Elliot, G., T. Rothenberg y J. Hamilton (1996), “Efficient Tests for an Autoregressive Unit Root”, *Econometrica*, Vol. 64, No. 4, pp. 813-836.
- Faust, J., S. Gilchrist, J. Wright, Z. and Egon (2011), “Credit Spreads as Predictors of Real-Time Economic Activity: A Bayesian Model-Averaging Approach”, *NBER WP*, No. 16725, January. pp. 1-41.

- Gilchrist, S., V. Yankov , and E. Zakrajsek (2009), “Credit market shocks and economic fluctuations: evidence from corporate bond and stock markets”, *NBER Working Papers*, No. 14863, April. pp. 1-50.
- Gilchrist, S. and E. Zakrajsek. (2011), “Decomposition of Hardy Functions into Square Integrable Wavelets of Constant Shape”, *Credit Spreads and Business Cycle Fluctuations. NBER WP*, No. 17021, May. pp. 1-37.
- Hamilton, James (1994), “Time Series Analysis”, *Princeton, New Jersey: Princeton University Press*.
- Helbling, T., R. Huidrom , M. Kose , and O. Christopher (2011), “Do credit shocks matter? A global perspective”, *European Economic Review*, Vol. 55, No. 3, April. pp. 340-353.
- Hendry, David (1995), “Dynamic Econometrics”, *Oxford University Press*.
- Johansen, Soren (1995), “Likelihood-based inference in cointegrated vector autoregressive models”, *New York: Oxford University Press*.
- Jorda, O., S. Moritz, and M. Taylor (2010), “Financial Crises, Credit Booms, and External Imbalances: 140 years of lessons”, *NBER Working Paper*, No. 16567, December. pp. 1-43.
- Lahura, E. and H. Vega (2011) “El Impulso Crediticio y el PBI en el Perú: 1992-2009”, *Banco Central de reserva del Perú. Febrero*, DT N 2011-01, Febrero. pp. 1-41.
- Meeks, Roland (2009), “Credit market shocks: evidence from corporate spreads and defaults, Working Paper”, *Federal Reserve Bank of Dallas.*, No. 0906, pp. 1-38.
- Ng, S. and P. Perron (2001), “LAG Length Selection and the Construction of Unit Root Tests with Good Size and Power”, *Econometrica*, Vol. 69, No. 6, November. pp 1519-1554.
- Perri, F. and V. Quadrini (2010), “International recessions”, Working Paper, University of Minnesota.
- Perron, P. and G. Rodriguez (2003), “GLS detrending, efficient unit root tests and structural change.” *Journal of Econometrics, Elsevier*, Vol. 115, No. 1, July. pp. 1-27.
- Perron, Phillips(1988), “Regression Theory for Near-Integrated Time Series.” *Journal of Econometrics*, Vol. 56, No. 5, September. pp. 1021 - 43.
- Perron, Phillips(1987), “Time Series Regression with a Unit Root.” *Journal of Econometrics*, Vol. 55, No. 2, March. pp. 277-301.
- Sargent, T. and P. Surico (2011), “Two Illustrations of the Quantity Theory of Money: Breakdowns and Revivals”, (*American Economic Review, American Economic Association*, vol. 101, No. 1, February. pp. 109-28.

- Schularick, M. and Alan M. Taylor (2009), "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles and Financial Crises, 1870-2008", *NBER WP*, No. 15512, November. pp. 1-38.
- Schwarz, G. (1978) "Estimating the Dimension of a Model", *Annals of Statistics*, Vol. 6, No. 2, March. pp. 461-464.
- Sims, Christopher, Stock, James y Watson, Mark W, "Inference in Linear Time Series Models with some Unit Roots(1990)", *Econometrica*, Vol. 58, No. 1, January. pp 113-144.
- Zivot, E. and D. Andrews (1992), "Further evidence of the great crash, the oil-price shock and the unit-root hypothesis", *Journal of Business and Economic Statistics*, Vol. 10, No. 3, July. pp 251-270.

APPENDICES

A Output growth and credit impulse.

Unit root tests suggest that log of seasonal-adjusted real GDP (LGDP) is a unit root process, containing both deterministic and stochastic trends. Thus, using GLS detrending as in Ng-Perron (2001), we can obtain the non-deterministic part of LGDP, denoted by GDP, which is by definition a unit root process.

GLS detrending was proposed by Elliot et al. (1996) in the context of unit root tests. Under the assumption that $LGDP \equiv y_t$ contains both a linear deterministic trend and a stochastic trend, then it can be modelled as a random walk with drift, $y_t = \beta_1 + y_{(t-1)} + u_t$, with solution:

$$y_t = y_0 + \beta_1 t + \sum_{i=1}^{t-1} u_{t-i}$$

or

$$\Delta y_t = \beta_1 + u_t$$

The main idea is to extract the deterministic component or deterministic trend, $y_0 + \beta_1 t$ to obtain a detrended series $GDP \equiv y_t^{DT}$:

$$y_t^{DT} \equiv y_t - y_0 - \beta_1 t = \sum_{i=1}^{t-1} u_{t-i}$$

To obtain this it is enough to estimate y_0 and β_1 . Elliot et al. (1996), proposed the following strategy based on quasi-differences, which was used in the above PP and Ng-Perron tests. First, a parameter α close to 1 must be chosen, so that it is possible to subtract αy_{t-1} from both sides of $y_t = y_0 + \beta_1 t + \sum_{i=1}^{t-1} u_{t-i}$:

$$\tilde{y} = (1 - \alpha)y_0 + [(1 - \alpha)t + \alpha]\beta_1 + v_t$$

where $y \tilde{y}_t \equiv y_t - \alpha y_{t-1}$ is a quasi-difference. Then \hat{y}_0 and $\hat{\beta}_1$ can be obtained as the OLS estimates of y_0 and β_1 . In this way, we obtain a detrended y series, y_t^{DT} , as $y_t^{DT} \equiv y_t - \hat{y}_0 - \hat{\beta}_1 t$. This detrending procedure is called Generalised Least Squares or GLS because OLS is applied to a regression equation with an error term v_t which is obtained from a GLS transformation $(1 - \alpha)$.

