Credit growth dynamics and banking crises

José Camarena

Diego Winkelried

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Abstract

A large body of literature grants a central role to the credit-to-GDP ratio as
being informative of cumulative vulnerabilities that jeopardize financial stability. It
is argued that the dynamics of this variable, in particular its accelerations, can
help anticipate banking crises and thus early warning systems often monitor its
evolution. We explore this claim by using the so-called $\ell_1$-filter which estimates
the trend component of a series as a piecewise linear function of time. Turning
points to this trend are very easy to identify and, when applied to the credit-to-GDP ratio, mark the beginning on regimes that may eventually lead to banking crises.
Using a panel of 95 countries over a 50-year period ending in 2011, we are able to
characterize such turning points and the dynamics of the credit-to-GDP ratio in the
pre-crisis regime. We find an enormous degree of heterogeneity in the behavior of
the credit-to-GDP ratio before the outbreak of a banking crisis, to the extent that
this indicator alone appears to be disassociated, at least cross-sectionally, with the
occurrence of banking crises.

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E-Mail: jcamarena@sbs.gob.pe, winkelried_dm@up.edu.pe

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2 José Camarena is Analyst at the Research Department of the SBS (Lima, Peru).

3 Diego Winkelried is Head of the Academic Department of Finance, Universidad del Pacifico (Lima, Perú).
I INTRODUCTION

The behavior of macroeconomic, financial and institutional variables is commonly evaluated in order to build Early Warning Systems (EWS) that trigger alerts if a set of identified conditions that typically precede the outbreak of banking crises is fulfilled. Despite the selected leading indicators of financial distress, a central issue for assessing the effectiveness of an EWS is its ability to anticipate the occurrence of a banking crisis (i.e. that the event occurs after the alert is triggered) giving enough time for preventive policy response (otherwise, the model would “confirm” rather than “predict” the event). Previous studies have usually analyzed the conditions of a set of variables lagged a certain number of periods before the start of crisis events. The number of lags is selected by a rule of thumb in consideration of the effectiveness requirements described above. However, an important limitation of this approach is that the situation at the selected past period (let’s say, 18 months before the onset of a banking crisis) could be the result of an earlier structural change (of one or more variables) which is not captured by the model. As the structural change that leads the model variables to its dangerous levels is not dated, probably the opportunity for taking earlier preventive action is lost.

As an example, let’s assume a one-factor EWS methodology that identifies dangerous levels of the credit-to-GDP gap 18 months before the start of banking crises (so that a critical threshold that helps to predict these events can be constructed). A clear weakness of this model is that the abnormal levels of the credit-to-GDP gap that eventually trigger the alert could be the result of a previous, sustained, acceleration of the credit-to-GDP ratio that occurred way before exceeding the critical threshold. In this way, a substantial time for risk mitigation policy (i.e. to press the break pedal of credit) would be missed and a response by the time the alert is triggered would probably be more costly (in terms of public funds or adjustment costs). Therefore, techniques that track structural changes in economic variables that can be linked to the progressive generation of vulnerabilities in the financial system may come in handy.

In order to fill this methodological gap, this paper develops a filter that dates clear turning points (or structural changes) in the mid- to long-term component (henceforth, the trend) of economic variables. The focus is on the mid- to long-term dynamics as from the policy maker’s point of view it would be attractive to evaluate if there are certain combinations of trend shifts that help to predict the occurrence of banking crises with further anticipation than the current EWS developed in literature. Specifically, we estimate the trend component by adapting the $\ell_1$-filter advanced in Kim et al. (2009). This filter resembles in many ways the celebrated Hodrick and Prescott (1997) filter, but has the peculiarity that the resulting trend is piecewise linear. Thus, the changes in slope of the estimated trend, which are very easy to detect, reflect structural breaks in the underlying time series. This feature of the $\ell_1$-filter makes it very suitable for the identification of regimes associated to differentiated behavior of the variable under analysis. As an illustration of the usefulness of the proposed methodology, the filter is applied to study the trend behavior of a variable commonly cited in the banking crisis literature: the credit-to-GDP ratio. Then, we use the filtered information, which could be regarded as a summary of the main features of the credit dynamics, to explore its ability to anticipate banking crises.

Besides the fact that the $\ell_1$-filter provides a convenient methodology to clearly identify turning points, the rationale of using such tool in empirical work follows from insights in Hausmann et al. (2005). These authors, in the study of economic growth, argue that time series data are often plagued with irrelevant information, not only noise but also short-run variation that obscures the trend developments that reflect the relatively few “big picture” events (i.e. the turning points of the trend) that are of economic importance. We reckon that such conclusion applies also to financial variables, especially if they are viewed as determinants of such important and extreme developments.

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1 The $\ell_1$ filter has been successfully applied in other empirical economic branches. For instance, Kim et al. (2009) compute the trend of the S&P 500 index to identify bearish and bullish episodes in the stock market, Yamada and Jin (2013) use the filter to determine the output gap in Japan, and Yamada and Yoon (2014) and Winkelried (2015) analyze the behavior of long-run trends in primary commodity prices. To the best of our knowledge, this paper is the first to use the $\ell_1$-filter in a financial economics application.
events as banking crisis.

Most of the methodological discussion that follows centers around results from the business cycle literature. In particular, the calibration of the $\ell_1$-filter render estimated trends that can be interpreted as the components that account for the movements of the time series of about 10 years or more. Borio (2014) shows that financial cycles are substantially longer than business cycles, and so even though our calibration lead to trends that would correspond to a long-run component from the perspective of the business cycle literature, such trends can well be regarded as short-run components, from a financial point of view.

In our empirical application, the average and median duration of regimes in the credit-to-GDP ratio $\ell_1$-trends is about 7 to 8 years. Hence, it can be expected that the $\ell_1$-trend for a given country drawn from our 50-year sample would exhibit about 6 to 7 regimes, or linear segments, and it turns out that most of the variation in the credit-to-GDP ratio is captured by its $\ell_1$-trend. For instance, the turning points in the raw data coincide with the kink point of the piecewise linear trend (a fact that can be observed in the examples shown in Figure 2 below, which are very representative of what happens for all countries). Thus, in agreement with the conclusions of Borio (2014), the $\ell_1$-trends rather than isolating are heavily influenced by “financial cycle fluctuations”.

