

Pro-cyclicality and non-linearities of the credit portfolio: evidence from Peru (1998-2015)

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Abstract

This paper explores the relationship between the financial cycle and the economic activity in the Peruvian context for the period 1998-2015 using a two-regime logistic smooth transition autoregressive model (L-STAR model). The results suggest that the total credit portfolio is strongly pro-cyclical and that this relationship is non-linear. This evidence supports the hypothesis that the agents participating in the Peruvian financial system (supply and demand of credit) are more enthusiastic during periods of sustained economic growth, amplifying the economic cycle. The results are robust on the use of different specifications and different dependent and transition variables. Finally, these results support the recalibration of both dynamic provisioning and counter-cyclical capital buffer rules implemented by the SBS since 2011.

Keywords: credit cycle, business cycle, non-linearities, pro-cyclicality, L-STAR model.

JEL Codes: E32, E44, E51

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1 Introduction

The asymmetric non-linear relationship between the financial cycle and the economic cycle has been a center of interest in the economic agenda for several years. A wide range of aspects of this relationship have been analyzed and discussed, from its origins to its consequences. Particularly, in the last couple of decades, the experiences of severe financial crises have led to concerns that credit -as the primary variable of the financial system- is excessively pro-cyclical, amplifying the shocks in the real economy and representing a potential risk to financial stability. As a result, changes in prudential regulation, accounting standards, risk measures, and the monetary policy itself were prompted with the objective of ensuring both macroeconomic and financial stability.

This discussion has also been of main importance in Peru, especially since the Superintendency of Banking, Insurance and Private Pension Funds (SBS) has imposed several macroprudential regulations to mitigate the potential effects of the boosting economic cycle on the credit cycle (e.g. dynamic provisioning and counter-cyclical capital buffers). However, there is still limited literature that has documented the relationship between the credit cycle and the economic cycle in the Peruvian context. On the one hand, there are attempts from Galindo (2011) and Amado (2014) in which this relationship is calibrated using DSGE models for the Peruvian economy, showing that macroprudential tools (e.g. counter-cyclical capital buffers) help mitigate GDP and credit growth volatility. On the other hand, some attempts from Muñoz (1998), Aguilar et al (2004), Aparicio and Moreno (2011) and Aparicio et al. (2013) have found evidence of a non-linear relationship between credit risk (NPL rates and provision expenses, mainly) and the economic activity in Peru.

Although this literature has recognized the presence of non-linearities between the economic cycle and the credit cycle, there is still a pending agenda to model this relationship using an adequate set of non-linear specifications in Peru and real-sector data. Bacigalupo

and Bacigalupo (2011), Azabache (2010) and Bazán (2011) have developed non-linear specifications (threshold and STAR models) to approach this asymmetric relationship, but using a small time horizon, giving too much emphasis to the expansionary part of the most recent Peruvian business cycle.

This paper intends to examine the relationship between the economic and credit cycles in the Peruvian financial system using a two-regime logistic smooth transition autoregressive specification (L-STAR model) for the period 1998-2015. This period includes the effects of the last economic/financial crisis and those from the most recent economic downturn, providing a better balance in the number of observations in the expansionary and downturn parts of the cycle. We use a 36-month window (three years) for the transition variables (GDP and employment variation) in the non-linear specification to incorporate the transmission effects from the economic activity to real credit in the long-run.

The rest of the paper proceeds as follows. In Section II, we present a brief literature review. Section III presents the empirical relationship between economic activity and credit in the Peruvian context. Section IV describes our empirical strategy. Our results and discussion are presented in Section V. Section VI concludes.

2 Literature review

The relationship between business and credit cycles has been deeply discussed in the economic literature. However, there is no consensus about the direction of the causality between these two variables. On the one hand, Goldsmith (1969) suggests that there is a positive relationship between the demand and supply of credit and economic growth. Levine (1997) also supports that the relationship goes from the financial system to economic growth, showing

evidence that financial systems deepness is strongly associated with economic development. On the other hand, King and Plosser (1984) suggest that an increase in productivity in any sector (boosting the economic activity) raises the demand for financial transactions, making the financial system respond to these shocks by increasing the supply of credit.

One of the reasons behind this lack of consensus might be the non-linear behavior of the credit cycle. For example, the hypothesis of financial frictions, which supports their asymmetrical behavior, has been documented in Blinder and Stiglitz (1983), Blinder (1987), Bernanke y Gertler (1989) and Kiyotaki (1998). For instance, Kiyotaki (1998) develops a DSGE model in which credit constraints arise because creditors cannot force debtors to repay their debts unless they are secured by collateral. This causes a financial friction that generates larger and more persistent fluctuations in output and asset prices in the presence of productivity shocks. Matsuyama (2004) explains the nature of the credit cycle through another DSGE model that shows heterogeneity among investment projects such as borrowing constraints and profitability. Finally, Kocherlakota (2000) also builds asymmetrical credit cycles through credit constraints.

The recent international financial crisis has renewed academic interest for studying the interdependence between financial and real variables along cycles. Therefore, the research is nowadays focused on the importance of modeling financial linkages through active banking sectors in economic models. According to Dib (2009), the source of the non-linearity is the different optimization structures of banks. Christiano, Motto, and Rostagno (2010) build a DSGE model that includes a banking sector and show that agency problems in financial contracts, liquidity constraints, and shocks that alter the perception of market risk and hit financial intermediation are critical triggers and propagators of economic fluctuations.

Hilbers et al. (2005) highlight three main drivers of rapid credit growth that the litera-

ture generally identifies: (i) during the development phase of an economy, credit grow more quickly than output (Favara, 2003; King and Levine, 1993; and Levine, 1997). This financial deepening argument is supported by empirical work suggesting that a more developed financial sector promotes economic growth; (ii) credit expands more rapidly than output at the beginning of a cyclical upturn due to firms investment and working capital needs, according to the conventional accelerator models (Fuerst, 1995; IMF, 2004); (iii) excessive credit expansions may result from inappropriate responses by financial market participants to changes in risks over time. According to the financial accelerator models, over-optimism about future earnings boosts asset valuations, leads to a surge in capital inflows, increases collateral values (increases the relative price of non-tradables), and allows firms and households to borrow and spend. If performance falls below these expectations, asset prices and collateral values decline. This reverses the financial accelerator, increasing the indebtedness of the borrowers, decreasing both their capacity to fulfill their loans and their access to new loans. These factors play an important role in extending a boom and increasing the severity and length of a downturn.

