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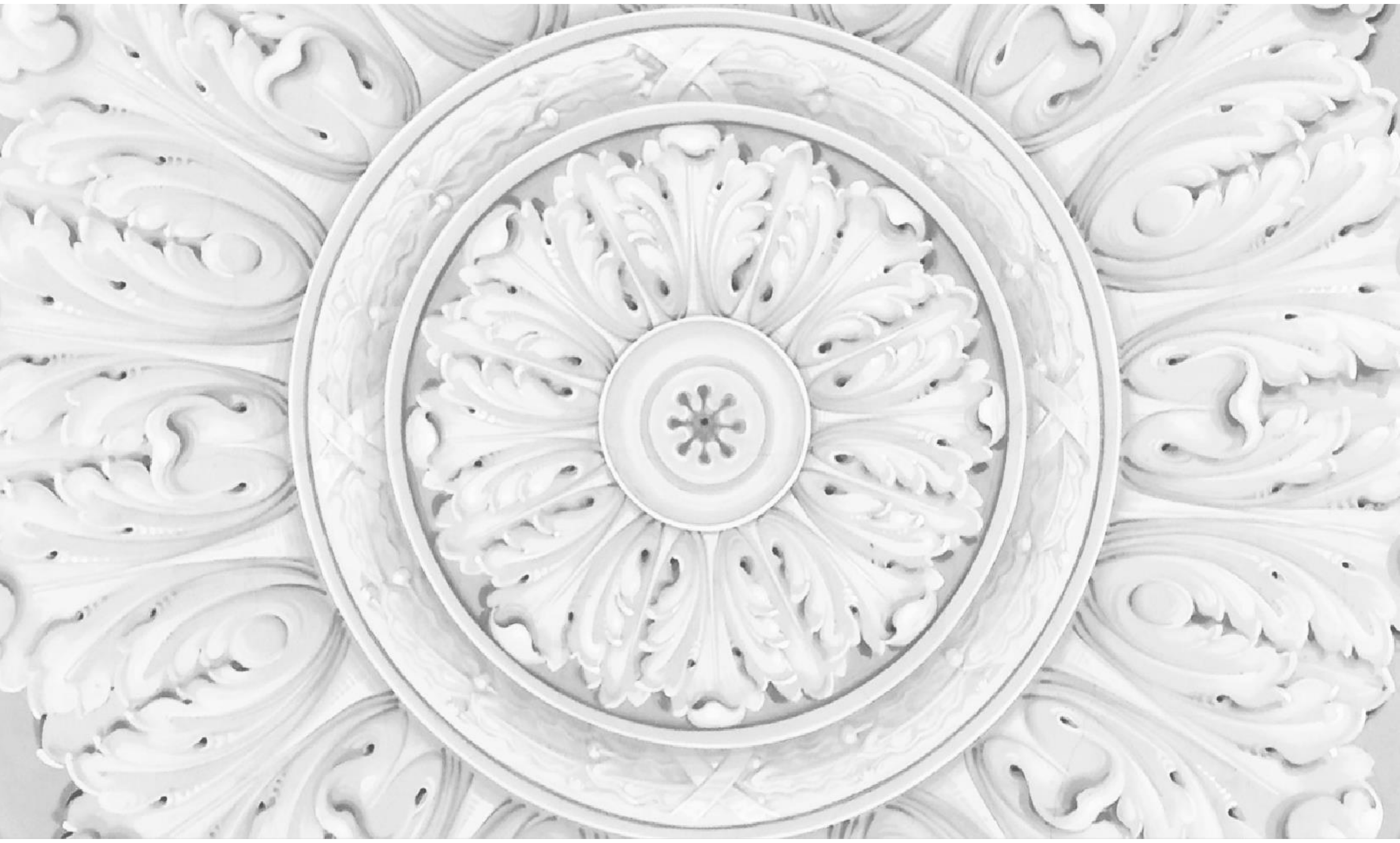

WORKING PAPER SERIES

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Real-time determination of credit cycle phases in emerging markets

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Abstract

We test the ability of early warning indicators that appear in the literature to predict credit cycle peaks in a cross-section of emerging markets. Our results confirm that the standard credit gap indicator performs satisfactorily. The robustness of real-time credit cycle determination may potentially (and with a risk of overfitting the data) be improved by simultaneously monitoring GDP growth, banks' non-core liabilities, the financial sector's value added and (to a lesser extent) the change in the debt service ratio.

