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Alexey Ponomarenko

Early warning indicators of asset price boom/bust cycles in emerging markets

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Alexey Ponomarenko*

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Abstract

We apply recently developed early warning indicators systems to a cross-section of emerging markets. We find that, with little or no modification, models designed to predict asset price booms/busts in advanced countries may be useful for emerging markets. The concept of monitoring a set of asset prices, real activity (especially investment) and financial (especially credit) indicators is generally found to be efficacious.

Keywords: early warning indicators, asset prices, emerging markets
JEL classification: E37, E44, E51.

*Research and information department, Bank of Russia. E-mail: paa11@cbr.ru

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1 Introduction

The recent financial crisis has underscored the growing importance of asset price fluctuations for macroeconomic performance. As is the case for developed countries, a number of emerging market economies (particularly in Central and Eastern Europe[1]) seem to be quite prone to such shocks, as the rapid rise and subsequent decline of asset prices have presumably contributed significantly to the pre-crisis overheating of these economies as well as to the following contraction. Therefore, a system of early warning indicators that would help with early identification of emerging imbalances in asset markets is a much sought-after tool for policy-makers.

Development of such a system via the country-specific approach is often impossible because of data limitations. Therefore the standard approach is to make estimations for a group of countries (that may or may not include the analyzed country) and apply the resulting model to the economy in question[2]. A number of recent studies use this method and report on models that can be used to predict asset price booms and busts. These may be valuable to the policy-maker. The caveat here is that most of these models have been fitted to explain asset prices fluctuations in industrialized countries. It is not clear how useful these models are for emerging markets, as movements in many of the macroeconomic variables used as early warning indicators are remarkably different in the developed and emerging markets. For example, one may find it difficult to distinguish between excessive credit growth that leads to an asset price bubble and the convergence of an underdeveloped banking sector to a level commensurate with the industrialized countries. For transition economies, it may also be challenging to identify “overheating” based on growth rates of real sector variables that fluctuate dramatically as the economy undergoes substantial transformation. In fact, asset prices as such are known to be volatile in emerging markets and therefore difficult to interpret. For this reasons the early warning indicators approach needs to be thoroughly studied before it finds use in predicting asset price cycles in emerging markets. Indeed, as emphasized in Reinhart and Rogoff (2009), data coverage is crucial for financial crisis analysis. The main contribution of this paper is the application of asset

[1] See Gardó and Martin (2010) and Égert and Martin (2008) for general review, Brixiova et al. (2010) for the specific case of Estonia, Kuodis and Ramanauskas (2009) for the case of Lithuania and Mumtaz et al. (2012) for the case of Russia.
[2] See Gómez and Rozo (2008) for the example of country specific analysis, Tenjo and López (2010) for the cross-section analysis and Chapter III in BIS (2012) for out-of sample application of existing models.

price boom/bust analysis to the new dataset on emerging markets (most notably former Soviet Union countries).

The rest of the paper is structured as follows. Section 2 provides a review of recent contributions in the development of asset price cycle early warning indicator models. Section 3 describes the dataset, comprising a cross-section of emerging markets economies, on which we conduct the empirical analysis. Section 4 outlines and implements methods to identify boom and bust events that occurred in emerging markets. Section 5 presents an evaluation of the efficacy of existing models for predicting asset price developments in emerging markets and reports on the models fitted here to predict asset price booms/busts in the purely emerging markets dataset. Section 6 concludes.

2 Literature review and modeling strategy

Although a number of recent studies address the issue of asset price fluctuations and designing early warning indicators for emerging markets none of these, to our knowledge, addresses specifically the problem of predicting asset price booms and busts. Herrera and Perry (2003) assess the relative importance of domestic and external factors for determining the probability of an asset price bubble for a cross-section of Latin American countries. Lo Duca and Peltonen (2011) is a comprehensive study that develops a model for predicting systemic financial stress episodes for a sample of countries that includes emerging markets. They find that (in particular, global) measures of asset price misalignments and credit booms are generally useful as leading indicators. Tenjo and López (2010) construct an early warning indicator system for banking crises in a group of Latin American countries, in which asset price indicators play a crucial role. Bunda and Ca’Zorzi (2010) study whether asset price and credit booms can be used as an early warning indicator of financial (banking or currency) crisis, on the basis of a mixed sample of advanced and developing countries. They identify a number of macroeconomic variables that help to distinguish between benign and costly episodes. Olaberría (2012) conducts an empirical analysis of the relationship between capital inflows and booms in stock prices and finds that there is a close association (in particular for debt related inflows). Égert and Mihaljek (2007), Stepanyan et al. (2010), Posedel and Vizek (2011) and Ciarlone (2012) examine house price developments in selected emerging economies and find a strong link between house-price fluctuations and macroeconomic fundamentals. Posedel and Vizek (2011) also find that house price persistence coupled with a slow and asymmetric house price adjustment to fundamentals process might have facilitated the house price boom in some transition countries.