The literature on credit cycles in emerging economies, including Mendoza and Terrones (2008, 2012) and Tornell and Westermann (2002, 2003), has established that credit expansions are associated with large macroeconomic expansions, widening current account deficits and real exchange rate appreciations. In line with this, the relationship between the financial sector and the real sector leads to an excessive volatility of the cycle, amplifying its expansionary effects and exacerbating downturns. Borio et al. (2001) argue that this pro-cyclicality in the behavior of the financial sector may be the origin of a strong instability once the expansionary phase of the cycle is reversed. Mendoza and Terrones (2008) also point out that periods of sustained economic growth tend to be associated with significant increases in the credit growth rate, and recessions, with sharp reductions of credit. Finally, Borio et al. (2001) specify that the main reasons behind this pro-cyclicality are the presence

of financial frictions, an inadequate perception of risk by financial institutions and regulatory institutions (ignoring the risk of the financial system as a whole).

This aforementioned pro-cyclicality has led to research about macroprudential policies in order to control the excessive volatility of the credit cycle. Hahm et al (2012) examine a large set of macroprudential policies in open emerging economies, such as loan-to-value and debt-service-to-income caps, capital requirements that adjust over the cycle, forward-looking provisioning, leverage caps and loan-to-deposit caps, etc. Song Shin (2013) describes a variety of types of early warning indicators of financial instability that should help financial regulators to identify credit booms. Finally, Cerutti et al. (2015) use an IMF survey to document the use of macroprudential policies for 119 countries over the 2000-2013 period.

Concerning the literature that covers this relationship in the Peruvian context, there have been several attempts that discuss the non-linearities and asymmetries between these two variables. Muñoz (1998) found some evidence that shows a non-linear relationship between the non-performing loans rate (NPL rate) from the Peruvian banking system and the economic activity through a panel data specification. Aguilar et al. (2004) also found evidence in the same direction using a dynamic panel model. Aparicio and Moreno (2011) find evidence that the provision expenses (proxy variable used for credit risk) have a non-linear relationship with some cyclical variables (GDP growth and employment growth) in the Peruvian financial system. In the same direction, Aparicio et al. (2013) develop a Markov-type transition matrix analysis in which migrations from Peruvian debtors between different credit classifications were conditioned to the economic cycle. This analysis showed that the probability of downgrade¹ for Peruvian financial debtors has a U-shape when plotted against economic growth for the period 2001-2011, inferring a non-linear relationship between the

¹The probability of a downgrade is defined as the likelihood of passing from a credit classification that reflects a lower probability of default to a credit classification that reflects a higher probability of default (Aparicio et al., 2013).

economic cycle and credit risk.

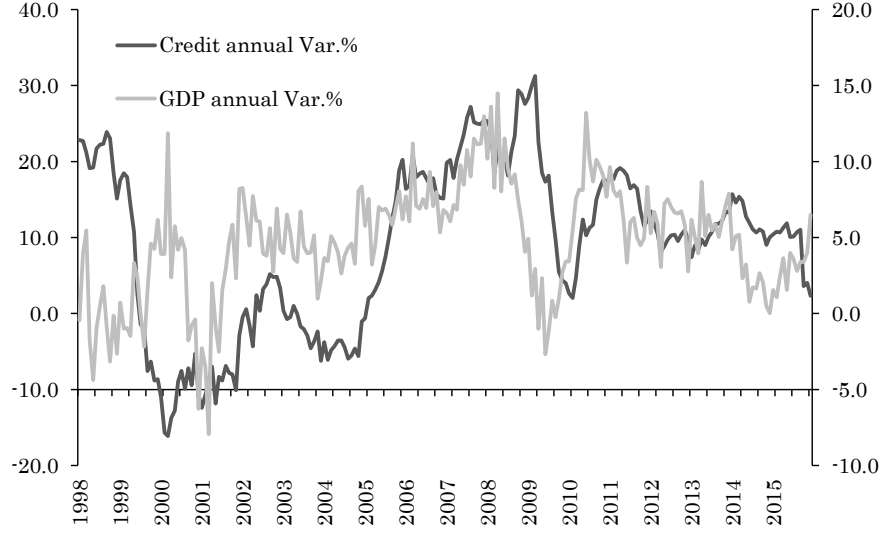
Finally, Bacigalupo and Bacigalupo (2011) developed a two-regime STAR model to model consumer credit behavior in Peru. The results obtained by these authors confirm the existence of two regimes in consumer credit growth. This evidence shows that when the 12-month GDP growth is higher than 5.7%, the behavior of consumer credit switches from one regime to another, intensifying the effect of GDP growth on the consumer credit growth, probably motivated by the excitement generated by lenders (encouraging them to expand credit in these periods). In the same direction, Azabache (2010) developed a threshold specification to model the non-linear relationship between the NPL rate and the economic cycle showing that these models over-perform compared to linear specifications. Bazan (2011) uses two non-linear models (L-STAR and Markov Switching) concluding that the credit cycle is deeper in the expansive regime of the economic activity.

3 Credit and GDP in Peru (1998-2015)

The Peruvian financial system has grown rapidly during the last two decades and so has credit. During the period 1998-2015, it is possible to distinguish two different states for credit² growth: between the years 2000 and 2004, credit registered an annual contraction of around 4.8%. In contrast, since 2005, credit grew at an average rate of 14.4%, which is almost twice the average GDP growth rate (especially during the period 2005-2009). As expected, this fast growth follows a similar path to the one of the GDP growth over the same period (see **Figure 1**). This evidence supports the pro-cyclicality of the credit in the Peruvian financial system during 1998-2015.

²Credit data is constructed using the database from the SBS, considering only the credit provided by the banking and non-banking institutions (financieras, cajas municipales, cajas rurales and edpymes). The credit provided by the State Bank (Banco de la Nación, Agrobanco and COFIDE) is not included in these series.

Figure 1: Credit and GDP (annual % change)



Source: SBS, BCRP

However, it is worth pointing out that this pro-cyclicality is not contemporaneous. It is more likely that GDP leads credit (if the causality is assumed this way) since economic agents are exposed to a sustained economic growth period, as discussed in the previous section. If this is true, we should observe a structural relationship between credit and lagged GDP (or a longer-term average GDP growth). **Table 1** presents a set of correlations between credit growth (annual and monthly³) and GDP average growth for 1998-2015 and for the pre-crisis period (1998-2008) considering different windows for the average GDP growth. For both 1998-2015 and the pre-crisis period, we observe: (i) a high positive correlation between the two variables, and (ii) a growing correlation between both variables when the monthly window increases for the average GDP growth. This evidence supports a non-contemporaneous relationship between credit and GDP in the Peruvian case, with Peruvian agents apparently looking at longer periods of GDP growth to expand/contract their supply/demand of credit.

Furthermore, evidence collected by other authors point out to a non-linear relationship

³The reason behind also considering a monthly credit % change is the nature of the variable itself: for our modeling purposes, we need a stationary variable. This will be discussed in the next section.