Keywords: credit cycle, countercyclical capital buffers, early warning indicators, emerging markets.
JEL Classification: E37, E44, E51.

CONTENTS

INTRODUCTION

There are good reasons to believe that correctly determining the current phase of the credit cycle is essential for efficient policymaking. Borio and Lowe (2002, 2004) document the property of the credit gap (the gap between the credit-to-GDP ratio and its long-term trend) as a very useful early warning indicator for banking crises. The association of general macroeconomic and financial developments with credit boom/bust cycles is also examined closely in a number of studies (see e.g. Mendoza and Terrones (2012)). Importantly, the close link between credit cycle indicators and credit losses is well documented (Dell'Ariccia et al. (2012); Geršl and Seidler (2015); Jokivuolle et al. (2015)).

The debate about the appropriate measure of the credit cycle intensified after Basel III introduced the credit gap as a measure of the credit cycle phase and a guide for setting countercyclical capital buffers (CCB) (BCBS (2010)). Although the useful properties of this indicator are confirmed generally for a broad array of countries and a long time span that includes the most recent crisis, criticism of this choice appears in the literature, focusing on several areas (see Drehmann and Tsatsaronis (2014) for a summary). The first strand of arguments is related to the ultimate relevance of the credit gap indicator as a measure of disequilibrium. In this paper, however, we will not address this issue and concentrate on the problem of the credit gap's practical measurement and the end-point problems (reported by e.g. Edge and Meisenzahl (2011)).

It is argued that the reliability of the credit gap indicator may be improved when used in combination with alternative indicators in an early warning indicator system (EWI) set-up. The interest in such supplementary indicators is also driven by the demand for a system that could provide a signal that is early enough to account for the 12-month implementation period for raising the capital buffers specified in the Capital Requirements Directive IV regulation. The literature on such EWIs developed for advanced countries is ample (see e.g. Detken et al. (2014) and Kalatie et al. (2015) for a comprehensive review) but noticeably scarcer for emerging markets.[1] The aim of this paper is to examine the applicability of the EWI approach to augmenting the credit gap indicator as a guide for setting countercyclical capital buffers specifically for emerging market economies. We reiterate that our focus is not on studying whether credit cycle indicators are in principle useful for policymaking. Instead we seek methods that would help to increase the reliability of credit cycle measures in real time and to predict their future developments in a timely manner.[2]

The rest of the paper is structured as follows. Section 2 outlines and implements methods to measure the credit cycle. Section 3 discusses the selection of early warning indicator variables. Section 4 describes the data set, comprising a cross-section of emerging market economies, on

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[1] See Guarín et al. (2014) and Valinskytė and Rupeika (2015) for such examples. Drehmann and Tsatsaronis (2014) also touch on the performance of the credit gap indicator in emerging markets.

[2] This approach is different from the standard credit cycle literature in which EWIs are developed to predict financial crises but is not uncommon for business cycle analysis (see e.g. Aastveit et al. (2016)).

which we conduct the empirical analysis. Section 5 presents the models fitted here to predict credit cycle peaks in the emerging market data set. Section 6 concludes.

1. MEASURING THE CREDIT CYCLE

We adopt a standard approach (as in e.g. Mendoza and Terrones (2012)) as our benchmark measure of the credit cycle: we calculate the credit gap by detrending the log of the credit-to-GDP ratio with the two-sided Hodrick–Prescott filter (λ=400000). We define its local maxima (over the 20-quarter window[3]) as peaks of the credit cycle if they exceed the threshold equal to the respective (country-specific) credit gap's 1.5 standard deviation.

The binary variable that is used as the dependent variable for the EWI is subsequently constructed basing on the obtained results. For the CCB to be raised before the transition to a contractionary credit cycle phase, the EWI should issue a signal at least one year before the turning point. Our binary variable therefore equals one over the horizon from five to twelve quarters prior to the identified peak.