Figure A-1

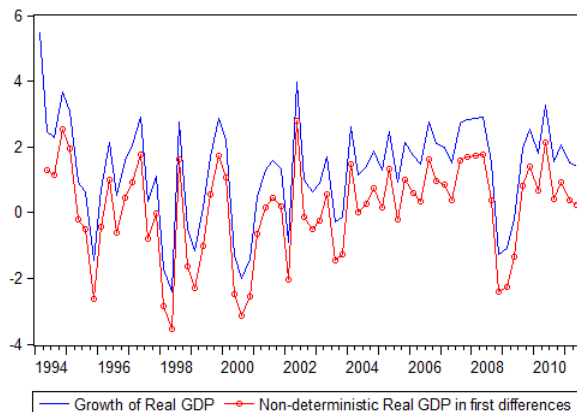
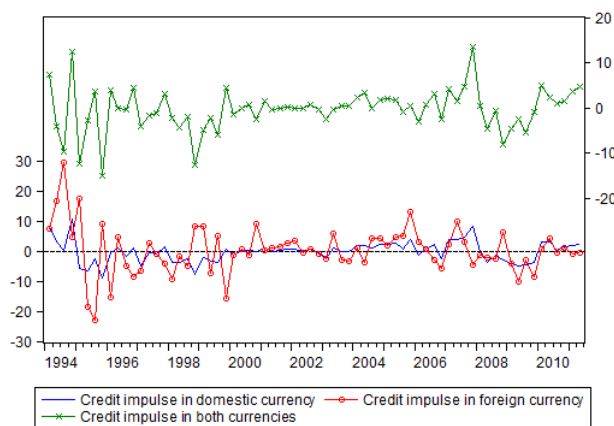


Figure A-1 compares the growth of seasonal-adjusted real GDP with the first difference of GDP (the non-deterministic part of LGDP or GLS-detrended LGDP). As expected, the correlation between the two series is 1: the two series are similar except by a constant value (1.1 percentage points).

Credit impulse is defined as the change in the rate of growth of real credit. Thus, the first difference of TCG, CGDC, and CGFC are measures of credit impulse.¹⁴ Credit impulses in domestic and foreign currency, as well as credit impulse for the sum of both aggregates, are presented in Figure A-2.

Figure A-2

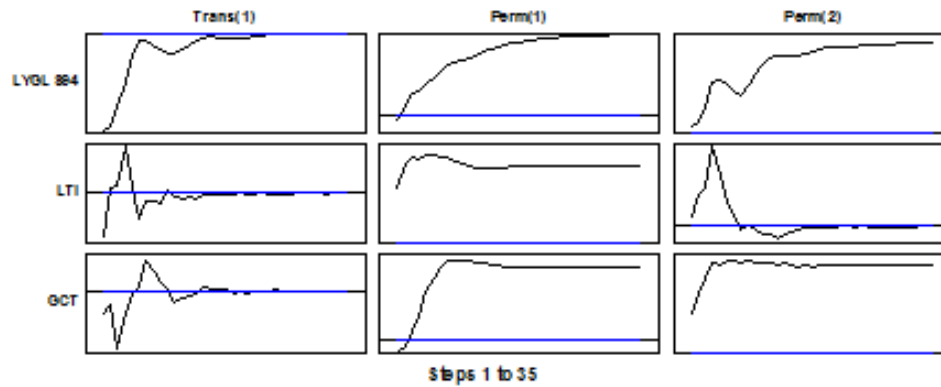


¹⁴Biggs et al. (2009) measures credit impulse as a percentage of GDP.

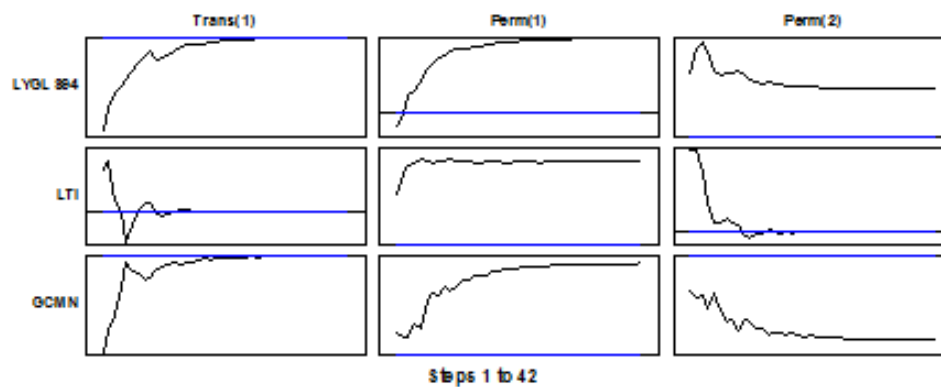
B Impulse-Response Functions using structural shocks

Figure A-3

Model 2



Model 3



Model 4