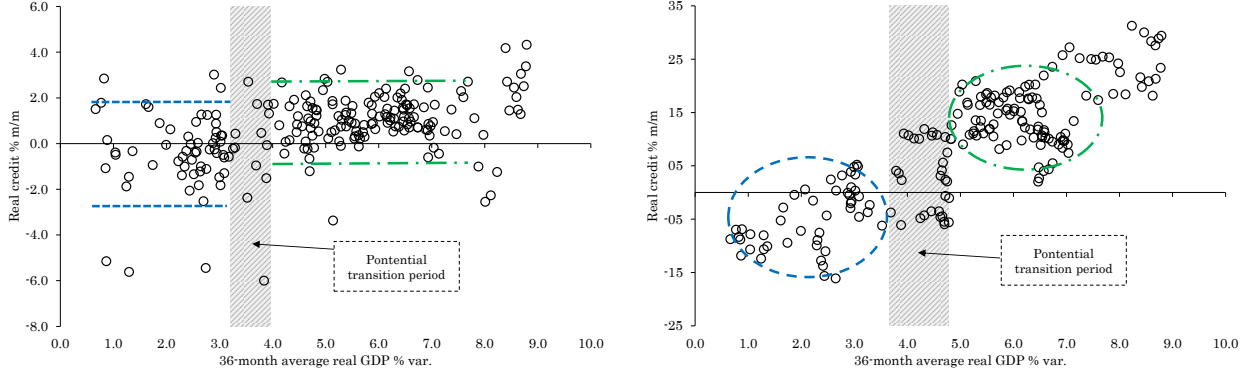
between both variables in the Peruvian context (see Section 2). Figure 2 presents a scatter plot between the 36-month average GDP % change, the credit monthly % change, and the credit annual % change. This relationship exhibits the best fit between the GDP and credit variations compared to other windows for the average of GDP variation. **Figure 2** allows us to infer a positive non-linear relationship between credit and GDP. Graphically, this non-linear relationship could be seen as two different regimes with different levels before and after certain thresholds. Before a 3.3 percent 36-month average GDP growth we observe a low-level regime (even with a slightly negative mean for the values of credit) and after a 4.2 percent 36-month average GDP variation we observe a high-level regime (with a mean of around 1 percent for credit variation). We observe a clear smooth transition between both regimes in the interval between 3 and 4 percent. This type of relationships should be modeled econometrically through a smooth transition autoregressive model (STAR model) for empirical purposes.

Table 1: Correlations between GDP average annual % change* and credit growth

<i>Annual credit growth</i>						
	<i>Months</i>					
<i>Period</i>	36	30	24	18	12	6
<i>1998-2008</i>	78.0%	76.8%	75.6%	70.4%	59.9%	48.0%
<i>1998-2015</i>	75.1%	73.9%	74.1%	70.5%	59.7%	44.2%
<i>Monthly credit growth</i>						
	<i>Months</i>					
<i>Period</i>	36	30	24	18	12	6
<i>1998-2008</i>	52.2%	51.8%	51.9%	51.1%	46.3%	39.6%
<i>1998-2015</i>	44.1%	43.0%	42.2%	42.4%	40.3%	36.7%

*The correlation between both variables is presented for different windows for the average % change of GDP.

Figure 2: Credit and GDP % change scatter-plot (1998-2015)*



*In the left (right) figure, the gray bands group most of the observations before 3.3 (3.5) percent GDP average % change. The green lines do the same with the observations after 4.2 (4.8) percent -and before 8 (7.5) percent-. The shaded zone stands for the tentative smooth transition in the relationship between both variables.

Source: SBS, BCRP

4 Empirical strategy

4.1 L-STAR model

For our non-linear representation of the relationship between total credit and GDP, we use the following smooth transition autoregressive (STAR) model⁴:

$$y_t = \phi'_1 x_t [1 - G(s_t; \gamma, c)] + \phi'_2 x_t G(s_t; \gamma, c) + \epsilon_t \quad (1)$$

where y_t is the dependent variable, $x_t = (1, \tilde{x}'_t)$ with $\tilde{x}'_t = (y_{t-1}, \dots, y_{t-p})'$ and $\phi'_i = (\phi'_{i,0}, \phi'_{i,1}, \dots, \phi'_{i,p})', i = 1, 2$. Also, the model admits the presence of some exogenous variables z_{1t}, \dots, z_{kt} that can be additional regressors inside the vector \tilde{x}'_t . The error ϵ_t is assumed as a martingale in differences with respect to the history of the dependent variable until the period $t-1$ that is denoted as $\Omega_{t-1} = \{y_{t-1}, y_{t-2}, y_{t-(p-1)}, y_{t-p}\}$, which implies that $E[\epsilon_t / \Omega_{t-1}] = 0$. The transition function $G(s_t; \gamma, c)$ is continuous function between 0 and 1.

In the initial model based on Teräsvirta (1994), the transition variable s_t is assumed

⁴We strictly follow Teräsvirta et. al (2000) for our econometric specification.

as the lagged endogenous variable. This means that $s_t = y_{t-d}$ for $d > 0$. However, as mentioned by Teräsvirta et. al (2000), the transition variable could also be an exogenous variable ($s_t = z_t$). This STAR model could be interpreted as a regime-change model that allows for the presence of two regimes, each one associated with the two extreme values of the transition function: $G(s_t; \gamma, c) = 0$ and $G(s_t; \gamma, c) = 1$, in which the transition from one regime to the other is smooth.

It is clear that different options of transition functions $G(s_t; \gamma, c)$ allow to model different behaviors in the regime change. A very common alternative for the transition function $G(s_t; \gamma, c)$ is the following first-order logistic function:

$$G(s_t; \gamma, c) = (1 + \exp \{ - \gamma(s_t - c) \})^{-1}, \quad \gamma > 0 \quad (2)$$

With this choice, the resultant model is known as the logistic STAR or the L-STAR model. The c -parameter in (2) could be interpreted as the threshold that separates both regimes, as the logistic function changes monotonically between 0 and 1 while s_t rises. The γ -parameter determines the smoothness on the change in the value of the logistic function, and therefore the smoothness in the transition between regimes. Mathematically, as γ grows bigger, the change in the transition function $G(s_t; \gamma, c)$ from 0 to 1 turns instantaneous in the value $s_t = c$.

In an L-STAR model, both regimes are associated with low and high values of the transition variable s_t relative to the c -threshold. According to Teräsvirta et. al (2000), this regime-change type is the most convenient to model the existing asymmetry surrounding the economic cycle. For our purposes, the dependent variable is the variation/change in the total credit ($credit_t$), while the transition variable is the variation/change in the real GDP (gdp_t). As discussed in the previous section we use a 36-month window (three years)

for the transition variable for one main reason: it is more likely that there are more significant effects transmitted from the GDP to the total credit after the agents are exposed to a sustained economic growth. Three years is a consistent window with a medium-term perspective. Moreover, as a robustness check, we apply the same empirical strategy using the probability of default (PD) as the variable characterizing the financial system, and employment as a measure of economic activity.