The rest of the paper is organized as follows. Section II reviews the literature on the role of credit variables as determinants of banking crises and as leading indicators used in EWS. Section III describes the $\ell_1$-filter with emphasis in how to suitably calibrate and interpret the resulting estimated trends. Section IV applies the $\ell_1$-filter to a vast dataset of credit-to-GDP ratios around the globe and explores the relationship between the turning points of the resulting trends, and the main features of the various underlying regimes, to the outbreak of banking crises. Section V concludes.

II LITERATURE REVIEW

Studies that develop and evaluate the performance of Early Warning Systems can be classified in two major categories according to the number of financial institutions affected by the predicted crisis event: (i) firm-specific and (ii) system-wide. At the firm-specific level, Bongini et al. (2002) provide an extensive view of the existing work of early warning indicators of bank fragility. At the system-wide level (which is the one we adopt in our empirical application), two main literature branches for building EWS can be found: (i) the limited dependent variable approach and (ii) signal extraction methods.

As stated in Davis and Karim (2008), in the limited dependent variable approach, a dichotomous (or categorical) variable that reflects the occurrence or non-occurrence of a banking crises in a specified period is modeled against a set of (lagged) macroeconomic, financial and institutional variables using a logit/probit regression model. On the other hand, signal extraction methods are non-parametric techniques that seek to predict the occurrence of an event based on the previous observation of abnormal levels of one or more variables. In order to identify the abnormal levels, each variable’s threshold is estimated (either in an specific country’s time series or in a country panel) such that an objective function (defined in terms of Type I and/or Type II errors) is optimized. Specifically, Type I error stands for the failure to call a crisis (i.e. that no signal is triggered but a crisis follows in a defined time window after the evaluated point), while Type II error stands for a false alarm (i.e. that an alert is triggered but no crisis follows in the posterior time interval). Depending on the policy maker’s preference for a signal extraction based EWS, the optimization problem would be to determine the threshold of each variable that minimizes either type of error.

Also, as there is an statistical trade-off between Type I and Type II errors, a popular approach introduced by Kaminsky and Reinhart (1999) is to minimize Type I and Type II errors simultaneously, as defined by the Noise-to-Signal Ratio (NTSR): $[\text{Type II error}/(1-\text{Type I error})]$. 


Turning separately to each branch of literature, Demirgüç-Kunt and Detragiache (1998) multivariate logit model of the probability of banking crises imposes as a seminal paper of the limited dependent variable approach. As explanatory variables, the following “traditional” regressors are considered: the rate of growth of real GDP, the external terms of trade, the real short-term interest rate, the ratio of credit to the private sector to GDP, the change in real credit, inflation, the rate of depreciation of the exchange rate, the ratio of M2 to foreign reserves, the government surplus as a percentage of GDP, the ratio of bank cash and reserves to bank assets, a dummy variable that indicates the presence of a deposit insurance scheme, indexes of the quality of the legal system, of contract enforcement, and of the bureaucracy. In the estimated model specifications, a causal relationship between the dependent and the explanatory variables is not assumed. Instead, regressors are included in the sense that a theoretical correlation with non-observable risk factors (credit, market, operational, among others) and parameters (such as risk aversion) can be established.

In the original specification of the logit model of Demirgüç-Kunt and Detragiache (1998) (estimated for an annual panel of 45-65 market economies between 1980-1994) “contemporaneous” variables are included with different lagged values for some of the regressors (mainly as a robustness check). The authors lean on previous signal-extraction papers that confirm the sign of the estimated coefficients as well as on theoretical assumptions to deal with endogeneity concerns. Besides, when lagging the model variables, most of their coefficients turn non-significant, which they interpret as a signal that the time it takes for negative economic shocks to be transmitted to the banking sector is quite short. When evaluating the in-sample performance of the best specification of the model, 17 out of 23 crisis episodes are predicted (8 cases contemporaneously, 6 cases with a one-year time interval before the crisis event, and 3 cases with a time interval of three or more years before the crisis event). Among the main findings, they conclude that low GDP growth, high inflation, and explicit deposit insurance programs (which induce moral hazard) are relevant predictors of financial distress.

Follow-ups of the study performed by the authors in 1999, 2000, 2002, and 2005 (Demirgüç-Kunt and Detragiache (1999), Demirgüç-Kunt and Detragiache (2000), Demirgüç-Kunt and Detragiache (2002), and Demirgüç-Kunt and Detragiache (2005), respectively), extend the sample size and deepen the analysis of the effects of financial liberalization, the institutional environment and the presence of explicit deposit insurance programs in the baseline model. Also, out-of-sample predictive power of the EWS design is evaluated by using routine forecasts of the explanatory variables. However, the original model (mostly based on contemporaneous variables) remains unchanged. Other authors follow this line. Barrel et al. (2010) estimate logit models of banking crises in OECD countries and find that capital adequacy and liquidity ratios, as well as property prices, are the most important predictors of financial distress for this block of advanced economies. This allows to exclude several of the traditional variables of the Demirgüc-Kunt and Detragiache literature from the EWS design. The authors remark that using a common set of regressors for an heterogeneous sample of countries (as in previous work) is inadequate because variables that trigger crisis alerts should depend on the type of the economy and the nature of the banking system. Also, with the intent of reducing endogeneity issues and to have “predictive” rather than “confirming” indicators of banking crises, all regressors are lagged at least one year (based on an ad-hoc rule).

Another approach is proposed by Bussiere and Fratzscher (2006), where a multinomial logit model with three regimes (a tranquil time, a pre-crisis regime, and a post-crisis/recovery regime) is implemented in replace of the traditional dichotomous banking crisis variable. The motivation behind the use of this empirical methodology is to correct for what they call a “post-crisis bias” (i.e. that economic variables go through an adjustment process after a crisis event, before reaching a more sustainable level or growth path). Their assessment concludes that the three-regime estimation

3High inflation is supposed to increase interest rate volatility and make it difficult for banks to perform maturity transformation.

4For example, advanced economies characterized by higher levels of financial intermediation and interconnectedness should not have the same crisis determinants as emerging economies.
approach contributes substantially to the forecasting ability of the EWS models.\footnote{It is important to mention that Bussiere and Fratzscher (2006) focus on studying “financial crises” (including currency crises) instead of the specific case of banking crises.}

On the side of the literature of signal extraction methods, the seminal work of Kaminsky and Reinhart (1999) calculate thresholds that determine abnormal behaviors of economic variables on an indicator-by-indicator basis. In order to build an EWS for banking crises, an alert is considered to be right if a banking crisis occurs 12 months following the warning signal, or if the warning signal is registered in the 12 months following the onset of the crisis. Then, as described at the beginning of this section, individual thresholds are selected for each variable by minimizing their NTSR. The authors conclude that variables related to the real sector (such as output and stock prices) appear to be considerably important to anticipate banking crises. The fundamental intuition of this technique remains intact in the posterior literature, with variations in one or more of the following components of the methodology: (i) the specification of the minimized objective function used to estimate thresholds, (ii) the type of indicator (univariate or composite) for which thresholds are determined and (iii) the time interval in which an alert is considered to be correct.

