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Identifying Threshold Effects in Credit Risk Stress Testing

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Identifying Threshold Effects in Credit Risk Stress Testing

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Abstract

Using data from Argentina, Australia, Colombia, El Salvador, Peru, and the United States, we identify three types of threshold effects when assessing the impact of economic activity on nonperforming loans (NPLs). For advanced financial systems showing low NPLs, there is an embedded self-correcting adjustment when NPLs exceed a minimum threshold. For financial systems in emerging markets in Latin America showing higher NPLs, there is instead a magnifying effect once NPLs cross a (higher) threshold. GDP growth apparently affects NPLs only below a certain threshold, which is consistent with observed lower elasticity of credit risk to changes in economic activity in boom periods.

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Contents Page

I. Introduction

Stress-testing exercises that focus on credit risk often face the problem of how to compensate for the lack of adequate market valuation of the quality of loan portfolios. In the absence of reliable market valuations, assessments by supervisory authorities or rating agencies help infer quantitative indicators of the quality of loan portfolios. Such assessments are, however, often insufficient and of low frequency (Blaschke and others, 2001), which complicate a general assessment of credit risk at a more aggregate level.

Partly because of these data limitations, credit risk modeling has been developed mainly by financial institutions operating in developed markets based on individual loan data. These institutions are normally capable of sophisticated modeling and adequate data quality control. Estimated expected losses are based on techniques comprising accounting analytical approaches, statistical predictions of default, Merton's option-theoretic approach, and migration analysis. Unexpected losses (or volatility of losses) have been estimated based on historical default volatility and volatility of holding period returns (J.P. Morgan, 1997). These approaches are not easily adaptable when individual loan data are not available.

At the aggregate level, the most commonly available indicator of loan portfolio quality is the actual default rate measured by the ratio of nonperforming loans to total loans (NPLs). When data of sufficiently good quality are available, two approaches can be used to assess the potential impact of economic variables on NPLs:

- A transition matrix could be constructed from a least-square fit to the cumulative default rates, for example, following a Markov process. This could be made conditional on the phase of the economic cycle or other variables;[2]
- Alternatively, regressions of NPLs against a set of economic variables could be performed directly.

The first approach has the advantage of a realistic representation of the behavior of loan default. The role of economic variables is limited, however, and specific features of the data become crucial. The second approach has the advantage of its relative simplicity and ability to incorporate more explanatory variables. However, it is less robust as it does not account for nonlinearities related to the starting credit quality of bank customers, it is not consistent with the nonnormality of the probability of default, and it normally does not constrain NPLs to remain within the range between 0 and 1.[3]

One way to incorporate nonlinearities which relies on data features to a lesser extent than Markov-based approaches, is to introduce thresholds beyond which causal relations are allowed to vary. One way to do this is to identify stressful situations based on proxy

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[2] For an application to emerging markets, see M. Segoviano (2000).

[3] A logit model cannot be easily applied at the aggregate level.

variables. However, there are reasons to believe that the thresholds would differ from country to country and bank to bank, and there is considerable subjectivity in the choice of critical values. Another way is to identify thresholds endogenously using econometric techniques.

This paper identifies endogenous thresholds applying *Self-Exciting Threshold Auto Regressions* (SETAR, originally proposed by Potter, 1995) to data for NPLs and growth in Argentina, Australia, Colombia, El Salvador, Peru, and the United States These countries were selected because reliability of data was found adequate, and their banking systems were not under a particular situation of stress in the corresponding sample periods. The methodology was also applied to Bulgaria, Nicaragua, Turkey, and Venezuela, with mixed results. These countries were, however, not incorporated into the exercise since information was only available for short time periods (Nicaragua), or showed pathological NPL levels (Bulgaria), or was just unreliable (Turkey and Venezuela).[4]

In the event, the relationship between NPLs and GDP growth was redefined by imposing the functional form of the normal distribution. In this way, endogenous GDP growth thresholds below which economic activity impacts negatively on NPLs were identified, implicitly constraining NPLs to remain between 0 and 1. This approach is based on the general observation that a prolonged boom would likely bring NPLs down close to a minimum delinquency rate, and thus a continuation of the boom or a moderate reversal would not have a strong impact on NPLs. Making an analogy with Merton’s approach, if the marginal nondelinquent borrower sees the present value of his assets decline, he would still not default as long as the value of assets exceeds that of liabilities.

The proposed methodologies allow for the identification of critical levels of NPLs and GDP growth that would constitute timely warnings about the potential deterioration of the loan portfolio. In this way, they have an advantage over other methodologies as the data itself would provide information beyond confirming the (obvious) negative relationship between GDP growth and NPLs. This paper tries to identify the level of NPLs and GDP growth that raises concerns about financial stability.