The modeling cycle suggested by Lutkepohl & Kratzig (2004) consists of three stages: specification, estimation, and evaluation. Specification starts with setting up a linear model that forms a starting point for the analysis. It can be modeled by using the VAR framework. The second part of specification involves testing for non-linearity and choosing the transition variable. Estimation involves finding appropriate starting values for the nonlinear estimation and estimating the model. Evaluation of the model usually includes graphical checks as well as various tests for misspecification, such as error autocorrelation, parameter non-constancy, remaining non-linearity, ARCH, and non-normality.

4.2 Data

The variables used in this paper are credit, GDP, employment and the probability of default, on a monthly basis. Regarding credit, data was taken from the Financial Stability Authority of Peru (SBS) and considers direct credit from the five main subsystems: Banks, Financieras, Cajas Municipales, Cajas Rurales and Edpymes. In order to obtain the real credit growth rate, we indexed nominal monthly credit in local currency by the consumer price index (IPC)⁵, applied a seasonal adjustment using Tramo-Seats, and calculated the first difference of its logarithm to obtain the monthly growth rate (referred from now on as $credit_t$).

⁵Obtained from the BCRP.

Our second dependent variable, the probability of default, is calculated by the Research Department of the SBS since 2005⁶. Given that the PD is constructed comparing two points in time, we can compute the difference between the variable 12 months ago to get a stationary series (referred from now on as pd_t). Both series, $credit_t$ and pd_t were tested for unit roots and proved to be stationary⁷, which is necessary when working with autoregressive models. Data goes as far as 1995 for $credit_t$ and 2003 for pd_t .

For the transition variables, employment and GDP, data was taken from the Peruvian Central Bank (BCRP). Our series of employment is a real index of urban companies with more than ten employees, with base on 2010, and goes as far as 1997. On the other hand, GDP corresponds to an index with basis 2007, with a starting point in 1994. The computation of the transition variables is as follows: for employment and GDP, we applied a seasonal adjustment using Tramo-Seats and calculated the real annual variation. Then, we named $employment_t$ and gdp_t to the average of the last 36 real annual variations of each corresponding variable. It is important to mention that both series are obviously not stationary (ie. we cannot reject the absence of a unit root), but this fact will not represent a problem to our model since we are using them only as transition variables. Moreover, such a representation is convenient in order to facilitate the forthcoming economic interpretation of our results.

5 Results

5.1 Main model

Following the modeling cycle mentioned before, we used a Box-Jenkins approach to determine the best linear model for credit. Our analysis suggests that credit is best explained by

⁶The algorithm can be found in the Appendix section at the back of the paper.

⁷See **Table A.1** and **Table A.2** at the back of the paper.

its first and fifth lag and a constant (see **Table 2**). The model presents an adjusted R2 of 0.25 and a Durbin-Watson statistic of 2.1, which denotes the absence of autocorrelation in the model. Furthermore, the test LM(j) and the correlogram confirm the absence of autocorrelation. Moreover, the White test rejects the presence of heteroskedasticity. Nevertheless, it is not possible to accept the null hypothesis of normality in the residuals through the Jarque-Bera test.

Table 2: Linear model results
(Dependent variable: $credit_t$)

	<i>Coefficient</i>	<i>St. Dev.</i>	<i>t-stat</i>	<i>p-value</i>
<i>Variable</i>				
<i>Cons</i>	0.279	0.100	2.777	0.006
$cred_{t-1}$	0.295	0.108	2.720	0.007
$cred_{t-5}$	0.333	0.087	3.836	0.000
<i>AIC</i>	3.4341	<i>adjusted R2</i>	0.2532	
<i>SC</i>	3.4767	<i>N</i>	247	
<i>HQ</i>	3.4512	<i>DW stat</i>	2.0674	

The second set of tests are related to the stability of the parameters. The CUSUM2 analysis (see **Figure A.1**) suggests a change in the parameters around the middle of 2001, staying in the limit of the 5% significance bands until mid-2010. The instability of the parameters allows us to infer that there might be a time period where credit exhibits a different behavior. Coincidentally, the dates mentioned before indicate the end of the two worst episodes for recent Peruvian financial history (2001 and the International Financial crisis). Moreover, the period between these two points in time was characterized by an exceptional economic growth, registering a GDP expansion of above 6%, in average. This is evidence that invite sus to think that credit growth has a different dynamic when the economy is in a good shape. Finally, the instability of the parameters is reaffirmed by rejecting the null hypothesis of the Chow-test with a breakpoint in 2001M06 (see **Table A.3**), indicating that the coefficients are not stable across regimes.

The results involving the stability of the parameters in our model suggest that the correct specification might be non-linear. To prove this theory, we chose a transition variable and conduct a linearity test. According to the previous discussion, the transition variable used is the 36 month average of GDP annual growth (gdp_t). The results indicate that the best model is an LSTR1 (see **Table A.4**). The model tested was constructed based on the linear approach already calculated: with a constant, the first and the fifth lag of $credit_t$.

Estimating an L-STAR model also requires to begin the non-linear approximation around a set of starting values for the estimated parameters of the model (γ, c). To obtain the starting values we use a grid search based on a non-linear optimization routine. The grid search creates a linear grid in c and a log-linear grid in γ . For each value of γ and c the residual sum of squares is computed. The values for γ and c that allow minimizing that sum are taken as starting values. We find out that these values are 3.93 for c and 119.3 for γ (see **Figure A.2**).

Using these starting values, it was not possible to find an optimal and parsimonious model. According to the graphical analysis from $credit_t$ and gdp_t , the first regime seems to end around a 3.3% value of gdp_t , while the second seems to start around 4.2%. Following this intuition, we used a starting value for c that locates not so close to the presumptuous end of the transition period (around 3.8), and, since our hypothesis suggests a smooth transition, we used a lower starting value of around 50 for γ . Once the starting values are established, the unknown parameters are estimated by using a form of the Newton-Raphson algorithm to maximize the conditional maximum likelihood function. The model obtained is presented in **Table 3**. Our results suggest that the transition between the two regimes starts after 36 months of an average real GDP annual growth of 3.5% (c threshold of 3.503).

Although γ is not statistically significant at the 0.05 level, this should not be a concern

as mentioned by Teräsvirta, van Dijk, and Franses (2000). According to these authors, the t-statistic for this variable does not share the typical asymptotical distribution with other t-statistics under the null hypothesis of $\gamma = 0$, due to identification problems.