Kaminsky (1999), for example, develops a composite indicator of banking crises by adding signal dummy variables (i.e. that take the value of one if a specific variable’s level exceeds a critical value) weighted by the inverse of their NTSR. For their signal dummy variables to enter the composite measure, each individual variable must have a NTSR lower than given threshold. Then, the resulting indicator can be applied as a quantitative measure of bank fragility. Borio and Lowe (2002) extend further the construction of composite indicators by estimating deviations from trend levels (“gaps”) of three variables related to the incubation of banking crisis: the ratio of private sector credit to GDP, equity prices (deflated by the price level) and the real effective exchange rate. Then, a variation of NTSR that gives a greater penalization to Type I errors is used to estimate individual thresholds for each series, considering after-signal evaluation windows of 1, 2 and 3 years. Finally, for each possible combination of indicators, a predictive performance evaluation is carried out to make recommendations on the most suitable sets of indicators for different kinds of economies.

Despite the extensive work developed in the two main branches of the system-wide literature, there is no absolute winner between both kinds of approaches. Studies such as Davis and Karim (2008) suggest that the logit is the most appropriate approach for global EWS while signal extraction should be preferred for country specific ones. However, as stated before, some EWS may be suitable for certain kinds of economies, while others not, so the focus should be instead given to the verification that the elected methodology adjusts to the policy needs, as discussed in Drehmann and Juselius (2014). For the purpose of the current paper, the literature review served to confirm that most of the EWS research has focused on identifying dangerous “pictures” of variables in specific points in time that serve to predict the imminent outbreak of banking crises. Little or no attention has been paid to the possibility that combinations of previous (not necessarily contemporaneous) shifts in the mid- to long-run behavior of economic variables could have been the factors that progressively led to some crisis events. Moreover, it is interesting to find that credit-to-GDP and credit growth may not be very informative leading indicators of banking crises\footnote{As additional sources for the discussion of the relevance of credit measures in predicting banking crises, see Laeven (2011) and von Hagen and Ho (2007).}. On the contrary, they are usually included as part of a broader set of regressors, where other variables tend to be the most statistically significant.

### III METHODOLOGICAL ISSUES

Next we describe the filtering procedure used in our empirical work. There exist a variety of techniques to estimate the trend component of a time series. As our interest is to study the changes in the trend behavior, the selected methodology should meet the practical requirement of being able to clearly identify turning points. Such changes may be interpreted as structural breaks marking the beginning of a new regime, and the $\ell_1$ approach described below is well-suited for this purpose.
Let us introduce some notation. Let \( z \in \mathbb{R}^n \) be a \( n \)-vector whose \( i \)-th element is denoted by \( z_i \). The length of \( z \) may be measured by alternative norms: namely, the Euclidean \( \ell_2 \)-norm \( \| z \|_2^2 = \sum (z_i)^2 \) or the \( \ell_1 \)-norm \( \| z \|_1 = \sum |z_i| \). On the other hand, consider a \( (n-2) \times n \) matrix \( D \) such that \( Dz \in \mathbb{R}^{n-2} \) is a \( (n-2) \)-vector whose entries correspond to the second differences of the entries of \( z \); the \( i \)-th element of \( Dz \) is \( \Delta^2 z_i = z_{i+2} - 2z_{i+1} + z_i \) for \( i = 1, 2, \ldots, n-2 \).

### III.1 The Hodrick-Prescott filter

The Hodrick and Prescott (1997) filter, henceforth the \( \ell_2 \)-filter, is admitted the most popular univariate method in economics for trend estimation, and its properties have been thoroughly documented (see, inter alia, King and Rebelo, 1993). Given an \( n \)-vector of data \( y \), the \( \ell_2 \)-trend is the vector \( x \) that minimizes

\[
Q_2(x, \lambda_2 \mid y) = \| y - x \|_2^2 + \lambda_2 \| Dx \|_2^2,\]

(1)

Estimating the \( \ell_2 \)-trend, \( x_2 \), can be regarded as a fitting problem, where the error \( \| y - x \|_2^2 \) is minimized subject to smoothing constraints captured by the penalty term \( \| Dx \|_2^2 \). The constant \( \lambda_2 \) controls the trade-off between goodness of fit and smoothness. The larger \( \lambda_2 \), the smoother the resulting \( \ell_2 \)-trend. It is well-known that if \( \lambda_2 \to 0 \), then the \( \ell_2 \)-trend converges to the original series, \( x_2 \to y \), whereas at the other extreme, if \( \lambda_2 \to \infty \), then \( x_2 \) approaches the linear trend that fits the data best.

Since (1) is a quadratic function of \( x \), its minimizer is a linear function of \( y \), i.e. it can be expressed as \( x_2 = A(\lambda_2)y \), where \( A(\lambda_2) \) depends on \( \lambda_2 \) but does not depend on \( y \). This linearity, well understood by practitioners, is manifested when the data is subject to an affine transformation. Given \( \lambda_2 \), if \( x_2 \) is the \( \ell_2 \)-trend of \( y \), then \( ax_2 + c \) is the \( \ell_2 \)-trend of \( ay + c \), where \( a \) and \( c \) are arbitrary scalars. In fact, it is simple to verify that \( Q_2(ax + c, \lambda_2 \mid ay + c) = a^2Q_2(x, \lambda_2 \mid y) \), which is proportional to \( Q_2(x, \lambda_2 \mid y) \). Thus, the objective functions of the original and transformed problems lead to the same filtering operation \( A(\lambda_2) \).