The paper is organized as follows: the next section describes the SETAR methodology in detail, including a comparison with the customary Markov-based approach, and presents the results of applying the SETAR methodology to data for the selected countries. Section III discusses the methodology used to infer the threshold level of GDP growth below which it has an impact on NPLs, and presents the results of applying the methodology to the corresponding data, and attempts to incorporate these findings within the framework of the SETAR methodology. Section IV summarizes and concludes.

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[4] NPL definitions vary (not a serious problem for parallel time-series regressions). NPLs in Argentina, Australia, Colombia and the United States are those that are 90 days past due, with some variations (loans affected by specific provisions in Australia, loans not accruing interest for the United States). NPLs are 60 days past due in El Salvador, and they go from 60 days due for consumer loans to 120 days for commercial and mortgage loans in Peru.

II. Identifying NPL Thresholds in the Relation Between Credit Risk and Growth

A. Methodology

Hamilton (1989) proposed a switching-regime Markov model that can account for rich dynamic behaviors such as conditional heteroscedasticity or asymmetry. In this section, we briefly present a simple version of Hamilton's model.

Assume the following model:

$$y_t = z_t + u_t \qquad (1)$$

where z_t is assumed to be nonstationary random walk, and u_t is assumed to be an error term which follows an AR(t) process of the form $\varphi(B)u_t = \varepsilon_t$, where ε_t is white noise.

Assume that the random walk drift evolves according to the following two-state Markov process:

$$z_t = \mu(S_t) + z_{t-1} = \alpha_0 + \alpha_1 S_t + z_{t-1} \qquad (2)$$

where:

$$P(S_t = 1/S_{t-1} = 1) = p$$
$$P(S_t = 0/S_{t-1} = 1) = 1-p$$
$$P(S_t = 1/S_{t-1} = 0) = 1-q$$
$$P(S_t = 0/S_{t-1} = 0) = q$$

The stochastic process S_t is assumed to be strictly stationary, with an AR(1) representation:

$$S_t = (1-q) + \lambda S_{t-1} + v_t \qquad (3)$$

where $\lambda=p+q+1$, and the error term has the following conditional probability distribution:

$$P(v_t = 1/S_{t-1} = 1) = p$$
$$P(v_t = -p/S_{t-1} = 1) = 1 - p$$
$$P(v_t = -(1 - q)/S_{t-1} = 0) = q$$
$$P(v_t = q/S_{t-1} = 0) = 1 - q$$

Also, it is assumed that:

$$E[v_t / S_{t-1} = 1] = E[v_t / S_{t-j} = 0] = 0, \forall j \geq 1$$

that is, it is uncorrelated with lagged values of S_t, but not necessarily independent.

The variance of the Markov process can be expressed as:

$$\alpha_1^2 \frac{(1-p)(1-q)}{(2-p-q)^2}$$

Now, (2) can be expressed as:

$$u_t = u_{t-1} - z_t - z_{t-1} - \alpha_0 - \alpha_1 S_t$$

Then, solving backwards yields:

$$u_t = z_t - z_0 - \alpha_0 t - \alpha_1 \sum_{i=1}^{l} S_i + u_0 \qquad (4)$$

Using the process for ε_t, and (4):

$$\varepsilon_t = \varphi(B)\left[z_t - z_0 - \alpha_0 t\right] + \varphi(1)u_0 - \alpha(1)\varphi(1)\sum_{i=1}^{l} S_i + \alpha(1)\sum_{j=1}^{r}\left(\sum_{k=j}^{r}\varphi_k\right)S_{t+j+1} \qquad (5)$$

Finally, assuming that the innovations are normally distributed, (5) can be used to evaluate the log-likelihood function, to obtain maximum-likelihood estimations.

The Markov model attempts to account for relatively complicated dynamics, and the switching-regime model would provide two sets of estimates (e.g., the GDP growth effect on NPLs per each state), if precise initial conditions are met. However, more often than not, even with good quality data, meeting initial conditions is not easily achievable. An alternative methodology is the use of a SETAR approach. Although this approach would provide for only one set of estimates correcting for the threshold effect, the SETAR model would explicitly find the endogenous threshold without requiring the precise initial conditions necessary for the application of switching-regime models.

The general principle underlying SETAR is the use of relatively simple econometric techniques to endogenously identify times of stress. There are different views in the literature on the way stress thresholds in general (and crisis periods, in particular) are identified. First, one could a priori define what a *stressful or fragile* position is (e.g., "there is a bank quality problem when 10 percent of loans are nonperforming" or "there is liquidity problem when reserves can only cover three months of imports"). But usually, the warning threshold would differ from bank to bank or from country to country and might change over time. The SETAR approach makes it unnecessary to use an ad hoc definition of stress and helps identify other statistical properties of the data.