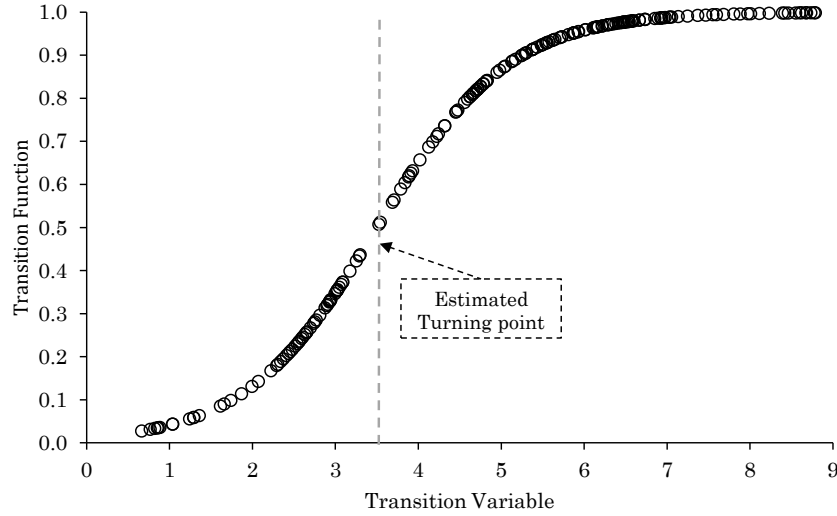
Table 3: L-STAR results
(Dependent variable: $credit_t$)

	<i>Coefficient</i>	<i>St. Dev.</i>	<i>t-stat</i>	<i>p-value</i>
<i>Linear Part</i>				
<i>Cons</i>	-0.569	0.315	-1.806	0.072
$cred_{t-5}$	0.188	0.069	2.713	0.007
<i>Non-linear Part</i>				
<i>Cons</i>	1.160	0.429	2.707	0.007
$cred_{t-1}$	0.364	0.098	3.718	0.000
γ	2.545	1.511	1.685	0.094
<i>C</i>	3.503	0.648	5.410	0.000
<i>AIC</i>	0.5820	<i>adjusted R2</i>	0.2922	
<i>SC</i>	0.6773	<i>N</i>	211	
<i>HQ</i>	0.6206			

To analyze the validity and robustness of the L-STAR results, we also run some misspecification tests (see **Table A.5**). These tests suggest that the number of lags was adequate to eliminate the autocorrelation problem, which is one of the most important problems with L-STAR models. The no remaining non-linearity tests suggest that there is another non-linearity that the model is not picking up. This could be related to the fact that the GDP registered high growth rates in the quarters preceding the financial crisis, generating a bunch of non-usual observations for the Peruvian economy (more than 8% of growth). Hence, the model could interpret this short time period as a different regime.

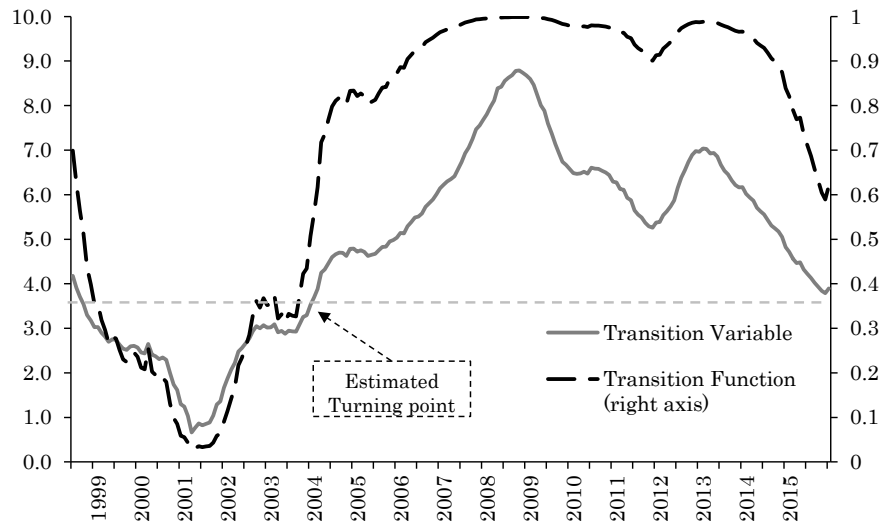
Furthermore, the parameter stability test shows that they are constant in each regimen. It is also possible to reject the null hypothesis of heteroscedasticity in the model through the ARCH-LM test. Also, it is not possible to accept the null hypothesis of normality in the

Figure 3: Estimated transition function and transition variable cross-plot, $credit_t$



Source: SBS

Figure 4: Estimated transition function and transition variable, $credit_t$



Source: SBS

errors through the Jarque-Bera test, although the errors present a mean of zero. This result is due to an excess of kurtosis and a bounded skewness to the left of the distribution.

Finally, we present a graphical analysis of the results from the L-STAR model. **Figure 3** and **Figure 4** present both variables, the estimated transition function, and the transition variable, as a cross-plot and as time series, respectively. The cross-plot shows a smooth transition between the two regimes, where the turning point in the transition function is

marked around a value of 3.5% for gdp_t . This value should be interpreted as the tentative value marking the end of the first regime and the start of the transition period to the second. Moreover, the transition function exceeds 0.8 when gdp_t is around 4.5%, or by late 2004, as shown in **Figure 4**. At this level of the transition function, we can consider this the start of the new regime of credit growth.

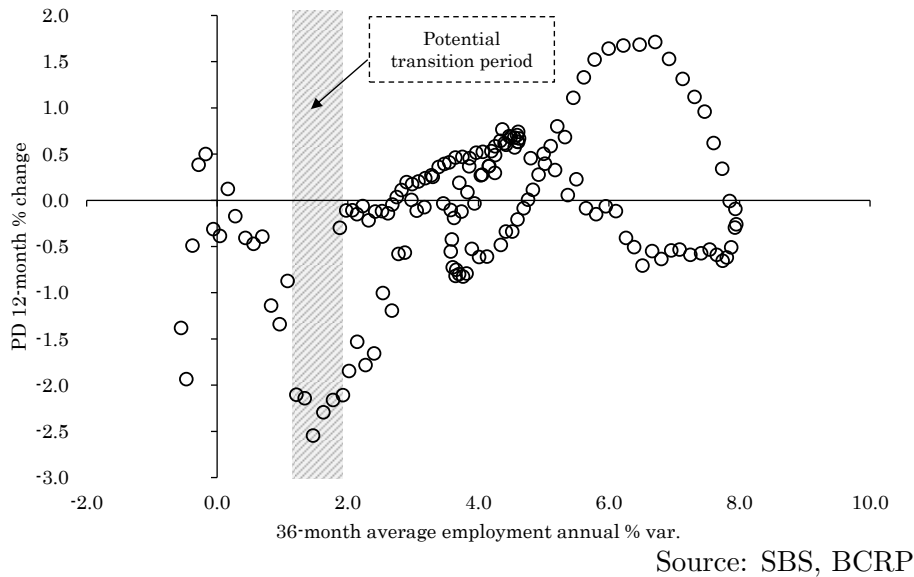
5.2 Robustness analysis: probability of default vs employment

In the previous sections, we have discussed that credit is not the only variable that can correctly characterize the financial cycle. As a form of robustness test to our previous analysis, we compute a model that tries to capture the relation between the probability of default, a variable that can also be used to characterize the financial cycle, and the economic activity.