We also calculate alternative (see e.g. Claessens et al. (2011); Drehmann et al. (2012)) credit cycle measures to check the robustness of the benchmark approach. Specifically, we use two alternative methods. The first is simple turning-point analysis (i.e. identifying the local maxima in the level of the credit-to-GDP ratio). The second implies identifying the local maxima of the cumulated credit-to-GDP ratio fluctuations with a frequency of 32–120 quarters (isolated via the band-pass filter). We find that the ex post estimates of the credit cycle are not sensitive to this choice and the binary variables constructed based on alternative approaches are highly correlated (see Table 6 in the Annex).[4] We therefore only report the results obtained using the benchmark approach to credit cycle measurement.

2. EARLY WARNING INDICATORS SELECTION

Our early warning system comprises a set of indicators that are presumably helpful in the real-time prediction of the turning points of the ex post credit gap measure. Naturally, the most obvious choice is the recursively estimated version of the credit gap itself. We also test the performance of the credit-to-GDP ratio in the form of annual growth.

[3] Drehmann et al. (2012) suggest using a 40-quarter window, but this seems to be irrelevant to our relatively short series: even with this definition we are only able to analyse at most one turning point for the countries in our cross-section.
[4] Arguably, this may indicate that that the identified peaks are well settled and are unlikely to be revised as further observations are added to the sample.

The choice of auxiliary variables is determined by the existing literature.[5] Borio and Lowe (2002) point out that, for timely identification of financial imbalances, the credit cycle should be analysed in combination with real-sector developments. We therefore include the annual growth of the real GDP in our data set.

Drehmann and Juselius (2012) suggest using the debt service ratio (*DSR*) to identify unbalanced credit developments. We use this indicator in the form of annual changes rather than in levels as this helps to improve its performance.

Hahm et al. (2013) find that increased banks' non-core liabilities (*NCL*) may also indicate the unsustainability of credit expansion as banks start to rely heavily on wholesale funding. We use banks' external liabilities to credit ratio as a proxy for this variable.

Finally, Banbula and Pietrzak (2016) point out that the increased contribution of the financial sector to the GDP growth (a proxy for banks' profit indicator) may be linked with excessive risk taking and therefore may be a good indicator to forecast financial risks. We use the share of the financial sector valued added in the GDP (*FSVA*) to reflect these developments.

All the variables (with the exception of the credit gap) are in deviations from recursively calculated country-specific means. The descriptive statistics and the variables' dynamics around the identified credit cycle peaks are reported in the Annex (Table 5 and Figure 2).

Admittedly, in our data set we do not have potentially useful variables from several notable categories. Most importantly, these are asset (property) prices of which the importance for financial imbalance analysis is underscored by Borio and Lowe (2002). This is due to scarce availability of such data for emerging markets. Secondly, these are measures of potential mispricing of risk (e.g. financial spreads and VIX indices). Such series for emerging markets are also scarce. Furthermore, considering that emerging financial markets are relatively less developed, the informational content of such measures may be limited. Finally, we deliberately do not include global (liquidity and market risk) variables in our data set. We already know from the existing studies (e.g. Alessi and Detken (2011)) that the global liquidity indicator would have performed exceptionally well in explaining the last wave of boom/bust episodes in 2005–2007. Due to our limited time sample, we deal almost exclusively with this most recent wave (see Section 4). Obviously, a global liquidity measure calculated based on monetary developments in advanced economies that is not country-specific with regard to the economies in our sample would explain all the boom/bust episodes observed during that period. Although this fact apparently deserves policymakers' attention, it can hardly be considered robust evidence of such an indicator's predictive power, as few other boom/bust episodes are available for examination. The effect of the global liquidity spillover may also be captured by the non-core liability variable.

[5] Considering that the cross-section of countries and the time sample used in our analysis are deliberately limited, the main objective of this paper is to verify the findings reported for advanced countries rather than suggesting novel approaches.

3. DATA

The composition of our cross-section of emerging market economies is determined by data availability.[6] Our main data source is the IMF IFS database, although we also use CEIC, the OECD statistical database and national central banks' and statistical agencies' websites (see Table 4 in the Annex for details). We use the DSR series reported by the BIS if available and the series collected by Donets and Ponomarenko (2015) otherwise. All the series have a quarterly frequency (although occasionally these are interpolated from annual data) and are seasonally adjusted.