The technique allows for the detection of "optimal" threshold levels for time series. It lets the parameter of a linear autoregressive model vary according to the values of a finite number of lags in the threshold. That is, the dependent variable is explained by its threshold and its lags. In the simplest case, assume one lag:

$$y_t = \alpha_0 + \alpha_1 T_t + \alpha_2 y_{t-1} + \alpha_3 T_t y_{t-1} + \varepsilon_t$$

where: *y* is the variable for which a threshold will be identified; and *T* is the threshold variable. Using this equation, the threshold is the value that yields the lowest standard error in the estimation.

B. Application to the Relation Between Credit Risk and Growth

SETAR estimations have been performed for six countries using quarterly data on real GDP growth and NPLs (see Box 1): Argentina (1995.4-2001.1); Australia (1994.3-2002.3); Colombia (1992.4-2001.2); El Salvador (1995.1-2003.1); Peru (1995.1-2003.1); and the United States (1992.1-2001.4). In the case of Australia, nonperforming loans are scaled by total assets.

Box 1. Real Activity and Credit Risk

As expected, averages and volatility of nonperforming loans were higher in the four developing countries (Argentina, Colombia, El Salvador, and Peru) relative to the values observed in developed countries (Australia and the United States). Patterns for individual countries are described below:

Basic Statistics (in percentage)1/

Country	Argentina		Australia		Colombia		El Salvador		Peru		United States	
	NPL	Growth	NPL	Growth	NPL	Growth	NPL	Growth	NPL	Growth	NPL	Growth
Sample	1995.4 - 2001.1		1994.3 - 2002.3		1992.4 - 2001.3		1995.1 - 2003.1		1995.1 - 2003.1		1992.1 - 2001.4	
Average	5.89	1.75	0.92	4.54	7.49	3.66	4.67	3.11	7.44	3.38	1.50	3.24
St. Dev.	2.38	4.99	0.53	1.75	2.72	0.82	1.05	3.35	2.02	3.93	0.79	1.33
Max.	10.79	9.22	2.54	9.16	12.78	4.90	7.31	11.99	10.34	14.40	3.70	4.90
Min.	1.59	-5.06	0.51	1.32	4.47	2.16	3.24	-3.27	4.70	-2.72	0.94	-0.35

Sources: National authorities, IFS.
1/ NPL for all countries is the share of nonperforming loans over total loans, except for Australia, for which the data obtained corresponds to the share on total assets.

Argentina. Nonperforming loans monotonically increased during the whole sample period, to accelerate at the beginning of 1999 coinciding with the beginning of an economic slowdown preceding the crisis. While GDP growth rates declined to -1.9 percent in 1999-2001 against 4.3 percent for 1995-1998, nonperforming loans increased from 4.4 percent to 8.0 percent.

Australia. Australia experienced an important expansion following sound macroeconomic policies characterized by a surge in productivity and increases in consumption and credit. GDP growth was, on average, 4.5 percent during most of the period of analysis, while the quality of loans monotonically improved, from around 2.5 percent in 1994 to 0.6 percent until 2002.

Colombia. Colombia experienced relatively high growth rates during 1992-2001, with occasional interruptions. The quality of loans experienced an important deterioration starting in 1998, with a moderate banking crisis taking place in 1999. Nonperforming loans averaged 10.4 percent in 1998-2001, against 5.5 percent for the period 1992-1997.

El Salvador. Structural reforms led to significant growth during most of the 1990's, with a deceleration starting in 1999 as a result of external shocks. Average GDP growth rates declined to 2 percent in 2000-2003, compared to 3.9 percent between 1995 and 1999. Nonperforming loans remained in the range of 4-6 percent for most of the sample period, increasing above 7 percent in 1999.

Peru. After expanding during the first half of the 1990s, a slowdown started in 1998-99, with some signs of a reversal at the end of the sample period. Nonperforming loans increased to 9.3 percent on average for 1999-2003, versus 5.6 percent from 1995 to 1998, with a decline in the GDP growth rate to 2.4 percent from 4.2 percent during the same period.

United States. The sample period was characterized by a continuous expansion following productivity gains. Real GDP grew on average at 3.2 percent, with nonperforming loans of 1.5 percent on average for the whole period. Nonperforming loans declined from around 3 percent in 1992-1993 to 1 percent in 1994-95, to remain at that level for the rest of the period.

The results presented in Table 1 show the following characteristics:

- **In general, the estimations have good overall fit**. Adjusted R-square and t statistics show robust results. Coefficients are statistically significant for the six countries.

- **The value of coefficients is as expected.** The coefficients for lagged values of NPLs have a positive sign and range from 0.55 (Colombia) to 0.84 (El Salvador).

- **The NPL thresholds identified by the methodology are low in developed economies.** The estimates are 1 percent for Australia and 1.5 percent for the United States The range is between 7 (El Salvador) and 10 percent (Colombia) for developing economies. This is consistent with higher average nonperforming loans in the sample period. It should be noted that the low threshold for Australia also reflects the use of NPL over assets as a dependent variable.