In contrast, there is a vast literature on asset price booms and busts in developed countries. We selected three studies dedicated to early prediction of asset price cycle developments and utilized different methods of identifying asset price boom/busts and a different modeling strategy. As outlined in chapter 6 of Papademos and Stark (2010) these models are used in a complimentary manner as part of the suite of models employed by the ECB for early detection of asset price misalignments by means of monetary analysis. The approaches these models are based on (i.e. signalling and discrete-choice) are also widely used in early warning indicators models for prediction of e.g. banking and currency crises. We therefore consider these models as appropriate example of existing state-of-the-art approaches to asset price booms/busts prediction.

Table 1 Selected approaches to asset prices boom/bust cycle prediction

Approach	*Asset prices indicator*	*Event predicted*	*Model*
Alessi and Detken (2011)	Real aggregate asset price index (deviations of levels from trend)	Boom	Stand-alone indicators
Gerdesmeier et al. (2010)	Nominal aggregate asset price index (q-o-q growth rates)	Bust	Discrete choice model
Agnello and Schuknecht (2011)	Real house prices (deviations of levels from trend)	Boom (bust) phases	Discrete choice model

There are some notable differences between the different approaches.

The first such difference is in the measurement of asset prices. Theoretically, the aggregate asset price index should be calculated using carefully constructed weights and should include prices for the selection of assets constituting a sizeable proportion of national wealth (see Borio et al. (1994) for a review). In practice, this approach is usually approximated by averaging between housing and equity prices, as there is an evident lack of data on national wealth in emerging economies. The caveat is that the drivers behind bubble formation in housing and in equity markets might be different, so that these types of assets should be considered separately for the purpose of constructing a system of early warning indicators. It is also questionable how representative the equity prices fluctuations are, given the relatively underdeveloped capital markets and presumably small share of equities in the national wealth of emerging economies. This may justify concentrating on housing prices when examining asset price fluctuations in emerging markets.

Another key choice is the method of boom/bust identification (see e.g. Stążka-Gawrysiak (2011) for discussion). The asset price indicator is usually examined in terms of growth rates or deviations from trend. The latter method may seem preferable, as it enables one to distinguish between changes in trend and cycle components; but it may also be sensitive to the de-trending method whereas the former method is more consistent and easily applicable. Both methods may be sensitive to outliers. Another method suggests analyzing asset prices developments in terms of phases of cyclical fluctuation, the severity of which is characterized by both amplitude and duration. This method is less sensitive to short-run fluctuations but may be more difficult as regards interpretation (e.g. one may argue that a prolonged period of steady asset price rise does not necessarily represent a boom).

The values of the constructed indicators, i.e. the deviations from trend, growth rate or phase severity, above (below) certain thresholds may then be labeled as booms (busts) [3]. The thresholds are usually defined in terms of percentiles or proportion of standard deviation. These may be country-specific (in which case we look for events that are exceptional for a given country) or computed for the whole cross-section (thus discriminating between the normal cyclical fluctuations that may be observed in most of the economies and outstanding boom/bust events).

The same issue is also relevant for explanatory variables that can be expressed in terms of country-specific percentiles. This transformation may seem appropriate for panel data analysis, as it takes into account potential cross-country differences in the scale of regressors. On the other hand this would limit the model's ability to avoid issuing the warning signal since by definition the value of the explanatory variable will be above the chosen threshold in some periods.

[3] We do not identify high or low cost asset price booms/busts, which would have been difficult, considering that most booms/busts in the sample occurred prior to the recent global crisis and were followed by a slowing

There is no clear indication in the literature that some of these methods should be considered superior to others. We thus consider all of the approaches and attempt to apply them to emerging markets data in order to assess the coherence of the results.