We collect data for 25 emerging market economies in total. Our time sample ends in 2015. Accordingly, the dependent binary variable (which leads the credit cycle peak by 5–12 quarters) may be calculated up to 2012. The explanatory variables are usually available starting from the early 2000s. This gives a time period of about a decade to evaluate our models, which effectively means that we are able to observe one credit cycle peak per country at most. Consequently, our cross-section contains 12 countries that experienced the transition from an expansionary to a contractionary credit cycle phase in 2007–2009, 5 countries where the transition happened at a different time and 8 countries where no credit cycle turning points can be identified (see Table 7 in the Annex for details).

4. EMPIRICAL ANALYSIS

We evaluate our models following Drehmann and Juselius (2014) and use the area under the ROC curve (AUC): a statistical methodology that captures the trade-off between true positives and false positives for the full range of policymakers' preferences.[7] As the data availability differs for various explanatory variables, we report the evaluation results for the full (indicator-specific) available time sample as well as for the common time sample.

[6] A significant challenge in constructing the early warning indicator system based on panel data is compiling an appropriate data set. One may find it logical to use a homogeneous cross-section that includes only relevant and similar economies. The caveat here is that it is also desirable to have a data set that is balanced as regards the presence of boom/bust occurrences. For example, if our data set only included Central and Eastern European countries (most of which experienced asset price booms/busts), we would be unable to test the performance of the system in a tranquil environment. We therefore do not limit our cross-section to any particular group of countries and thus include all emerging markets for which adequate data are available.

[7] We have examined the models' performance in terms of other measures, such as areas under precision recall curves (recommended by Murphy (2012) for samples with rare true events). Our results seem to be robust to the choice of performance measurement.

4.1 Stand-alone indicators

We begin by examining individual indicators' performance by means of the "signalling" approach. This approach assumes an extreme non-linear relationship between the indicator and the event to be predicted and transforms the indicators into binary signals: if a given indicator crosses a critical threshold, it is said to send a signal. The signal is assumed to be issued when the indicator's value exceeds a threshold (the same for all countries) defined in terms of the recursively calculated (country-specific) percentile. We perform the variable-specific evaluation of indicators' performance (in terms of the AUC indicator) under a variety of percentile thresholds. As described in Section 2, we expect the signal to be issued 5–12 quarters before the peak. The results are reported in Table 1 (the actual ROC curves are presented in Figure 3 in the Annex).

We find that the performance of the credit gap indicator (AUC equals 0.68) is similar to the results of the evaluation conducted by Drehmann and Tsatsaronis (2014) for emerging markets at the respective forecast horizon. It is marginally outperformed by the credit growth variable but not by the other auxiliary indicators.

Table 1. Stand-alone indicators' AUC

	Credit gap	Credit growth	GDP growth	DSR	NCL	FSVA
Full available time sample	**0.67**	**0.68**	**0.55**	**0.60**	**0.52**	**0.60**
Common time sample	**0.68**	**0.70**	**0.58**	**0.62**	**0.52**	**0.58**

4.2 Discrete choice models

As the second approach we set up an early warning indicator system in the form of a discrete choice model using the binary indicator described in Section 2 as a dependent variable. This approach makes use of pooled[8] probit regression techniques to evaluate an indicator's contribution to predicting a peak of the credit cycle. This method enables us to take into account correlations between different indicator variables and to evaluate the statistical significance of individual variables. The results are reported in Table 2 (the actual ROC curves of the estimated models are presented in Figure 4 in the Annex).

[8] We do not employ fixed-effect probit regressions in our analysis because, as noted by Davis and Karim (2008), this approach would lead to information loss for countries that did not experience a credit cycle peak. In fact, we believe that fixed-effect analysis is irrelevant to our models, as all the explanatory variables are detrended or demeaned.

We begin by including all the explanatory variables in the model simultaneously (Model 1). The credit gap is found to be highly statistically significant. Contrary to its performance as a stand-alone indicator, credit growth is not useful in combination with other variables, as is the change in the DSR. These variables may be excluded without decreasing the AUC indicator (Model 2). The other three auxiliary variables remain statistically significant.