- **Thresholds seem to be of a different nature for advanced and emerging financial systems.** Thresholds are significant in most cases, the exceptions being Argentina (for the combined Threshold-NPL effect), and El Salvador. However, the threshold coefficients for Argentina, Colombia, El Salvador, and Peru have a positive sign, while they are negative for Australia and the United States This implies that, once the threshold is crossed, a magnifying effect is triggered, worsening the quality of loans for developing economies, while in developed countries, once the threshold is crossed, some kind of self-correcting mechanism starts to operate. This may reflect systemic safeguards activated by financial market participants, including supervisory authorities, to prevent NPLs from deteriorating further.

- **The interaction between the threshold variable and NPLs also shows differences between developed and developing countries.** For Australia and the United States, the coefficients are positive, while they are negative for Argentina, Colombia, El Salvador, and Peru. For Australia and the United States, once the threshold is crossed, the corresponding coefficients of lagged NPLs get closer to one (higher inertia). For Australia, the NPL (-1) coefficient increases in absolute terms from 0.64 to 0.86, while it increases from 0.8 to almost 1.0 for the United States On the other hand, when the threshold is crossed for the remaining emerging economies, past values of nonperforming loans turn closer to zero (with the exception of El Salvador), which implies a higher volatility of NPLs. Again, developed economies show self-correcting mechanisms to reduce NPL volatility once a certain (lower) threshold is crossed, unlike emerging economies.

- **Real GDP growth negatively affects credit risk across the sample.** Significance, as measured by the t statistic, is low (for El Salvador, the corresponding coefficient is of the opposite sign and not significant). Semi-elasticities of NPL relative to GDP growth vary widely, ranging from 0.0056 (Australia) to 0.1387 (Colombia).

Table 1. SETAR Regressions

Dependent Variable	**Argentina**	**Australia**	**Colombia**	**El Salvador**	**Peru**	**United States**
Non-Performing Loans						
Predetermined Variables 1/		**2/**				
Constant	0.0014	0.0025***	0.0322***	0.0064**	0.0139***	0.0030**
	(0.0009)	(0.0004)	(0.0069)	(0.0042)	(0.0051)	(0.0012)
GDP Growth	-0.0135*	-0.0056*	-0.1387***	.0237	-0.0624**	-0.0221**
	(0.0077)	(0.0032)	(0.0518)	(0.0242)	(0.0285)	(0.0109)
Non-Peforming Loans (-1)	0.6993***	0.6412***	0.5552***	0.8391***	0.7985***	0.7968***
	(0.2070)	(0.0451)	(0.0856)	(0.0840)	(0.0762)	(0.0829)
Threshold	0.0052**	-0.0017***	0.1079***	0.2261	0.0561***	-0.0047***
	(0.0014)	(0.0005)	(0.0157)	0.1642	(0.0170)	(0.0015)
Non-Performing Loans (-1) x Threshold	-0.6498	0.2181***	-0.7961***	-3.1256	-0.5272***	0.2000**
	(0.5806)	(0.0472)	(0.1525)	(2.3532)	(0.1885)	(0.0847)
Adjusted R-Square	0.6012	0.8897	0.8387	0.6444	0.8076	0.8909
Optimal NPL Threshold (in percent)	8.0	1.0	10.0	7.0	8.0	1.5
DW	1.7841	2.1125	2.1600	1.7451	1.8044	2.0732
Sample period	1995.4-2001.1	1994.3-2002.3	1992.4-2001.2	1995.1-2003.1	1995.1-2003.1	1992.1-2001.4
Observations	22	32	34	32	31	40

Notes.

1/ Standard errors are shown in parenthesis. ***, **, * denote 1%, 5% and 10% of significance respectively.

2/ For the case of Australia, non-performing loans are expressed as a percent of total assets.