Furthermore, the linearity of the \( \ell_2 \)-filter allows us to study its properties in the frequency domain. The \( \ell_2 \)-filter is a low-pass filter, designed to preserve variation in the data associated to low frequencies (in the time domain, the medium-to-long term) and to attenuate or to remove high-frequency (short-term) variation. This aspect of the filter is quite useful to calibrate the value of \( \lambda_2 \) and to give a precise interpretation to the estimated trend. For data sampled \( s \) times per year (\( s = 1 \), annual; \( s = 4 \), quarterly) and a cutoff period of \( T \) years, setting

\[
\lambda_2 = \frac{1}{16} \sin \left( \frac{\pi}{Ts} \right)^{-4}
\]

(2)

produces a trend that can be interpreted as the component of the series that isolates the series fluctuations of \( T \) years or more, whereas the residual series \( y - x_2 \) captures variation of less than \( T \) years (see Gomez, 2001). In the business cycles literature, where the \( \ell_2 \)-filter is extensively used, the popular choice of \( \lambda_2 = 1600 \) for quarterly data (\( s = 4 \)) is associated with a cutoff period of \( Ts = 39.7 \) quarters or \( T = 9.9 \) years, which reflects the consensus that fluctuations in economic data beyond approximately 10 years are to be attributed to trend developments (see King and Rebelo, 1993). The same cutoff period of 9.9 years corresponds to \( \lambda_2 = 6.6 \) for annual data (\( s = 1 \)), which in turn corresponds closely to the value of \( \lambda_2 = 6.25 \) proposed by Ravn and Uhlig (2002). Since \( \lambda_2 \) is an increasing function of \( T \), then the \( \ell_2 \)-trend is unsurprisingly smoother for larger values of \( T \).

Nonetheless, the \( \ell_2 \)-filter does not identify the turning points in the trend clearly, since the it estimates curved paths around low frequency transitions. The \( \ell_1 \)-filter provides such refinement.

### III.2 The \( \ell_1 \)-filter

Kim et al. (2009) propose an interesting variation to the Hodrick and Prescott filter. In particular, the \( \ell_2 \)-norm in the penalty term in (1) is replaced by an \( \ell_1 \)-norm, so the \( \ell_1 \)-trend is obtained by
minimizing

$$Q_1(x, \lambda_1 \mid y) = \|y - x\|^2 + \lambda_1 \|Dx\|_1.$$  

The constant $\lambda_1$ is also a smoothing parameter, and Kim et al. (2009) show that like the $\ell_2$-filter, the $\ell_1$-trend converges to the original data vector, $x_1 \to y$, when $\lambda_1 \to 0$, whereas it converges to the least squares linear trend as $\lambda_1 \to \infty$.

The $\ell_2$-norm in the Hodrick and Prescott ensures that $\Delta^2 x_1$ takes relatively small values, whereas the $\ell_1$-norm induces these values to be exactly zero. Hence, unlike the $\ell_2$-trend which is a continuous function of time, the $\ell_1$-trend is a piecewise function of time that connects $k+1$ linear segments, where $k$ is the number of changes or “structural breaks” in the series. See Yamada and Jin (2013), Yamada and Yoon (2014) and Winkelried (2015) for further discussion on the workings of this filter.

The distinctive characteristic of the $\ell_1$ filter of producing a piecewise linear trend, allows us to identify turning points straightforwardly. The turning points are, in fact, kink points connecting two adjacent linear segments, and each kink point marks a change in the underlying trend dynamics.

Figure 1 shows how $\ell_1$ compares to $\ell_2$ in practice and illustrates rather eloquently the suitability of the $\ell_1$ approach to identify turning points, even visually. Note that if the trend is estimated over a series in logarithms, the slope of each segment measures the mean growth rate of the contained data points, and the changes in the trend growth rate at the kink points can be easily quantified.

III.3 Calibration of the $\ell_1$-filter

A remaining open question is how to suitably calibrate $\lambda_1$. This task is complicated by the fact that, unlike the $\ell_2$-trend, the $\ell_1$-trend is a nonlinear function of $y$, schematically $x_1 = B(\lambda_1, y)y$ where $B(\lambda_1, y)$ depends on $\lambda_1$ and $y$, which prevents us to obtain clear-cut expressions like (2) for this filter.

The main difficulty seems to be that an adequate calibration of $\lambda_1$ needs to be data-dependent. This can be illustrated in several ways. For instance, Kim et al. (2009) show that the $\ell_1$-trend becomes invariant to $\lambda_1$, and equal to the least squares linear trend, for all $\lambda_1 \geq \lambda_{\text{max}} = \|(D'D)^{-1}D'y\|_\infty$, where $\|z\|_\infty = \max_i |z_i|$ is the $\ell_\infty$-norm. That $\lambda_{\text{max}}$ depends on $y$ points out, of course, to the data-driven nature of the choice of $\lambda_1$. On the other hand and more formally, it is not difficult to verify that if $x_1$ is the $\ell_1$-trend of $y$, then $ax_1 + c$ is not the $\ell_1$-trend of $ay + c$ unless $\lambda_1$ changes to reflect the transformation of the data. Indeed, now we have

$$Q_1(ax + c, \lambda_1 \mid ay + c) = a^2Q_1(x, \lambda_1 \mid y),$$

which is not proportional to $Q_1(x, \lambda_1 \mid y)$. Thus, given $\lambda_1$, the objective functions for the original and transformed problems imply different filtering operations, respectively $B(\lambda_1, y)$ and $B(\lambda_1/a, ay + c) \neq B(\lambda_1, ay + c)$.

Thus, when $\lambda_1$ is set in an arbitrary fashion, the nonlinearity of the $\ell_1$-filter hinders the interpretability of the estimated trend. Given the analogies with the $\ell_2$-filter that originally motivated the $\ell_1$-filter, a sensible course of action is to choose $\lambda_1$ such that the resulting $\ell_1$-trend, whose properties are obscure, resembles an $\ell_2$-trend whose properties as a low-pass filter are well understood. Put it differently, since the $\ell_2$-trend with parameter $\lambda_2$ amounts to a $T$-year trend, where $T$ is implicitly defined in (2), then the “closest” $\ell_1$-trend might well be interpreted as a $T$-year piecewise linear trend.