We experiment further by considering the bivariate interactions of the variables (Model 3). We find that we may marginally improve the model's performance by interacting the credit gap with the financial sector's value added and the change in the DSR with GDP growth.[9]

Table 2. Probit models (z-statistics in parentheses)

	Model 1	*Model 2*	*Model 3*
Credit gap	1.6 (3.0)	1.4 (3.0)	1.7 (3.2)
Credit growth	0.0 (0.0)	-	-
GDP growth	8.1 (5.2)	5.7 (4.4)	7.6 (4.9)
DSR	-0.3 (-0.1)	-	-5.0 (-1.2)
NCL	3.1 (4.0)	1.9 (2.6)	3.1 (4.0)
FSVA	9.3 (1.8)	13.2 (2.6)	3.7 (0.6)
DSR*GDP growth	-	-	188.1 (2.1)
Credit gap*FSVA	-	-	81.5 (2.3)
C	-1.4 (-19.6)	-1.32 (-21.8)	-1.36 (-20.6)
Observations	***959***	***1017***	***959***
McFadden R-squared	***0.1***	***0.07***	***0.11***
AUC (full time sample)	***0.74***	***0.71***	***0.76***
AUC (common time sample)	***0.74***	***0.74***	***0.76***

The fact that the multivariate models are able to outperform the stand-alone indicators is not unexpected, but there is always a risk that this could be achieved by overfitting the data. Examining the out-of-sample performance of the models may help to assess the seriousness of these concerns. We therefore report the results of conventional (see e.g. Murphy (2012)) cross-validation procedures.[10] We split the data set into five folds; then, for each fold k ∈ {1, . . . , 5}, we estimate our models using all the folds but the *k*th and test the *k*th in a round-robin fashion. We

[9] Presumably this finding shows that, by using such interactions, it is possible to distinguish between the cases when the credit gap or DSR growth is driven by credit expansion and the cases when it is driven by GDP contraction.
[10] The credit peak occurrences appear in one wave, precluding the models' recursive estimation, which may be regarded as another way to examine the problem of overfitting in time series analysis.

then compute the AUC over all the folds (Table 3). We use two alternative ways to determine the composition of each fold. The countries in our cross-section are divided into five regional subgroups[11] (as reported in Table 7 in the Annex). In the first approach, we compose balanced folds by randomly including one country from each region. In the second approach, our folds are constituted exclusively by countries from the same region. Arguably, if the resulting models' performance is worse in the second case (i.e. if replacing the data from the neighbouring countries with other data makes the model's parametrization less appropriate for a given economy), it may indicate the heterogeneity among the countries in the cross-section. In addition to the five-fold approach, we employ the "leave one out" strategy (i.e. we use the approach on all the data cases except for country *i* and then test on country *i*), which is less demanding but may be preferable for small samples.

Table 3. Cross-validation results (AUC for the common time sample)

Cross-validation method	*Model 1*	*Model 2*	*Model 3*
Five-fold (balanced)	0.63	0.67	0.66
Five-fold (regional)	0.65	0.69	0.7
Leave one out	0.64	0.68	0.68

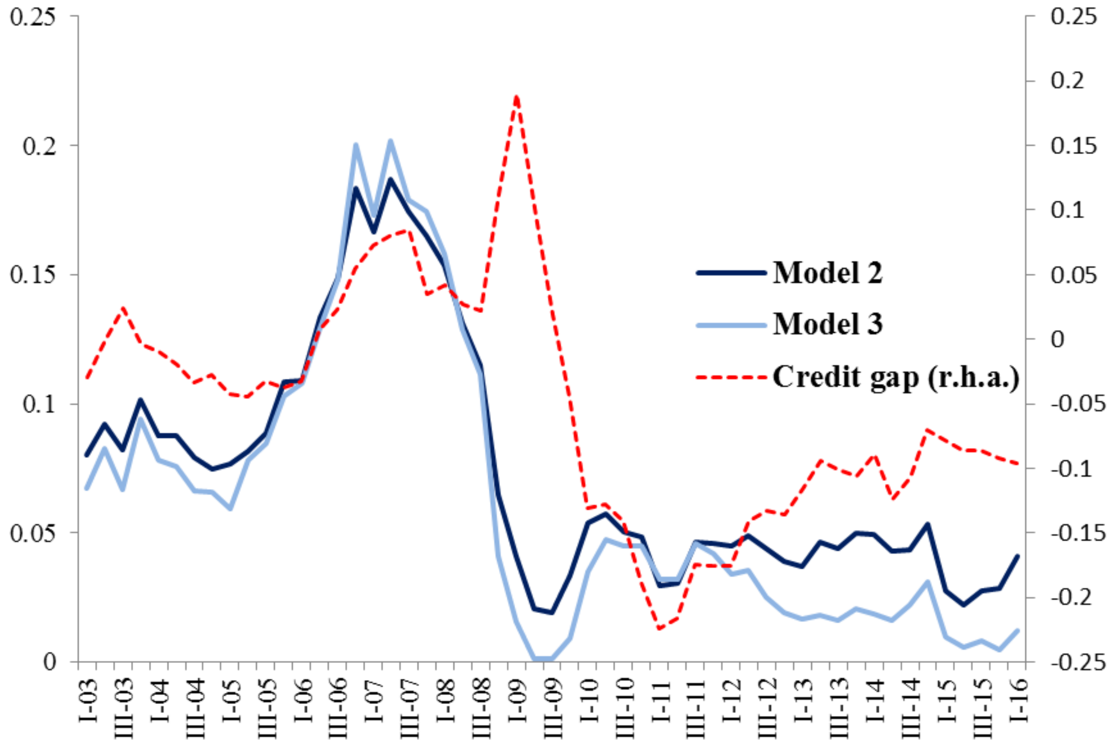
The results indicate that, although the out-of-sample performance of the multivariate models is still satisfactory, they do not outperform the best stand-alone indicators (credit gap and credit growth). This suggests that the better in-sample performance of multivariate models may at least partially be associated with overfitting the data. Interestingly, it seems that in this case using the models parametrized based exclusively on data observed in countries of different regions is not particularly problematic.