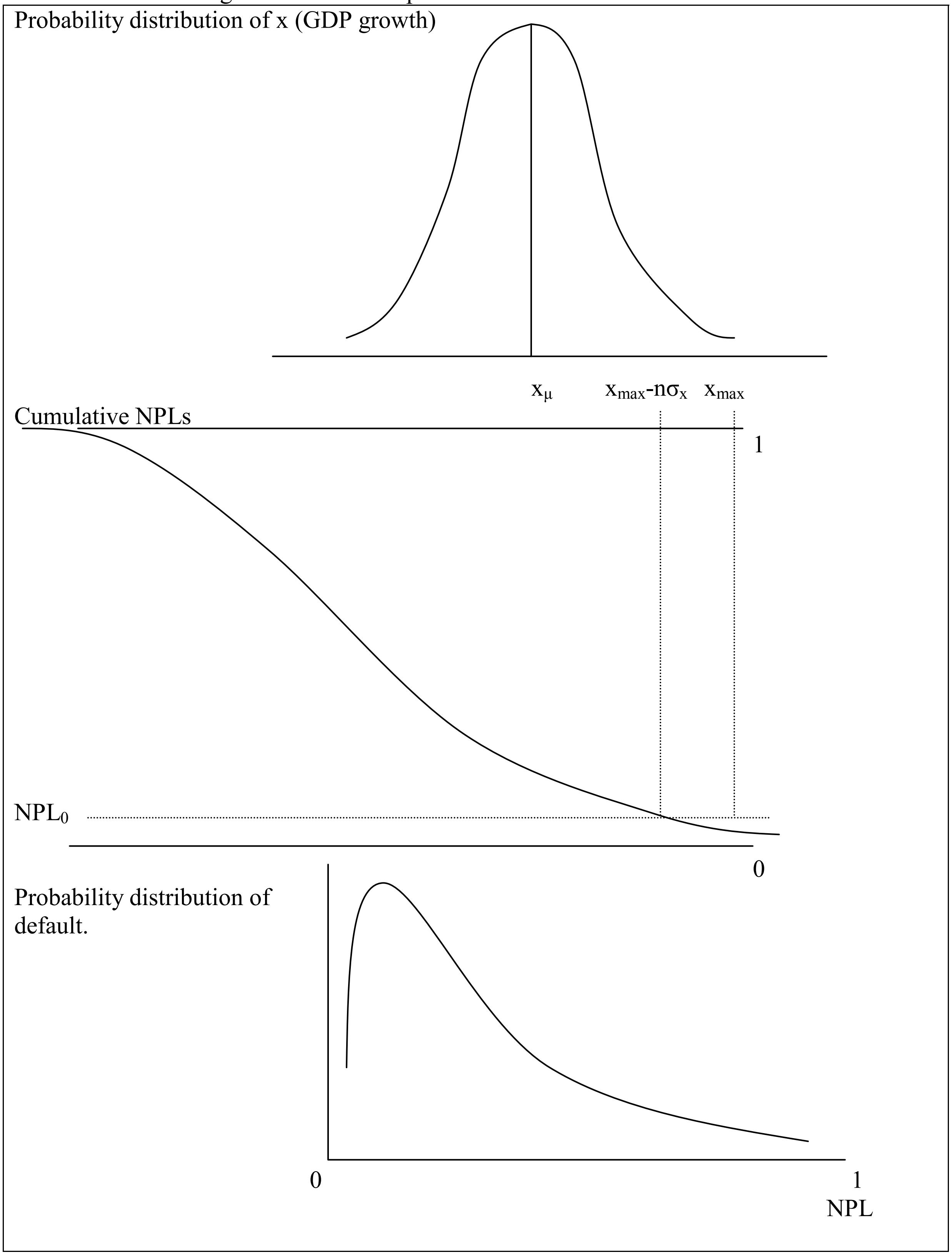
III. Identifying GDP Growth Thresholds

A. Methodology

It is likely that nonlinearities could also be present in the relationship between GDP growth and NPLs. In particular, within the business cycle, there may be values of GDP growth for which a deceleration of economic activity makes NPL increases more likely. Also, the results reported in the preceding section seem to suggest that allowing for nonlinearities in the relationship between GDP growth and NPLs in the corresponding specification would improve the fit. The SETAR methodology does not allow for nonlinearities in the explanatory variable. Therefore, we perform a complementary exercise assuming that the relationship between NPL and GDP growth follows the functional form of a normal distribution. Denoting GDP growth as x, at times of economic boom (high x), further increases of x would not only not improve compliance by 'good borrowers' (statistical impossibility) but also NPLs would have reached a level closer to a structural minimum. Likewise, a moderate deterioration of x would not affect the default rate.

Figure 1 shows the nature of the relationship between x and NPLs. The top chart shows the probability distribution of GDP growth (shown as symmetrical only for convenience). A high x (x_{max}) represents boom periods. Moving to the middle chart, changes in x within the vicinity of x_{max} will generally not affect NPLs, which would remain at NPL_0. For declines in x larger than a given number (n) of standard deviations of x (σ_x), NPLs will start declining. The bottom chart shows the corresponding probability of default, relating the probability distribution of x with the corresponding NPL. The resulting skewed probability of default is consistent with empirical evidence (Wilson, 1998).

Figure 1. Relationship Between GDP Growth and NPLs



In formal terms, *x* affects negatively NPL for $x < x_{max} - n\sigma_x$:

$$NPL = \int f(x)dx = \int \frac{e^{-(x-\mu)^2/(2\sigma^2)}dx}{\sigma\sqrt{2\pi}}$$

Note that σ and μ are the embedded mean and standard deviation in the normal distribution function (it is not equivalent to x_μ and σ_x). The following features are worth mentioning:

- Using a symmetric function such as the normal distribution to relate NPL and GDP growth is consistent with a skewed distribution of the probability of default, which is consistent with the empirical evidence;
- NPL values are restricted to be between zero and one and are directly related to an explicit default probability function;
- As the functional form is a priori specified, the unknown value to be identified is the threshold below which changes in *x* impact on NPLs along the chosen function.