Finally, the choice of explanatory variables must be made. The selected studies echo the approach outlined in Borio and Lowe (2002) implying that the combination of asset prices, real sector and financial (e.g. money or credit) variables should be monitored for timely prediction of asset price bubbles. We will adopt a similar strategy.

One notable nuance is that Alessi and Detken (2011) also add global liquidity variables to their models. We do not use explicit measures of global liquidity for the following reasons. As was pointed out in Alessi and Detken (2011), the global private credit gap 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 will be dealing almost exclusively with this most recent wave (see Section 4). Obviously a global liquidity measure calculated on monetary developments in advanced economies and not being 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 no other boom/bust episodes are available for examination. Therefore instead of relying on the global liquidity measure we will attempt to capture the spillover[4] from advanced economies using country-specific capital inflow indicators as a proxy for financial exposure[5]. In this we will follow Herrera and Perry (2003), Tenjo and López (2010) and Olaberría (2012) who use capital flow variables in their models.

of output growth, irrespective of asset price developments. The question of whether an asset price boom/bust could amplify the output losses is pursued in a different strand of literature.

[4] Admittedly the contagion effect may impact emerging economies not only via the stoppage of capital inflows but also via the deterioration of foreign assets' quality (see Rose and Spiegel (2010) for discussion) since the resulting demand for liquidity and assets sales could also affect conditions in domestic assets markets. However the lack of data on bilateral foreign assets holdings for most of the countries in our sample prevented us from conducting this kind of analysis.

[5] Admittedly these two categories of variables cannot be viewed as complete substitutes, as the interplay between global liquidity and capital inflow variables may not be very distinct. Forbes and Warnock (2011) for example show that global money supply growth is rarely associated with capital inflows episodes. Interestingly, Brana et al. (2012) do not find a definite impact of global liquidity on asset prices, based on panel VAR estimates for a cross-section of emerging markets, while Kim and Yang (2011) find a link between asset prices and capital inflows in emerging Asian economies using a similar modeling framework.

3 Dataset

A significant challenge in constructing the early warning indicators system based on panel data is putting together an appropriate dataset. One may find it logical to use a homogenous cross-section that includes only relevantly similar economies (like Tenjo and López (2010) who use the cross-section consisting of Latin American countries). The caveat here is that it is also desirable to have a dataset that is balanced as regards the presence of boom/bust occurrences. For example, if our dataset 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 did not limit our cross-section to any particular group of countries and so included all emerging markets where adequate[6] housing price data were available. Scant availability of these data proved to be the main limitation on the number of countries in the cross-section and in most cases determined the time span of the dataset in our unbalanced panel. Accordingly (as reported in Table 2) the time sample used in our analysis covers the period from 1993Q1 to 2011Q2, but is highly country-specific (in most cases starting from the early 2000s).

Table 2 Emerging markets housing prices data availability

Argentina	1993Q1-2011Q2	Hungary	2001Q4-2011Q2	Poland	2005Q2-2011Q1
Armenia	2002Q1-2009Q1	Indonesia	2002Q1-2011Q2	Russia	1996Q4-2011Q2
Azerbaijan	2001Q1-2009Q3	Israel	2001Q1-2011Q1	Serbia	2003Q1-2010Q4
Bulgaria	1993Q1-2011Q2	Kazakhstan	2001Q1-2009Q3	Singapore	2004Q4-2011Q2
China	1997Q4-2011Q2	Korea	1993Q1-2011Q2	Slovakia	2005Q1-2011Q2
Colombia	1997Q1-2011Q2	Latvia	2005Q1-2009Q3	Slovenia	2003Q1-2011Q1
Croatia	2000Q4-2010Q4	Lithuania	1998Q4-2011Q1	South Africa	1993Q1-2011Q2
Estonia	1997Q1-2009Q3	Malaysia	1999Q1-2010Q4	Thailand	1995Q1-2011Q2
Georgia	2003Q1-2009Q3	Mexico	2005Q1-2011Q1	Ukraine	2000Q2-2009Q3
Hong Kong	1993Q1-2011Q2	Philippines	2004Q4-2011Q1		

[6] We advisedly do not use construction costs or housing utilities price indicators, as these may not be good proxies for housing prices in emerging markets. For example in many former Soviet Union countries housing utilities prices are largely administered by the government.