Following the same methodology as for credit, we start with a graphical analysis of the correlation between pd_t and gdp_t , looking for evidence that suggests a non-linear connection. The graph, which can be found in the **Figure A.3**, shows indeed a non-linear relation between these variables. Nevertheless, it does not appear to be clear or correctly defined. As a response to this obstacle, we use the same approach but with $employment_t$ (annual growth of employment, in a 36-month window average) as the variable of economic activity rather than gdp_t . The resulting graph (see **Figure 5**) shows a clear non-linear relation between the two variables, which its first turning point around an employment growth of 1.5%, and a second turning point around 5%. What is more, the graph suggests that before 1.5% of average employment growth, the PD tends to decrease when employment increases. After this threshold, the two variables appear to be positively correlated. This first approach seems to support our main hypothesis.

The reason for the superiority of $employment_t$ exploiting the presumptuous non-linearity

Figure 5: PD and employment % var. scatter-plot (2003-2015)*



in the pd_t rather than gdp_t could be the time window used for the analysis. Since we have data for pd_t since 2003 only, the analysis does not take into consideration the economic downturn of 2000-2001. However, employment took longer to recover from the crisis. For this reason, $employment_t$ reflects that economic downturn, even until 2004.

Following the same steps used to model $credit_t$, we start with a linear representation of pd_t . The model is shown in **Table A.6**, and consists of the first, second, and fifth lags ($pd_{(t-1)}, pd_{(t-2)}, pd_{(t-5)}$). Our model presents an R-square of 0.90 and a Durbin-Watson stat of 1.9. Nevertheless, there seems to be a sort of autocorrelation involving the third lag. Moreover, the White test rejects the presence of heteroskedasticity. The errors are not normally distributed.

The second set of tests we apply to the model are related to the stability of the parameters. The CUSUM2 analysis is more conclusive than in the credit model: the parameters are unstable, and deviate from the 5% significance bands since late 2004 until early 2011. After that, the coefficients again deviate until the first quarter of 2014. The dates and the dynamic of the parameters are similar to the ones of $credit_t$, which supports the validity of

our previous analysis. The instability of the parameters is reaffirmed by rejecting the null hypothesis of the Chow-test with a breakpoint in 2004M09 (see **Table A.7** and **Figure A.4**).

Next, we compute the non-linear model, following the same approach used for credit. Our model results as an AR(5), and is shown in **Table 4**:

Table 4: L-STAR results
(Dependent variable: pd_t)

	<i>Coefficient</i>	<i>St. Dev.</i>	<i>t-stat</i>	<i>p-value</i>
<i>Linear Part</i>				
<i>Cons</i>	0.008	0.017	0.446	0.656
pd_{t-1}	0.648	0.069	9.410	0.000
pd_{t-3}	1.180	0.140	8.459	0.000
pd_{t-4}	-0.156	0.080	-1.954	0.053
pd_{t-5}	0.306	0.091	3.367	0.001
<i>Non-linear Part</i>				
pd_{t-2}	0.502	0.096	5.261	0.000
pd_{t-3}	-1.089	0.157	-6.954	0.000
pd_{t-5}	-0.486	0.100	-4.855	0.000
γ	158.076	3767.529	0.042	0.967
<i>C</i>	1.336	0.130	10.246	0.000
<i>AIC</i>	-3.1500	<i>adjusted R2</i>	0.9430	
<i>SC</i>	-2.9447	<i>N</i>	145	
<i>HQ</i>	-3.0666			

The results suggest that the transition between the two regimes starts after 36 months of an average employment growth of 1.34% (c threshold of 1.336). It is also worth mentioning that the signs of the coefficients and their magnitudes change between the two regimes. Regarding the γ parameter, its high estimated value (158.07) allows us to infer that the transition is not as smoothed as the one estimated for $credit_t$. In this case, the reasons behind the relatively higher standard errors are related to numerical matters.

The misspecification tests (see **Table A.8**) ran for the LSTAR model suggest that there

are still some of the deficiencies from the linear model: there is some autocorrelation between the second and fifth lag. Moreover, there appears to be a remaining non-linearity that the model is not reflecting. This could be explained by the anomalous behavior of pd_t after a value of 5% for $employment_t$. The errors are not normally distributed -although they have a mean of zero- and there is evidence of heteroscedasticity in the model. Nevertheless, the parameters are constant across the regimes.

Figure A.5 presents the estimated transition function from the L-STAR model. This function achieves the value of 1 at a 36-month average real employment annual growth of 1.45%, which is the tentative initial value of the end of the first regime and the start of the transition period to the second. As it has already been mentioned, this function has a less smoothed transition than in the case of $credit_t$, which indicates a significantly more abrupt change between regimes.

5.3 Finding the optimal threshold

In the previous section, we show the results of our efforts to, in the first place, prove the existence of a non-linear relation between the financial cycle and the economic activity, and on top of that, find the threshold that indicates the start of the transition from one regime to another. For this purpose, we compute two models with different variables for measuring the financial system and the economic activity as well. In this section, we combine both results by basically checking their consistency.

The L-STAR model estimated for credit growth will be our baseline, leaving the one estimated for the PD as the auxiliary one. This is due to the following reasons: (i) our credit data is more extensive than our PD data; (ii) PD involves a calculation process that might be subject to errors.

Having said that, the optimal threshold that defines the beginning of the smooth transition period from one regime of the financial cycle to another should be around 3.5% of 36-month-average GDP growth, based on the L-STAR model for credit. Furthermore, in order to incorporate the results from the L-STAR model for PD, we should look for the rate of GDP growth that is consistent with the employment growth threshold found in the model. A simple way to do this is by looking at the scatter plot for both variables (see **Figure A.6**). It can be noticed that GDP and employment obviously move in the same direction, and more important, that a 36-month average employment growth of 1.33% represents a 36-month average GDP growth of around 4.5%-4.7%.