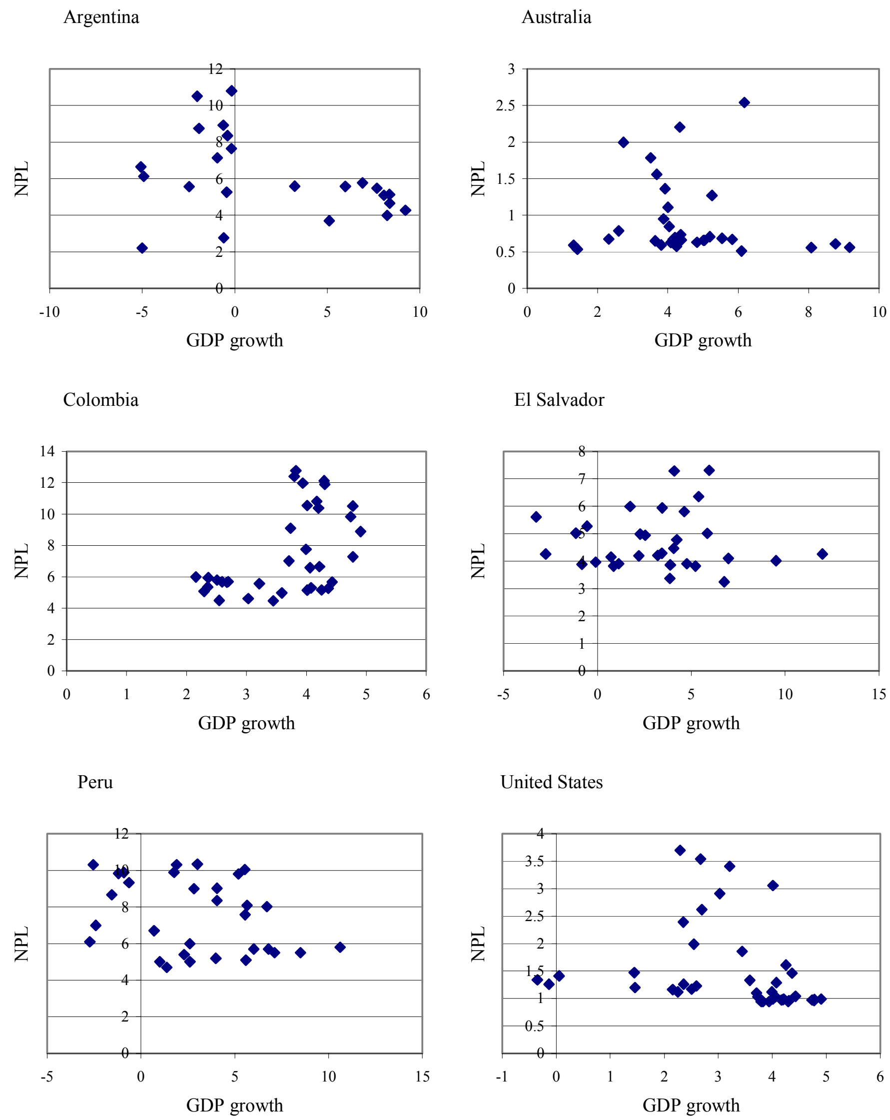
B. Application to the Relation Between Credit Risk and Growth

In this section, the unknown *n* is obtained by minimizing numerically the sum of residual squares for alternative values of n, imposing the additional condition that the highest value for *x* within the sample would lie at the midpoint of the 'buffer zone' below NPL_0 in the middle chart in Figure 1.

Figure 2 shows that, for most countries (with the exception of Colombia), high rates of growth are generally associated with low nonperforming loans and relatively low dispersion between NPLs at high levels of growth. However, the visual evidence is not clear-cut, as the sample periods are too short to show more than one business cycle, which would allow to show more observations corresponding to boom or bust periods.