To elaborate, let $x_2(\lambda_2)$ denote the $\ell_2$-trend that uses $\lambda_2$ as a smoothing parameter, and $x_1(\lambda_1)$ denote the $\ell_1$-trend that uses $\lambda_1$ as a smoothing parameter (to avoid clutter, we leave the dependency on $y$ implicit). Define the same fitting error

$$E(\lambda_1, \lambda_2) = \|y - x_2(\lambda_2)\|^2_2 - \|y - x_1(\lambda_1)\|^2_2.$$  

Following Yamada and Jin (2013), we can determine the value of $\lambda_1$ that makes (4) equal to zero for a given $\lambda_2$. Here, we have that for a positive and finite $\lambda_2$, $E(0, \lambda_2) > 0$ and $E(\lambda_1, \lambda_2) < 0$ for any $\lambda_1 \geq \lambda_{\text{max}}$. However, given that the number of linear segments in $x_1(\lambda_1)$ may change
discreetly with a marginal change in $\lambda_1$, $E(\lambda_1, \lambda_2)$ may not be continuous in $\lambda_1$. Hence, a suitable value of $\lambda_1$ in this case may be, for instance, a minimizer of $|E(\lambda_1, \lambda_2)|$, which brings (4) as close to zero as possible. Such minima always exist and satisfy $\lambda^*_1 \in (0, \lambda_{\max})$. Thus, the $\ell_1$-trend that minimizes the above criterion given $\lambda_2$ may be interpreted as a $T$-year piecewise linear trend.

III.4 Further polishing

By calibrating $\ell_1$-filter through the minimization of (4), we are allowing the Hodrick and Prescott to identify a neighborhood around a potential turning point and the $\ell_1$ filter to choose the most appropriate knot in terms of goodness of fit. However, the $\ell_1$ trend itself should be regarded as a preliminary estimate since, in principle, nothing constrains the corresponding kink points to be reasonably apart in time, or to mark statistically different regimes. To ensure that such requirements are met, we use the following procedure:

1. Obtain a preliminary $\ell_1$ trend with the $\lambda_1$ that minimizes $E(\cdot)$, for $\lambda_2 = 6.25$, following the suggestion of Ravn and Uhlig (2002). This is so because of data are annual in our analysis. Of course, if data of other frequencies were to be used, suitable values of $\lambda_2$ can be determined following Ravn and Uhlig (2002) or Gomez (2001).

2. The kink points of the $\ell_1$ trend are identified as the years $t$ where the absolute value of $\Delta x_{2,t} - \Delta x_{2,t-1}$ is greater than 0.01.

3. In order to clean the set of kink points from knots associated to short-term fluctuations that generate shifts in the piecewise linear trend (and, in consequence, extra kink points), a separation constraint is imposed. There must exist at least 5 years between the occurrence of two different kink points. For instance, if a kink point takes places in 1970, the earliest following knot will occur at 1976.

4. Given the identified kink points, a piecewise linear trend of the selected variable is estimated as the predicted value of a linear continuous spline regression with breaks at the kink points:

$$y_t = \beta_0 + \beta_1 t + \sum_{p=1}^K \beta_{p+1} D_p(t - t_p) + \text{error}_t,$$

where $y_t$ refers to the selected variable, $t$ to a time trend variable ($t = 1, 2, 3, ...$), $K$ to the number of kink points of the series, $D_p$ to a dummy variable equal to one if $t \geq t_p$ and zero otherwise, and $t_p$ to the value of the trend variable at the period of kink point $p$.

5. A kink point of the new piecewise linear trend series is considered to be “relevant” if the coefficient associated to the dummy variable $D_p(t - t_p)$ is statistically significant at a 5 percent confidence level.

6. Finally, the piecewise linear trend is reestimated as the fitted values of a linear continuous spline regression with breaks at the “relevant” kink point. In order to reach the final specification of the model: (i) equation (5) is estimated, (ii) the knots associated to non-significant $D_p(t - t_p)$ terms are discarded as kink points, (iii) equation (5) is reestimated with the reduced number of kink points, and (iv) steps are (ii) and (iii) are repeated until only significant terms remain.

Clearly, the thresholds applied in this procedure would affect the number of relevant kink points used to build the piecewise linear trend. Nevertheless, in our application below the described procedure identifies unambiguous shifts in the behavior of the credit-to-GDP series.

IV EMPIRICAL EXPLORATION

Next the $\ell_1$ filtering methodology is applied to the (private) credit-to-GDP ratios from a large number of countries. This variable is conceptually important as its accelerations are often associated with the accumulation of vulnerabilities in the financial sector (see Buyukkarabacak and
Thus, it is of interest to explore whether the $\ell_1$ helps isolating events in the evolution of the credit-to-GDP ratio that may be informative about the outbreak of future banking crises.

IV.1 Data

Three data sources are used. First, the Global Financial Development Dataset (GFDD) of the World Bank [2013] provides annual series of the credit-to-GDP ratio, in an unbalanced panel from 1960 to 2011. Only countries with more than 20 information points and a population above 1 million inhabitants in the last observable year are considered. This renders a sample of 95 countries with, on average, 42 data points.

Second, the dates of the outbreak of banking crises and their duration are obtained from Reinhart and Rogoff (2010). Third, as in Buyukkarabacak and Valev (2010), this crises information is complemented using Laeven and Valencia (2012) systemic banking crises database, either by identifying any missing events in the Reinhart and Rogoff’s dataset or by expanding its time span up to 2011. Despite that both sources do not use exactly the same definition of a banking crisis, the resulting database captures very well the outbreaks of financial stress periods relevant to our study.

IV.2 Turning points classification

We identify a total of 285 kink points, an average of 3 kink points (4 linear segments) for each country. Of these, 84 mark the beginning of a regime that develops into a banking crisis, whereas 127 are the beginning of regimes that end with another kink, i.e. that contains no periods of banking crises. The remaining 74 are turning points whose associated regimes end with sample and are thus discarded, leaving a total of 211 kink points for the subsequent analysis.

It is convenient to classify the kink points according to their most salient features, essentially by comparing the slopes of the $\ell_1$ trend before and after the turning point. Figure 2 shows selected cases of turning points leading to banking crises. Panels (a) and (b) show, respectively for the Philippines in 1975 (towards the 1981 crisis) and Spain in 2003 (a regime ended with the 2008 financial crisis), kink points associated to Accelerations (34 cases in total). Here, the $\ell_1$ trend shows initially a positive slope that becomes steeper after the turning point. Another popular situation is that of a Recovery (64 cases in total), where initially the $\ell_1$ displays a negative slope that is reverted after the kink point. Panels (c) and (d) provide illustrations of such rebound, respectively, for Mexico in 1987 (previous to the 1994 crisis) and Norway in 1980 (leading to the 1987 crisis).