4.3 Application to Russia

We found that the estimated models yielded reasonable results for the Russian economy (Figure 1). Both models captured the build up of risks prior to the credit cycle peak in 2009Q1. Importantly, they produced in the true sense early warning by issuing the strongest signals in 2006-2007. In comparison the credit gap's developments were less distinct, although in general also informative.

[11] These are Eastern Europe (former Soviet Union), Eastern Europe (other), Latin America, Southeast Asia and Other.

Figure 1. Credit gap and estimated conditional probability of a credit cycle peak in Russia



CONCLUSIONS

Basel III uses the gap between the credit-to-GDP ratio and its long-term trend as a measure of the credit cycle phase and a guide for setting countercyclical capital buffers. The criticism of this choice centres on several areas. The main concerns are the practical measurement and the end-point problems. Recent studies find that several indicators that do not require detrending may be successful in identifying the build-up of financial imbalances. The interest in such supplementary indicators is also driven by the demand for a system that could provide a signal that is early enough to account for the 12-month implementation period for raising the capital buffers specified in the Capital Requirements Directive IV regulation.

We contribute to the existing literature in several ways. Firstly, we concentrate on the applicability of our analysis to the cross-section consisting exclusively of emerging market economies (25 in total). The sample obtained is large enough for interpretable econometric analysis, although its informational content is limited, since, for the most part, only one (most recent) wave of credit cycle peaks can be analysed.

Secondly, instead of trying to predict banking crises, we develop a model to predict the turning points in the credit cycle as measured by ex post credit gap fluctuations (we find that ex post measures of the credit cycle are insensitive to the measurement approach).

Our results confirm that the standard credit gap indicator performs satisfactorily in real time. Although the growth rates of the credit-to-GDP ratio perform equally well as a stand-alone indicator, there is no gain in combining them with the gap measure. Instead, we confirm that credit growth is more likely to be unsustainable if accompanied by higher real growth rates. The robustness of real-time credit cycle determination may also be improved by monitoring banks' non-core liabilities, the financial sector's value added and (to a lesser extent) the change in the DSR by means of a multivariate discrete choice model (although with a risk of overfitting the data).

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ANNEX

Table 4. Data sources

Indicators	*Sources*
GDP GDP deflator	IMF IFS National statistical agencies' websites
Credit (banks' claims on the private domestic sector) Banks' liabilities to non-residents	IMF IFS Central banks' websites; CEIC
DSR	BIS Donets and Ponomarenko (2015)
Financial sector's (financial and insurance activities) value added	OECD National statistical agencies' websites CEIC

Table 5. Descriptive statistics of the variables

Variable	*Mean*	*Std Deviation*	*Min.*	*Max.*
Credit gap	-0.02	0.17	-0.82	0.35
DSR	0.00	0.02	-0.15	0.08
NCL	0.00	0.08	-0.38	0.29
Credit growth	-0.10	0.38	-3.36	0.46
GDP growth	0.00	0.04	-0.24	0.25
FSVA	0.00	0.01	-0.05	0.06