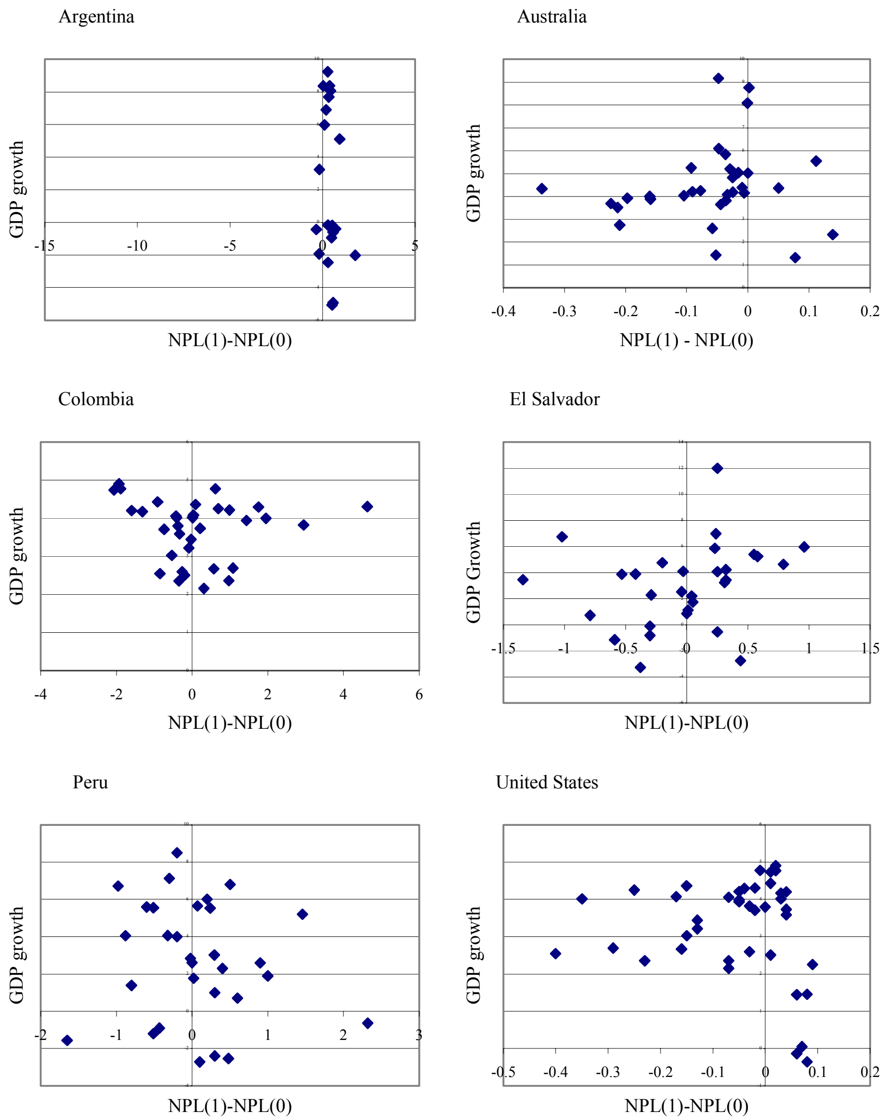
Figure 3 aims at illustrating that NPLs generally tend to remain at the level of the preceding period at high GDP growth rates. Evidence is again not clear-cut, presumably because of the nonlinearities in both NPL and GDP growth, including the changing volatility identified in the SETAR exercise for emerging economies. Evidence of stable levels of NPL at high rates of GDP growth is clearer for Argentina and Australia, and to some extent for Peru and the United States

Figure 2. GDP growth and NPLs



Source: IFS and National Authorities.

Figure 3. GDP growth and change in NPL



Source: IFS and Natiional Authorities.

Below are the results of the exercise, as summarized in Table 2:

- **Applying the ad hoc methodology results in a good overall fit.** Despite wide differences in the peak growth rate observed in the period, mean average growth, and standard deviation of GDP growth, the results for most countries show that applying this methodology could be justified (including Colombia, for which visual inspection seemed to indicate that the methodology may not be appropriate). One caveat is that this is only possible for a negative GDP growth threshold in the case of Argentina.[5]

- **GDP-growth thresholds generally lie between 1 and 2 percent.** The exception is Colombia, which shows a GDP-growth threshold of 2.75 percent, presumably indicating that the loan portfolio is more sensitive to declines in the GDP growth rate relative to the other countries in the sample. The United States and, surprisingly, El Salvador are the financial systems showing more potential resilience: GDP growth rates would need to decline below 1.1 percent to show an impact on NPLs.

- **The results are more significant for countries with more reliable information on NPLs (Australia and the United States)**. This may be related to the higher volatility of GDP growth and NPLs for emerging economies.

Table 2. GDP-Growth Thresholds

Dependent Variable	**Argentina**	**Australia**	**Colombia**	**El Salvador**	**Peru**	**United States**
Nonperforming loans						
Mean GDP growth	2.0	4.5	3.7	2.9	3	3.2
Maximum GDP growth	9.2	9.2	4.9	12.0	10.0	4.9
GDP growth standard deviation	4.925	1.75	0.82	3.19	3.43	1.33
Mean NPL	6.1	0.9	7.5	4.7	7.5	1.5
n	2.37	4.17	2.6	3.399	2.6	2.86
GDP-growth threshold	(2.45)	1.84	2.75	1.13	1.77	1.09
R-Square	0.720	0.919	0.746	0.690	0.629	0.970
Observations	23	32	34	31	30	40

Source: Staff estimates.