We used equity prices as another indicator of asset prices. For real sector variables, we used SNA indicators (GDP, fixed capital investment and private sector consumption). We used broad money (or if unavailable the broadest aggregate reported) for the monetary indicator and credit to private sector for the credit indicator. We used gross indicators of capital inflows. See Tables 10-11 in the Appendix for data description.

We were unable to retrieve the appropriate time series of equity prices for Azerbaijan and Georgia and of capital flows for Azerbaijan, Philippines and Serbia. Therefore these countries are excluded from the analysis wherever the respective indicator was involved. And, for Azerbaijan and Georgia, the housing price index is used instead of the aggregate price index.

All time series are quarterly (seasonally adjusted via X-12, where appropriate). Where variables in real terms were unavailable, GDP deflators were used to deflate, and where quarterly frequency data were unavailable, time series were interpolated via cubic splines.

4 Identification of asset price booms and busts

We employ three alternative approaches to identify the stages of asset price cycles.

- *Booms identification*. Following Alessi and Detken (2011) we apply a Hodrick-Prescott filter (λ=100000) to the real aggregate[7] asset price indices. Periods in which the index value exceeds the trend plus 1.5 times the standard deviation of the series are defined as booms.
- *Busts identification*. Following Gerdesmeier (2010) we examine the quarterly growth rates of the nominal aggregate asset price index and define as busts those periods in which the nominal aggregate asset price index declined by more than its mean quarterly change minus 1.5 times the standard deviation of the series.
- *Boom (bust) phases identification*. Following Agnello and Schuknecht (2011) we employ “triangular approximation” to distinguish between boom, bust and

[7] The aggregate asset price index was estimated as the weighted average between housing and equity price growth. Similarly to Gerdesmeier et al. (2010) the weights are inversely proportional to the variables’ volatil-

neutral phases of the asset price cycle. We de-trend the real housing prices indices via a Hodrick-Prescott filter (λ=100000) and then "smooth" the cycle fluctuations by extracting the rapidly adjusting trend with a Hodrick-Precott filter (λ=10). We identify the turning points and compute the persistence of the period from trough to peak (the upswing) and from peak to trough (the downturn) and the magnitude of the price changes over these periods. We consider each housing price phase as a triangle where the height is the magnitude and the base is the persistence/duration, and we use the computed squares of these triangles as severity metrics for the upswings and downturns. We extract the whole distribution of triangle squares and label the values lower than the first quartile as bust phases and values higher than the third quartile as boom phases (See Figures 2-3 in the Appendix for illustrations).

Because different methods may potentially yield conflicting results, it is important to ensure that the boom/bust identification scheme is robust. In theory the events identified by different methods should be part of the same cycle and thus be synchronized. That is, booms should be followed by busts and busts should be preceded by booms. Both events should also occur during respective phases (given the methods that we employed, it is most likely that a boom occurrence would mark the end of a boom phase and a bust event would happen at the start of a bust phase). The degree of our results' compliance to these assumptions is reported in Table 3.