Table 6. Concordance between alternative binary variables (fraction of time for which two series are equal)

	Benchmark	Turning point analysis	Frequency-based filter analysis
Benchmark	1	0.886	0.818
Turning point analysis	0.886	1	0.826
Frequency-based filter analysis	0.818	0.826	1

Table 7. Cross-section of countries

Countries	*Time sample (available for all indicators)*	*Credit cycle peaks*	*Regional sub-group*
Belarus	2005q1–2012q2	2010q1	I
Brazil	2001q4–2012q2	-	III
Chile	2003q1–2012q2	2008q4	III
China (Hong Kong)	2000q1–2012q2	-	IV
China	2000q1–2012q2	2003q2	IV
Colombia	2001q4–2012q2	-	III
Czech Republic	2001q1–2012q2	-	II
Estonia	2004q4–2012q2	2009q2	I
Georgia	2001q4–2012q2	2008q4	I
Hungary	2001q1–2012q2	2009q1	II
India	2004q2–2012q2	2006q4	V
Indonesia	2001q4–2012q2	2005q3	IV
Kazakhstan	2001q4–2012q2	2007q3	V
Korea	2001q4–2012q2	2009q1	IV
Lithuania	2004q4–2012q2	2009q3	I
Macedonia	2006q4–2012q2	2008q4	II
Malaysia	2001q4–2012q2	-	IV
Mexico	2001q4–2012q2	-	III
Moldova	2001q4–2012q2	2008q2	I
Poland	2004q1–2012q2	2009q1	II
Russia	2003q1–2012q2	2009q1	V
Slovenia	2005q4–2012q2	-	II
South Africa	2001q4–2012q2	2007q4	V
Thailand	2001q4–2012q2	-	IV
Turkey	2002q1–2012q2	-	V

Figure 2. Early warning indicators (distribution of observed values around the credit peaks in the cross-section of emerging markets)