As explained before, the results of the L-STAR model for credit is our baseline, so this analysis suggests that the optimal threshold considering both credit and PD should be above the 3.5% GDP growth. Moreover, since the L-STAR model for PD indicates a relatively rapid transition from one regime to another at 1.33% of employment growth (i.e. 4.5%-4.7% GDP growth), the optimal threshold should necessarily be below 4.5% of GDP growth. Therefore, the optimal threshold must lie around 4% of 36-month average GDP growth.

6 Concluding remarks

Our work leads to one main conclusion that could actually be separated into two parts-regarding the relationship between the financial cycle and economic activity. First, using an LSTAR model, we find that this relationship is indeed nonlinear; for this analysis, we used the monthly credit growth rate and the GDP annual moving average growth rate with a 36-month window as the transition variable. This result is in line with the work from Bazán (2011), Aparicio & Moreno (2011), etc., which also conclude that the financial sys-

tem, measured as credit growth, has a nonlinear behavior. Moreover, we prove the validity of our results by using the same methodology but with other variables: probability of default as a measure of the financial system and employment measuring economic activity. These ideas support the need of macroprudential policies such as dynamic provisioning and counter-cyclical capital buffer rules implemented by SBS to moderate credit growth rates in high expansionary phases of the economic cycle.

The second part of the conclusion relates to the threshold that indicates the start of the transition from one regime to another. Considering the two L-STAR models estimated, we come to the conclusion that this threshold is located around 4% of 36-month average GDP growth. In general lines, this evidence supports that the agents participating in the Peruvian financial system (supply and demand of credit) are more enthusiastic during periods of sustained economic growth, amplifying the economic cycle. Since both dynamic provisioning and counter-cyclical capital buffer rules in Peru are set to activate when GDP growth exceeds 5.0%, these results are useful for the recalibration of this threshold, in line with the moderation of Peruvian potential GDP growth observed in recent years.

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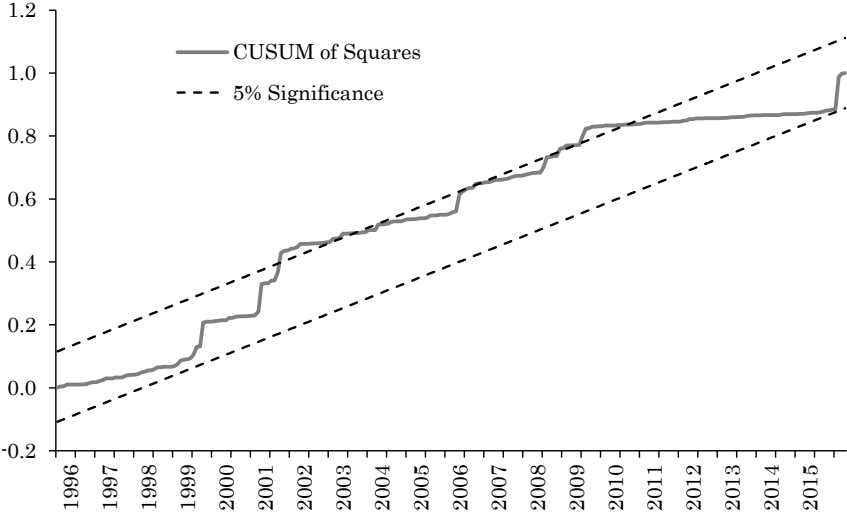
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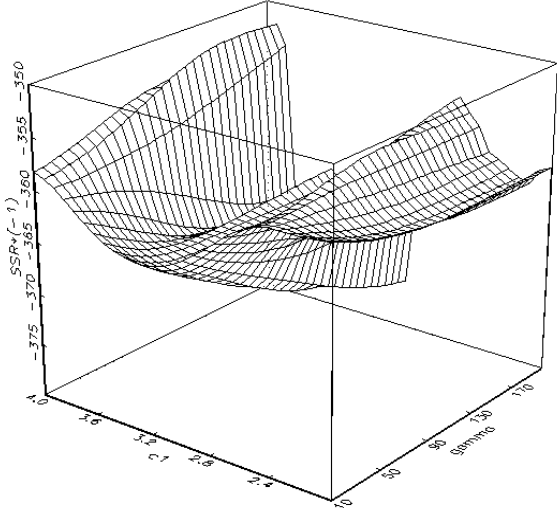
Appendix - Figures

Figure A.1: CUSUM2 Test for $credit_t$ linear model



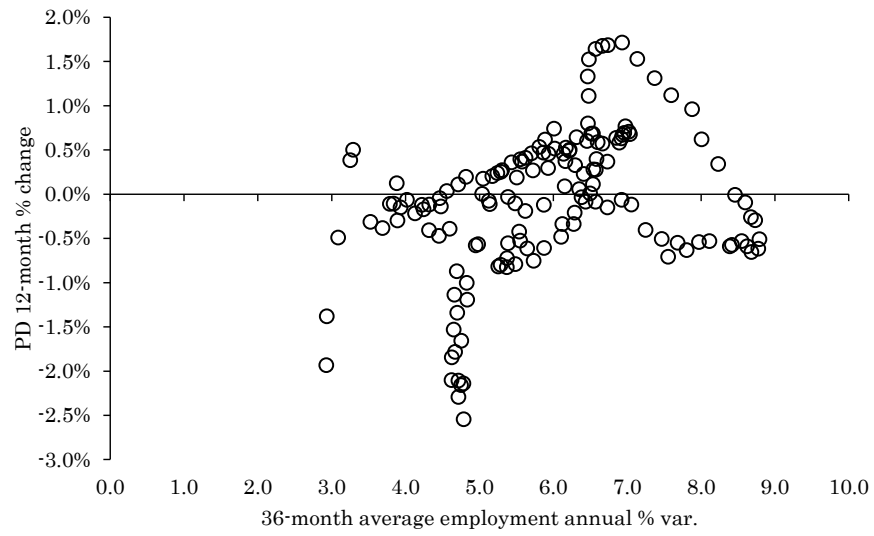
Source: SBS

Figure A.2: Grid search to find starting values for $credit_t$ model



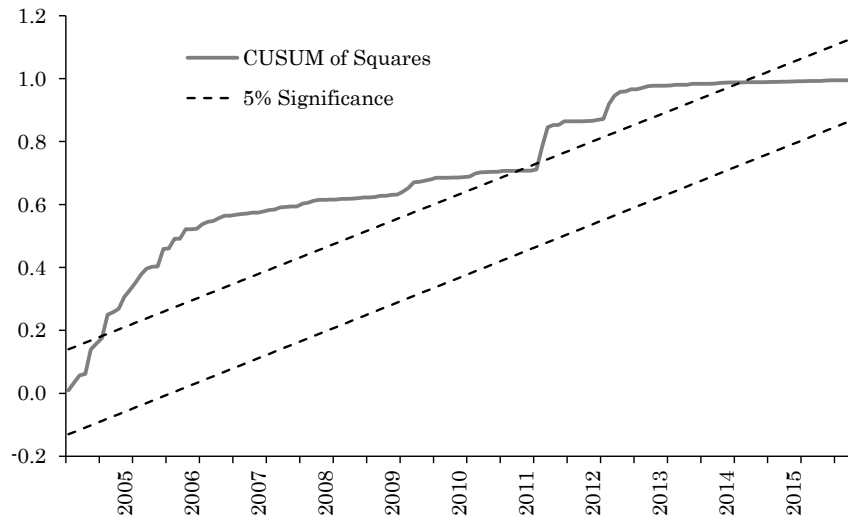
Source: SBS

Figure A.3: PD and GDP % var. scatter-plot (2003-2015)