The third type, that we call Slowdown (103 cases in total), refers to the case where the kink point reduces the growth rate of the trend, from a regime where it was positive. Panel (e) shows the case of Denmark in 2002 (leading to the 2008 financial crisis), whereas panel (f) shows the case of Nigeria in 1983, where the kink point marks the start of a contractive period ending up in the 1992 crisis. The final case corresponds to free-falls, where an initial negative slope is exacerbated after the kink point. Panel (g) shows the dramatic case of Cameroon in 1990 (leading to a crisis in 1995) and panel (h) illustrates the case of the Dominican Republic in 1988 (leading to a crisis also in 1995). It is worth mentioning, however, that only 10 cases fall in this category. Given the reduced number of instances, we decide to group free-falls with slowdowns are will refer to them collectively as Slowdowns (113 cases in total). Remember that what characterizes a slowdown is a reduction in the growth rate of the $\ell_1$ after the kink point.

Table II presents cross tabulations to show how the different types of kink point are distributed across regions, country income level and decade of occurrence. Most accelerations are recorded in OECD countries (17 out of 34), most recoveries come from Latin America (20 out of 64) and the rest of the developing world (“others”, 22 out of 64), and slowdowns are more evenly distributed across various regions of the globe. On the other hand, when classifying the kink points by income
level, we find that a vast majority of kink points (about 70 percent) are from emerging markets, notably recoveries (about 80 percent) and, to a lesser extent, slowdowns (70 percent). Finally, when exploring the occurrence of kink points chronologically, it is noted that the 1980s and the 1990s are the decades with more kink points. The 1990s are especially interesting since most of the accelerations (about 30 percent) and recoveries (about 40 percent) are recorded then.

IV.3 Turning points and banking crises

Does the occurrence of a kink point (of a given type) mark the beginning of a regime, in terms of the behavior of the credit-to-GDP ratio, that eventually develops in a banking crises? Do the kink points anticipate these stressful events?

Table 2 provides a first answer. It shows the classification of kink points by whether they preceded a banking crisis. At first, it can be noticed that out of the 84 crises episodes in our sample, 15 corresponds to accelerations and 29 to recoveries. These types have in common that the growth rate of the credit-to-GDP ratio is increase after the kink, whereas in the slowdown the growth rate is decreased. Thus, we estimate $\Pr(\text{Growth rate increase | crisis}) \simeq 0.52$ and $\Pr(\text{Growth rate decrease | crisis}) \simeq 0.48$. Thus, at this stage that banking crisis are preceded by essentially any type of regime.

On the other hand, exploring the rows of the table, the fact that out of the 211 kink points in our sample 84 are followed by a crisis gives an estimate of $\Pr(\text{crisis | kink point}) \simeq 0.40$. This figure is roughly maintained by type, namely $\Pr(\text{crisis | acceleration}) \simeq 0.44$, $\Pr(\text{crisis | recovery}) \simeq 0.40$ and $\Pr(\text{crisis | slowdown}) \simeq 0.35$. Thus, even though there is some indication that slowdowns tend not to develop into a crisis, in general the association between the occurrence of a kink point, its type and the occurrence of a crisis is weak. In other words, once a kink point is recorded, it seems equally likely that the new regime will end up in the outbreak of a banking crisis. A formal statistic test is not able to reject the null hypothesis of no association between the occurrence of a kink point, and the probability of a subsequent crisis. This conclusion is based on the categorical analysis of occurrence of events, but it also holds when the kink points are characterized in a more continuous fashion. We first focus on the characteristics of the 84 kink points that anticipated crisis in our sample.

Figure 3 shows the duration of the regime leading to a banking crisis. In particular, it shows the relative frequency of an indicator variable pointing out the outbreak of a crisis $h$ years after the kink point (which corresponds to $h = 0$), as a function of $h$. From panel (a) it is clear that the median kink point that anticipates a crisis does so by 7 years, though the distribution of regime duration is rather spread and skewed to the right. From panels (b) to (d) we observe that slowdowns seem to take longer and accelerations tend to produce crisis quicker in more instances, but the differences are not altogether very significant across kink types. For instance, many accelerations that anticipated a crisis did so by more than 10 years.

Figure 4 shows how credit dynamics evolve around a banking crisis. Panel (a) reveals the expected result that after the crisis the credit-to-GDP ratio reduces, at least the median, along with the fact that its cross-sectional variability also decreases pointing out to a widespread deterioration of the ratio. Similarly, panel (c) shows a clear long-lasting deterioration of the growth rate. This results follow almost trivially for the very definition of a banking crisis entertained in our sources, i.e. Reinhart and Rogoff (2010) and Laeven and Valencia (2012).

What is interesting to notice is the wide heterogeneity of the credit-to-GDP ratio and its growth rate around a crisis. In Panel (c) we observe that those crisis associated to accelerations occurred in countries with relatively high credit-to-GDP ratios, say OECD countries as suggested in Table 1 whereas recoveries and slowdowns leading to crisis are mostly registered in countries with low credit-to-GDP ratios, say Latin American countries as suggested in Table 1. This is true for periods before and after the crisis. Thus, the level of the credit-to-GDP seems to be a poorly associated to a banking crises in the sense that it can take a great range of values in periods surrounding the
collapse. Panel (d) suggests a similar conclusion for the growth rate. In the case of accelerations and recoveries it is clearly positive and relatively large before the crisis, whereas in the case of slowdowns, it is negative. Thus, we again observe banking crises preceded by a wide range of patterns in the trend growth values. Notice that after the crisis the behavior of the growth rate seems to be rather comparable across kink point types, which again follows from the very definition of a banking crisis. The dramatic decrease in accelerations and recoveries in the growth rate follows because a fast-growing regime is coming to an end.

We now address the more interesting issue on the predictive content of the kink points. For this, we compare the main characteristics – namely, the change in the growth rate, the post-kink point growth rate, the credit-to-GDP ratio at the kink point and the regime duration – of the 84 kink points leading to a crisis to the remaining 127 that did not produce a crisis.

Table 3 presents the corresponding descriptive statistics and formal hypothesis tests on the equality of the means (t test), the medians (U test) and the distributions (rank-sum test). Let z denote one characteristic of the kink point (i.e., its duration). The null hypotheses of the tests in Table 3 can be regarded as different ways, with varying degrees of generality, to assess the independence condition \( f(z | \text{crisis}) \simeq f(z) \). Provided that this conditions if fulfilled, Bayes rule implies \( f(\text{crisis} | z) \simeq f(\text{crisis}) \), where \( f(\text{crisis} | z) \) is the object of interest. The results in Table 3 point to a disassociation between the salient features of the credit-to-GDP ratio and the occurrence of banking crises. The various null hypothesis of equality cannot be reject in the vast majority of cases. These results are a summary manifestation of the fact that in our dataset the dynamics of the credit-to-GDP are so diverse before the outbreak of a crisis as to render this variable uninformative.