Table 3 Methods' synchronization

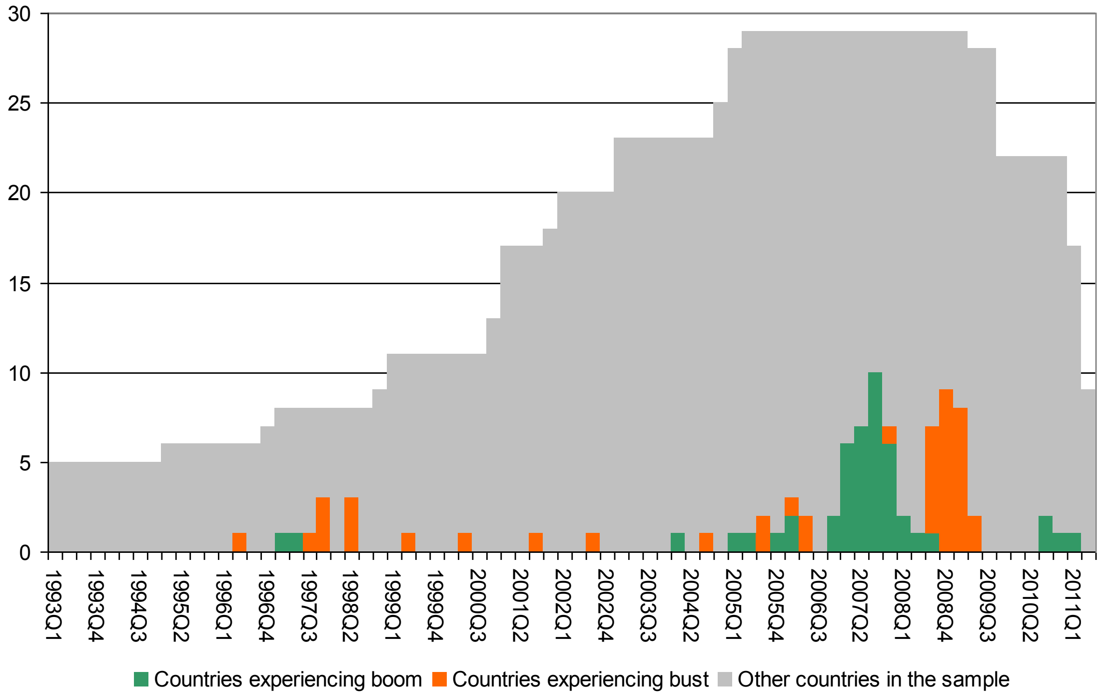
Event	Number of events identified	% of booms followed by busts within 2 years / % of busts preceded by booms within 2 years	% of booms associated[8] with boom phase / % of busts associated with bust phase
Booms	68	66%	69%
Busts	64	50%	69%

ity, i.e. Δ*Asset prices* = $\sigma_{sp}/(\sigma_{sp} + \sigma_{hp})$ Δ*Housing prices* + $\sigma_{hp}/(\sigma_{sp} + \sigma_{hp})$ Δ*Equity prices*, where σ is the standard deviation of the respective variable.

[8] We counted those boom and bust observations that were within or adjacent respectively to boom or bust phase periods.

The lack of total synchronization between methods is not surprising (Borgy et al. (2009) for example report that roughly half of booms are followed by busts in developed economies). For further analysis, we decided to count only those observations that were both identified as boom/bust *and* were associated with the respective phases. Presumably this will allow us to disregard both the outliers and the prolonged but tranquil upswings (downturns). By doing so, we expect to increase the robustness of our analysis. Thus we arrive at our final datasets.

Figure 1 Number of countries experiencing booms/busts



The overall size of the sample seems sufficient for meaningful empirical results (we identified 45 booms and 32 busts in a total 1263 observations). Yet this new dataset is substantially smaller than the developed countries' datasets (which include about 2700 observations) that were used to estimate the aforementioned models. Another caveat is that in our dataset there is basically only one (most recent) wave of boom/bust episodes available for analysis. This means that modifying the existing models to fit the new dataset might lead to the loss of empirical credibility. This tradeoff should be carefully considered when the models are compared and put into practical use.

5 Empirical analysis

We employ the standard approach to assessment of model performance (as in e.g. Kaminsky et al. (1998)). The signal is assumed to be issued when the indicator of interest exceeds a certain threshold. For early-warning purposes, we expect the model to start issuing the signal six quarters before a boom/bust occurrence.

Table 4 Model performance

	Boom/bust episode (within 6 quarters)	No boom/bust episode (within 6 quarters)
Signal issued	A	B
No signal issued	C	D

In this matrix, A is the number of quarters in which the indicator issued a good signal, B is the number of quarters in which the indicator issued a bad signal, C is the number of quarters in which the indicator failed to issue a signal when the boom/bust occurred and D is the number of quarters in which the indicator did not issue a signal when in fact there was no boom/bust. We define the loss function of the policy maker as

$$L = \theta\ (C/(A+C)) + (1- \theta)\ (B/(B+D)) \tag{1}$$

For our analysis we assume equal preferences for issuing false signals and missing boom/bust occurrences by setting θ=0.5. Following Alessi and Detken (2011) we employ the "usefulness" indicator to assess the models:

$$U = \min\ [\theta, 1- \theta] - L \tag{2}$$

One may conclude that the indicator is useful for the policymaker if the loss incurred by ignoring the signal is higher than the loss incurred taking it into consideration (i.e. if the "usefulness" indicator is positive). We rely on this indicator to determine the optimal threshold. As a secondary indicator we use the noise-to-signal ratio:

$$NtS = (B/(B+D)) / (A/(A+C)) \quad (3)$$

We will also report separately the Signal (A/(A+C)) and Noise (B/(B+D)) indicators.