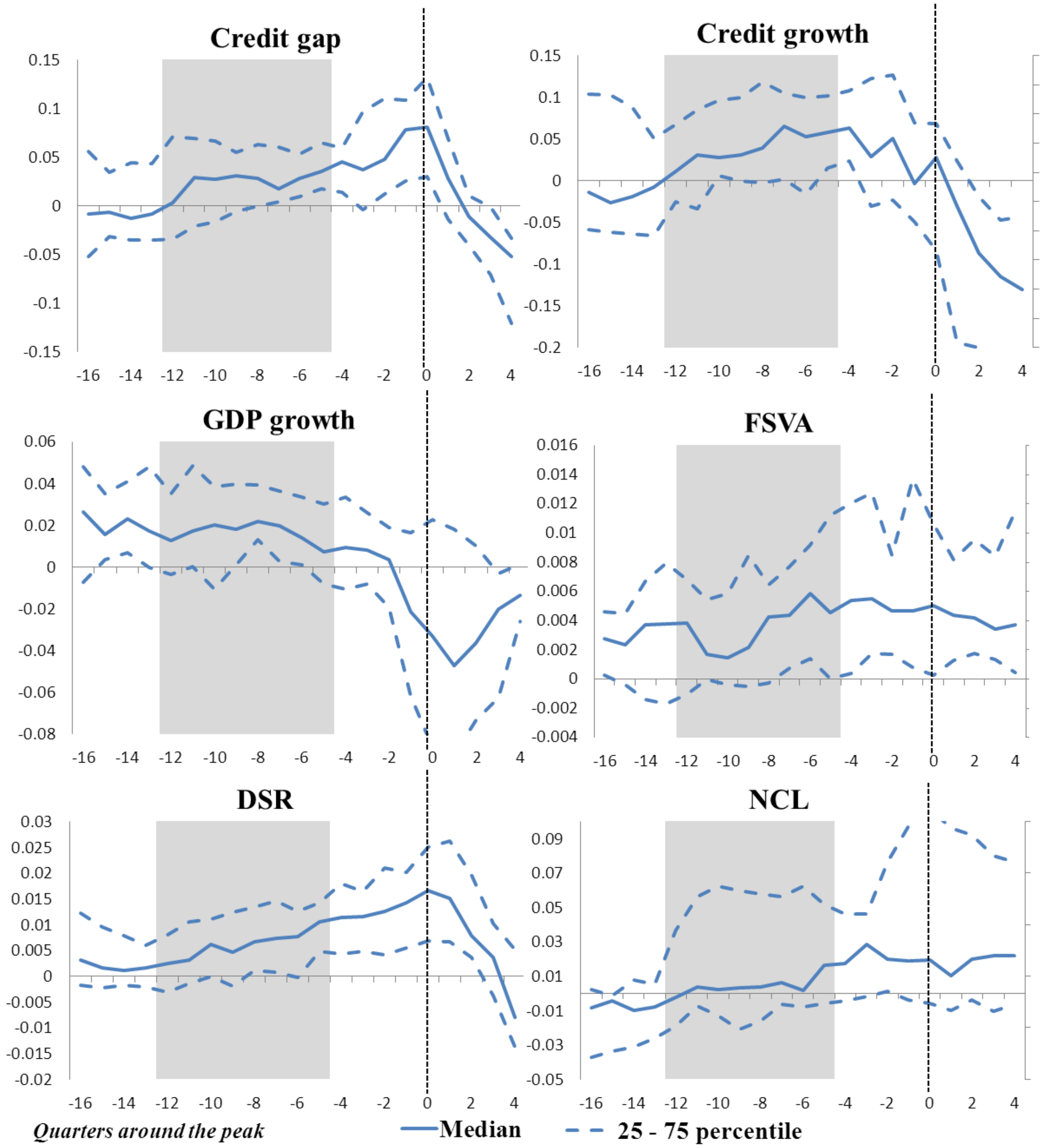

Figure 3. Stand-alone indicators' ROC curves

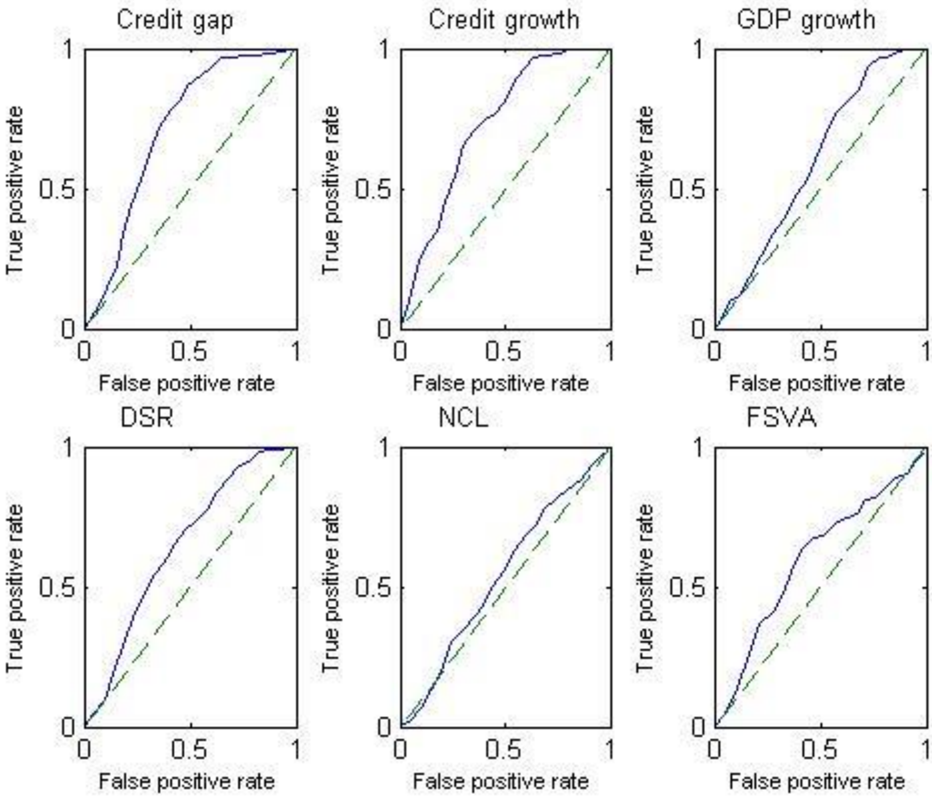

Figure 4. Probit models' ROC curves