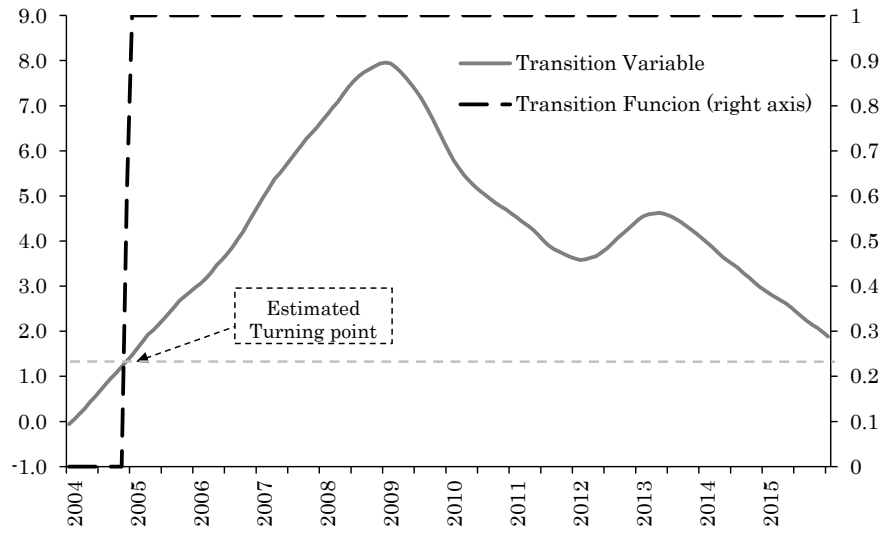
Source: SBS, BCRP

Figure A.4: CUSUM2 Test for pd_t linear model



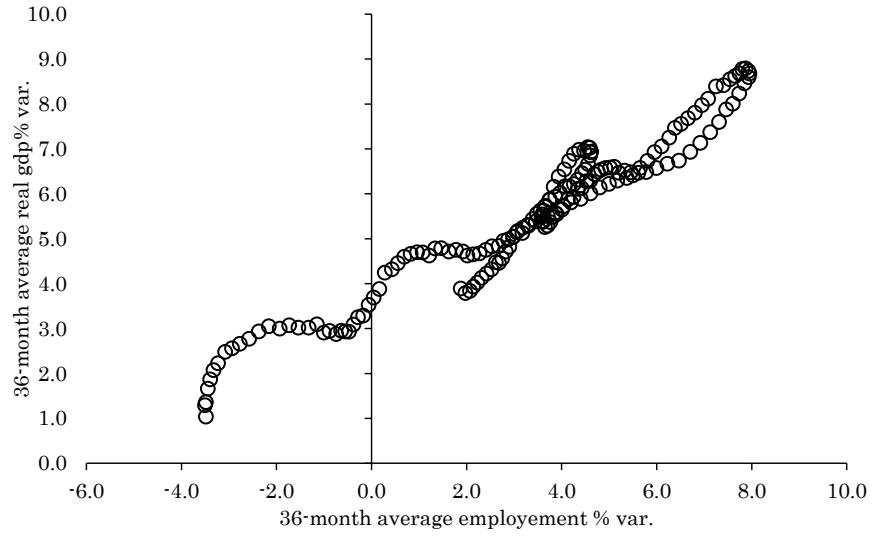
Source: SBS

Figure A.5: Estimated transition function and transition variable, pd_t



Source: SBS

Figure A.6: GDP and employment % var. scatter-plot (2001-2015)



Source: SBS, BCRP

Appendix - Tables

Table A.1: ADF Unit Root Test
(Dependent variable: $credit_t$)

	<i>t-stat</i>	<i>p-value</i> *
<i>Exogenous: None</i>	-2.792	0.005
<i>Exogenous: Constant</i>	-3.235	0.019

*MacKinnon (1996) one-sided *p-values*.

Table A.2: ADF Unit Root Test
(Dependent variable: pd_t)

	<i>t-stat</i>	<i>p-value</i> *
<i>Exogenous: None</i>	-3.660	0.000
<i>Exogenous: Constant</i>	-3.582	0.007

*MacKinnon (1996) one-sided *p-values*.

Table A.3: Chow Breakpoint Test for $credit_t$: 2001M06

<i>Sample: 2003M12 2015M12</i>	
<i>F-statistic</i>	3.125
<i>Log likelihood ratio</i>	9.427
<i>Prob. F(3,139)</i>	0.027
<i>Prob. Chi-square(3)</i>	0.024

Table A.4: Testing Linearity against STR
(Dependent variable: $credit_t$)

<i>Variables in AR part: Cons ; cred_{t-1} ; cred_{t-5}</i>					
<i>Sample range: 1998M06, 2015M12</i>					
	F	F4	F3	F2	suggested model
<i>p-value</i>	0.000	0.063	0.104	0.000	LSTR1

Appendix - Others

Definition of the probability of default

With the information provided by the RCD⁸, the probability of default is computed as:

$$PD_t = \frac{\sum_{i=1}^{N_{t-12}} D_{i,t-12} \times I(a_{i,t} > 60 \mid 60 \geq a_{i,t-12})}{\sum_{i=1}^{N_{t-12}} D_{i,t-12} \times I(60 \geq a_{i,t-12})}$$

Where:

- PD_t : Ratio of default in month t .
- $D_{i,t}$: Debt of individual i in month t .
- $a_{i,t}$: Days past due of individual i in month t .
- $I(\cdot)$: Indicatrix function, 1 if the argument is true; 0 otherwise.
- N_{t-12} : Number of individual in the financial system in month $t - 12$.

This ratio indicates what proportion of individuals who were in a situation of days past due less than 60 days in $t - 12$ went to a situation of days past due greater than 60 days, 12 months after this situation. For example, if the PD of January 2011 was 10%, this indicates that of 100 Soles that were in a situation of days past due less than 60 days in January 2011, ten of these migrated to a situation of days past due greater than 60 days in January 2011.

⁸Database at a debtor-level of the SBS.