We will not be able to fully replicate the real-time analysis (as in e.g. Lo Duca and Peltonen (2011) who conduct recursive estimation of their models) because in our sample most of the information on boom/busts occurrences comes in one batch. Therefore the models are estimated and thresholds are optimized *ex-post*. We will however do the transformations of the explanatory variables (i.e. de-trending and percentile calculation) recursively.

5.1 Stand-alone indicators

Our first approach is to follow Alessi and Detken (2011) and rely on the dynamics of individual macroeconomic variables to predict the boom occurrence. In doing this we apply the "signalling" approach first developed by Kaminsky et al. (1998), which represented a major contribution to the literature when it appeared and became a benchmark choice for early warning indicators system construction. 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.

We select three macroeconomic variables from three categories (asset prices, real sector and financial variables) to be used as early warning indicators. We choose the variables (as well as their transformations) that were found to be most useful in Alessi and Detken (2011)[9]. We also include capital inflow measures to our set of indicators. As pointed out in Krugman (2000), foreign direct investment inflows help smooth cycles in domestic asset prices and should not be linked to booms. We therefore include an indicator of total capital inflows and one that excludes foreign direct investment.

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 make the variable-specific evaluation of indicators' performance under the

[9] We use the results reported in Table 4 in the Annex of the working paper version of the article (ECB WP No. 1039).

optimized (in terms of "usefulness" indicator) percentile threshold. We report these optimal percentiles in column 3 and the respective "usefulness" indicator in column 4 of Table 5. We also report noise-to-signal ratios and their sub-components in columns 5-7. As in Andreau et al. (2007), we also calculate the composite index as the weighted average of signals issued by stand alone indicators with weights proportional to "usefulness". The index is normalized to have values between 0 and 1. The assumed threshold value for the composite index is 0.5.

Table 5 Stand alone indicators' performance

Category	Variable	Percentile	U	NtS	Signal	Noise
Asset prices	Real agg. asset prices (y-o-y growth)	60	0.17	0.47	0.65	0.31
	Real housing prices (de-trended)	75	0.14	0.54	0.62	0.33
	Real equity prices (de-trended)	90	0.07	0.6	0.36	0.22
Real sector	GDP (de-trended)	75	0.09	0.64	0.51	0.33
	Investment (y-o-y growth)	50	0.11	0.7	0.72	0.51
	Consumption (y-o-y growth)	65	0.13	0.56	0.57	0.32
Financial indicators	Real money (y-o-y growth)	65	0.1	0.63	0.52	0.33
	Real credit (y-o-y growth)	50	0.1	0.72	0.7	0.51
	Long term interest rate (de-trended)	45	0.02	0.95	0.7	0.66
Capital inflows	Total capital inflows	90	0.13	0.5	0.53	0.27
	Non-FDI capital inflows	75	0.13	0.58	0.63	0.36
	Composite index		0.18	0.45	0.67	0.3

Asset prices, real sector variables, money and credit are deflated via GDP deflator. Capital inflows are summed over four quarters and are in ratios to GDP. Deviations from trend are calculated via applying recursive Hodrick-Prescott filter (λ=100000) to series in logarithms.

Most of indicators perform reasonably well in terms of performance indicators that are generally comparable with those reported by Alessi and Detken (2011). The values of optimal threshold percentiles are also close to those in the original model. Asset price (in particular aggregate index and housing prices) and capital flow indicators seem to be the best performing categories, followed closely by real sector and financial variables (with the exception of the interest rate indicator). Constructing the composite index by averaging the signal issuance over the whole set of indicators helps to improve the system's performance. In our opinion these results confirm the applicability of the Alessi and Detken (2011) system of early warning indicators to emerging markets.