### IV.4 A robustness check

As discussed in Demirgüç-Kunt and Detragiache (1998) and Bussiere and Fratzscher (2006), the behavior of economic and financial indicators may be distorted around crisis events, muddling the identification of relationships between variables. In order to control for this potential source of noise, Table 4 estimates the previous statistics based on a sample of kinks that “depart from normal conditions”.

A kink point in year \( t \) is said to depart from normal conditions if the economy did not experience a state of banking crises in the time frame \( t - 3 \) to \( t + 3 \). By adopting this approach, it is ensured that the kink points evaluated occur at least three years after the end of a banking crises episode. Also it is ensured that turning points caused by future crisis events are excluded from the sample. The main conclusions remain robust to this specification of the sample.

### V CLOSING REMARKS

The \( \ell_1 \)-filtering approach provides a very simple method to break down the evolution of a time series into linear segments that can be interpreted as regimes that are simple to characterize. Moreover, the identification of the turning points that give rise to such regimes is a straightforward exercise. When applying this method to the credit-to-GDP ratio of a large number of countries we find a wide diversity of patterns in the behavior of this variable, to such extent that the knowledge of the beginning of a new regime in this ratio, along with its basic features such as its duration or strength, provides little information on whether such regime would eventually degenerate in a banking crisis. This is true even for regimes associated to a fast-growing credit-to-GDP ratios, thereby defying the conventional wisdom.

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7 We performed a number of logit regressions to explore the relationship between kink point types, their characteristics and the subsequent occurrence of banking crisis. No conclusion is changed by the analysis, whose results are available upon request.

8 Despite the time an economy takes after a banking crisis in order to return to normal conditions is not a consensus in literature, we take 3 years as a reasonable time frame for our robustness check purposes.
It is important to remark that our conclusions are driven mainly by the heterogeneity of the credit-to-GDP ratio cross-sectionally. Banking crises are the result of the confluence of several factors, and conditioning on simple characteristics (even though a priori sensible) such as the type of turning point of the pre-crisis regime may not be enough to pin down such heterogeneity in order to unveil the informational content of the credit-to-GDP ratio as a leading indicator of a crisis. This may also be explaining why the extant literature on the determinants of banking crisis have reached certain consensus on the importance of macroeconomic factors such as the position on the business cycle or the real interest rates in explaining crisis, whereas the conclusions on the role of credit seem to be less clear-cut.

Yet, the $\ell_1$-filtering methodology, and its corresponding precise and easy identification of turning points, can be useful in the study of country cases and the design of early warning systems for these particular situations. For instance, in Figure 5 we present the cases of Bolivia and Uruguay where, unlike the cross section, the map from kink points to banking crises is very clear. In these cases, each kink point leads to a banking crisis that in turn produces another kink point. Such a detailed case by case study is beyond the scope of this paper, but we reckon it gives an important role to the $\ell_1$-filter as a valuable empirical tool for future research efforts.
REFERENCES


Figure 1: Credit-to-GDP ratio and trends for Greece

(a) Data

(b) $\ell_1$ and $\ell_2$ trends

(c) $\ell_1$ and $\ell_2$ trends growth rate
Figure 2: Kink points preceding banking crises

(a) Philippines (Acceleration in 1975)

(b) Spain (Acceleration in 2003)

(c) Mexico (Recovery in 1987)

(d) Norway (Recovery in 1980)

(e) Denmark (Slowdown in 2002)

(f) Nigeria (Slowdown in 1983)

(g) Cameroon (Free-fall in 1990)

(h) Dominican Rep (Free-fall in 1988)
Figure 3: Duration of regimes leading to a banking crisis

(a) All kink points

(b) Acceleration

(c) Recovery

(d) Slowdown

Notes: Relative frequencies of the outbreak banking crises after a kink point is registered in period $h = 0$. The sample corresponds to the 84 kink points preceding banking crises.
Figure 4: Credit-to-GDP ratio around the occurrence of a banking crisis

(a) Trend level (all kink pts)

(b) Trend level (by kink pt type)

(c) Trend growth rate (all kink pts)

(d) Trend growth rate (by kink pt type)

Notes: Box plots based on the sample of 84 kink points preceding banking crises. In panels (a) and (c) the banking crisis occurs in period 0. In panels (b) and (c), “BC” shows the results of the year where the banking crisis is recorded, “Before” of the previous 5 years, and “After” of the subsequent 5 years.
Table 1: Classification of kink points by type

<table>
<thead>
<tr>
<th>By region</th>
<th>Acceleration</th>
<th>Recovery</th>
<th>Slowdown</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asia</td>
<td>8</td>
<td>4</td>
<td>16</td>
<td>28</td>
</tr>
<tr>
<td>Latin America</td>
<td>4</td>
<td>20</td>
<td>28</td>
<td>52</td>
</tr>
<tr>
<td>OECD</td>
<td>17</td>
<td>13</td>
<td>31</td>
<td>61</td>
</tr>
<tr>
<td>Sub-Saharan Africa</td>
<td>1</td>
<td>5</td>
<td>7</td>
<td>13</td>
</tr>
<tr>
<td>Others</td>
<td>4</td>
<td>22</td>
<td>31</td>
<td>57</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>By income level</th>
<th>Acceleration</th>
<th>Recovery</th>
<th>Slowdown</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advanced economies</td>
<td>18</td>
<td>14</td>
<td>33</td>
<td>65</td>
</tr>
<tr>
<td>Emerging markets</td>
<td>16</td>
<td>50</td>
<td>80</td>
<td>146</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>By decade</th>
<th>Acceleration</th>
<th>Recovery</th>
<th>Slowdown</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1960s</td>
<td>6</td>
<td>3</td>
<td>12</td>
<td>21</td>
</tr>
<tr>
<td>1970s</td>
<td>7</td>
<td>15</td>
<td>23</td>
<td>45</td>
</tr>
<tr>
<td>1980s</td>
<td>5</td>
<td>16</td>
<td>46</td>
<td>67</td>
</tr>
<tr>
<td>1990s</td>
<td>10</td>
<td>27</td>
<td>27</td>
<td>64</td>
</tr>
<tr>
<td>2000s</td>
<td>6</td>
<td>3</td>
<td>5</td>
<td>14</td>
</tr>
</tbody>
</table>