[5] If the GDP-growth threshold is too low, this may mean that the methodology does not apply for meaningful ranges of GDP growth.

To combine these findings with the SETAR methodology, we ran the SETAR regressions, including values for GDP growth only below the corresponding thresholds for each case. However, because of the number of zeros (which is also high in the case of the threshold variable), convergence is not easily achieved, and only results for the United States show that GDP growth is still significant after applying this variation of the SETAR methodology (Table 3). Further exploration of methodologies to incorporate nonlinearities in GDP growth must be conducted to account for the simultaneous triggering of thresholds within the same specification.

Table 3. SETAR Regressions Incorporating GDP-Growth Thresholds

Dependent Variable	Argentina	Australia	Colombia	El Salvador	Peru	United States
NPL						
Predetermined Variables 1/		2/				
Constant	0.5078**	0.2218***	1.5187***	3.6464***	1.4363***	0.1934***
	(0.2185)	(0.0523)	(0.3786)	(1.1934)	(0.3666)	(0.0531)
GDP growth	-0.0418	-0.0109	-0.0253	0.0256	-0.0432	-0.3188*
	(0.0385)	(0.0258)	(0.1144)	(0.0960)	(0.0894)	(0.1764)
NPL (-1)	0.9619***	0.6439***	0.7500	0.0614	0.7648***	0.8174***
	(0.0376)	(0.0747)	(0.0484)	(0.2956)	(0.0539)	(0.0444)
Threshold	0.8557***	-0.1780*	0.8999***	-0.23667*	0.6725***	-0.8218***
	(0.2400)	(0.0922)	(0.1819)	(0.1310)	(0.1369)	(0.1799)
NPL(-1) x Threshold	-0.7976***	0.2191**	-0.6660***	0.7169**	-0.5754***	0.3069***
	(0.2502)	(0.0851)	(0.1981)	(0.3121)	(0.1488)	(0.0707)
Adjusted R-Square	0.8812	0.8893	0.8386	0.6337	0.8541	0.8916
NPL Threshold (in percent)	8.9871	1.0109	10.8704	4.2400	9.1000	1.9400
DW	1.8908	2.2122	2.0351	1.5150	2.6369	1.9969
Sample Period	1995.3 - 2001.2	1994.3 - 2002.3	1992.4 - 2001.2	1995.1 - 2002.4	1195.1 - 2002.4	1992.1 - 2002.1
Observations	24	33	35	32	32	41

Notes:

1/ Standard errors are shown in parenthesis. ***, **, * denote 1 percent, 5 percent, and 10 percent of significance respectively.

2/ For the case of Australia, nonperforming loans are expressed as a percentage of total assets.

IV. Conclusions

We identify three types of threshold effects in analyzing the relationship between economic activity and credit risk. At relatively low levels of nonperforming loans, there is a self-correcting mechanism once nonperforming loans reach a level of between 1–1.5 percent of total loans (or assets). This is reinforced by a closer relation between current and lagged values of NPLs. At higher levels of nonperforming loans, there is a magnifying effect resulting from crossing that threshold, when NPLs reach between 8–10 percent of total loans. This is also reinforced by increased volatility in this indicator after a threshold level is surpassed. Finally, GDP growth also shows evidence of a more significant impact on NPLs below a threshold of about 1–2 percent of GDP growth.

Self-Exciting Threshold Auto Regressions prove to be useful to identify some of these patterns, while it does not require particular initial conditions as do regime-switching methodologies. It allows identifying a specific level at which different degrees of concern are warranted for supervisory purposes. If NPLs increase beyond a minimum threshold, and a reversion is not quickly observed, it should be a reason for vigilance, as this would mean that systemic safeguards may have weakened. If the second threshold is crossed, then the possibility of an explosive situation would require more decisive action. Magnifying effects at this level are quite significant for the emerging economies analyzed in this paper.

Part of the reason for this different behavior seems to be related to the differential impact of GDP growth on NPLs at different stages of the business cycle. A complementary methodology based on the imposition of a normal distribution function in the relation between NPLs and GDP growth is consistent with a skewed probability of default commonly accepted in the credit risk literature as the appropriate representation of probabilities of default. While SETAR does not allow identifying these differential elasticities, the complementary methodology does identify different levels of GDP growth that would trigger a stronger response of NPLs. Despite imposing values between zero and one for NPLs, goodness of fit is quite satisfactory, especially for developed economies for which information on NPLs is more reliable.

Both methodologies show promising results that would merit further development. In particular, how to incorporate the nonlinearities of explanatory variables would merit further research. This could allow for combinations of threshold effects in other explanatory variables, ideally within a multivariate framework.

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