Total 34 64 113 211

Table 2: Crisis occurrence by kink point type

<table>
<thead>
<tr>
<th></th>
<th>Crisis</th>
<th>No Crisis</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acceleration</td>
<td>15</td>
<td>19</td>
<td>34</td>
</tr>
<tr>
<td>Recovery</td>
<td>29</td>
<td>35</td>
<td>64</td>
</tr>
<tr>
<td>Slowdown</td>
<td>40</td>
<td>73</td>
<td>113</td>
</tr>
</tbody>
</table>

Total 84 127 211

Notes: The Pearson’s $\chi^2$ statistic (2 degrees of freedom) is 1.989, and its corresponding (Fisher’s exact) p-value is 0.361.
Table 3: Tests for equality of means, medians and distributions (full sample)

<table>
<thead>
<tr>
<th></th>
<th>Average</th>
<th>Median</th>
<th>Rank-sum test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Crisis</td>
<td>No Crisis</td>
<td>t test</td>
</tr>
<tr>
<td>Change in growth rate</td>
<td>0.125</td>
<td>−3.042</td>
<td>0.226</td>
</tr>
<tr>
<td>Acceleration</td>
<td>6.617</td>
<td>7.255</td>
<td>0.716</td>
</tr>
<tr>
<td>Recovery</td>
<td>15.224</td>
<td>18.114</td>
<td>0.235</td>
</tr>
<tr>
<td>Slowdown</td>
<td>−13.256</td>
<td>−15.865</td>
<td>0.340</td>
</tr>
<tr>
<td>Post-kink growth rate</td>
<td>3.142</td>
<td>1.238</td>
<td>0.156</td>
</tr>
<tr>
<td>Acceleration</td>
<td>8.476</td>
<td>9.427</td>
<td>0.606</td>
</tr>
<tr>
<td>Recovery</td>
<td>9.085</td>
<td>9.625</td>
<td>0.760</td>
</tr>
<tr>
<td>Slowdown</td>
<td>−3.166</td>
<td>−4.914</td>
<td>0.235</td>
</tr>
<tr>
<td>Credit-to-GDP at kink</td>
<td>42.240</td>
<td>34.591</td>
<td>0.122</td>
</tr>
<tr>
<td>Acceleration</td>
<td>58.523</td>
<td>33.373</td>
<td>0.042</td>
</tr>
<tr>
<td>Recovery</td>
<td>28.128</td>
<td>16.654</td>
<td>0.087</td>
</tr>
<tr>
<td>Slowdown</td>
<td>46.364</td>
<td>43.509</td>
<td>0.691</td>
</tr>
<tr>
<td>Regime duration (years)</td>
<td>8.810</td>
<td>8.575</td>
<td>0.673</td>
</tr>
<tr>
<td>Acceleration</td>
<td>8.333</td>
<td>8.053</td>
<td>0.822</td>
</tr>
<tr>
<td>Recovery</td>
<td>8.000</td>
<td>8.314</td>
<td>0.606</td>
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<tr>
<td>Slowdown</td>
<td>9.575</td>
<td>8.836</td>
<td>0.451</td>
</tr>
</tbody>
</table>

Notes: The first row of each variable contains statistics for the full sample (i.e. all kink points), whereas the rest are conditional on the type of kink point. The columns “Crisis” and “No crisis” show either sample averages or medians conditional to the occurrence or not of a banking crisis after the kink point. The figures for the tests are p-values: the “t test” is the standard t test for the equality of the population means under heteroscedasticity, the “U test” is Mann and Whitney’s nonparametric test for the equality of the population medians, and the “Rank-sum test” is Wilcoxon’s test for the equality of the distributions underlying the two samples.
Table 4: Tests for equality of means, medians and distributions (subsample excluding kink points near crises)

<table>
<thead>
<tr>
<th>Change in growth rate</th>
<th>Crisis</th>
<th>No Crisis</th>
<th>t test</th>
<th>Rank-sumtest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crisis</td>
<td>0.125</td>
<td>-3.042</td>
<td>0.296</td>
<td>1.099</td>
</tr>
<tr>
<td>No Crisis</td>
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<td>6.899</td>
<td>0.194</td>
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<tr>
<td>Acceleration</td>
<td>15.224</td>
<td>1.8114</td>
<td>0.235</td>
<td>6.998</td>
</tr>
<tr>
<td>Recovery</td>
<td>-13.267</td>
<td>-15.865</td>
<td>0.340</td>
<td>17.927</td>
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<tr>
<td>Slowdown</td>
<td>-3.142</td>
<td>1.238</td>
<td>1.906</td>
<td>12.471</td>
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<tr>
<td>Post-kink growth rate</td>
<td>8.476</td>
<td>9.695</td>
<td>0.780</td>
<td>6.111</td>
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<td>Acceleration</td>
<td>-3.166</td>
<td>4.141</td>
<td>0.232</td>
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<td>Recovery</td>
<td>5.952</td>
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<td>Slowdown</td>
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<td>3.591</td>
<td>0.122</td>
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</tr>
<tr>
<td>Credit-to-GDP at kink</td>
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<td>Acceleration</td>
<td>26.128</td>
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<td>Recovery</td>
<td>46.384</td>
<td>43.519</td>
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<tr>
<td>Slowdown</td>
<td>8.810</td>
<td>8.575</td>
<td>0.673</td>
<td>8.000</td>
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<tr>
<td>Regime duration (years)</td>
<td>8.333</td>
<td>8.053</td>
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<td>7.800</td>
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<tr>
<td>Acceleration</td>
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<tr>
<td>Recovery</td>
<td>9.575</td>
<td>8.586</td>
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<tr>
<td>Slowdown</td>
<td>9.575</td>
<td>8.586</td>
<td>0.451</td>
<td>8.000</td>
</tr>
</tbody>
</table>

Notes: See notes to Table 2.
Notes: In the case of Bolivia, an initial kink point in 1979 (slowdown) leads to the 1986 banking crisis. The effects of this crisis are captured by a kink point in 1985 (recovery), marking the beginning of a growth regime that ends with the 1994 crisis. This crisis, in turn produces a kink point in 1993 (slowdown) which anticipates the last recorded crisis in 1999. In the case of Uruguay, a recovery is registered in 1973 leading to the 1981 crisis. A similar pattern then emerges with a recovery in 1992 and the last recorded crisis in 2002.