5.2 Discrete choice models: existing models' out-of-sample performance

As a second approach we construct an early warning indicator system in the form of a discrete choice model. This approach makes use of probit regression techniques to evaluate an indicator's contribution to predicting a boom or bust. As pointed out in chapter 6 of Papademos and Stark (2010), this approach has several beneficial features compared to the "signalling" approach. First, the discrete-choice approach allows a test of the usefulness of the threshold concept. Second, this method enables one to take into account correlations between different indicator variables. Finally, the approach allows the statistical significance of individual variables to be evaluated. This methodology consists of running probit regressions on the panel data set and comparing several specifications of the probit models, whereby an assessment of the specifications is made on the basis of probability scores and goodness-of-fit.

We begin by simulating the discrete choice models presented in Table 2 in Gerdesmeier et al. (2010) on our sample and assessing their performance in predicting the bust occurrences in emerging markets.

Accordingly, we construct our binary dependent variable, which equals one in the period one to six quarters prior to the bust occurrence (identified as described in Section 4) and equals zero in all other periods.

In order to capture potential differences in equilibrium values and scales of explanatory variables in developed and in emerging market countries we modify the models by de-meaning those variables that are not de-trended and re-estimating the common intercept term (while fixing all other coefficients) in the pooled probit regression framework[10]. As another test of model robustness, we also report the fully re-estimated models. Interestingly, the coefficients of the re-estimated Specification A model (at least in cases of credit growth and investment/GDP variables) seem to be consistent with the original results, which may be regarded as a confirmation of the model's applicability to emerging markets.

Next we simulate the models and calculate the formal performance indicators. We do this for the optimized probability threshold as well as for the benchmark threshold probability (0.5) as recommended in Roy and Kemme (2012). As in Gerdesmeier et al. (2010) we also report the quadratic probability score (QPS) and log probability score (LPS) to assess the goodness of fit of the models.

Table 6 Performance of Gerdesmeier et al.(2010) Specification A probit model

Variable/coefficient [p-values in brackets]	(1) unmodified model	(2) de-meaned variables and re-estimated constant	(3) de-meaned variables and all re-estimated coefficients
Nominal credit y-o-y growth	0.016	0.016	0.013 [0.00]
Nominal credit y-o-y growth(-4)	0.024	0.024	0.008 [0.09]
Investment/GDP ratio	0.023	0.023	0.068 [0.00]
Nominal equity prices nominal y-o-y growth(-1)	0.006	0.006	-0.00 [0.18]
Annual changes in long term interest rate	0.126	0.126	0.014 [0.32]
constant	-1.444	-1.33 [0.00]	-1.13 [0.00]

Performance indicators
[performance under benchmark threshold probability=0.5 in brackets]

Optimal threshold probability	*0.75*	*0.2*	*0.25*
U	*0.1 [0.07]*	*0.1 [0.04]*	*0.18 [0.04]*
NtS	*0.42 [0.64]*	*0.48 [0.26]*	*0.2 [0.12]*
Signal	*0.4 [0.59]*	*0.48 [0.13]*	*0.47 [0.09]*
Noise	*0.17 [0.38]*	*0.23 [0.03]*	*0.09 [0.01]*
QPS	*0.21*	*0.1*	*0.09*
LPS	*0.34*	*0.18*	*0.15*
No. of obs	963		

[10] We do not employ fixed-effects probit regressions in our analysis because, as noted in Davis and Karim (2008), this approach would lead to information loss for countries that did not experience a boom/bust.

Table 7 Performance of Gerdesmeier et al.(2010) Specification B probit model

Variable/coefficient [p-values in brackets]	(1) unmodified model	(2) de-meaned variables and re-estimated constant	(3) de-meaned variables and all re-estimated coefficients
Nominal credit y-o-y growth (de-trended)	0.071	0.071	-0.01 [0.5]
Nominal housing prices y-o-y growth (de-trended)	0.029	0.029	0.00 [0.73]
Annual changes in long term interest rate	0.125	0.125	0.02 [0.01]
Investment/GDP ratio	0.02	0.02	0.08 [0.00]
constant	-0.978	-1.08 [0.00]	-1.04 [0.00]

Performance indicators
[performance under benchmark threshold probability=0.5 in brackets]

Optimal threshold probability	*0.6*	*0.25*	*0.2*
U	*0.05 [0.05]*	*0.06 [0.03]*	*0.16 [0.03]*
NtS	*0.37 [0.51]*	*0.56 [0.28]*	*0.37 [0.1]*
Signal	*0.17 [0.27]*	*0.34 [0.1]*	*0.59 [0.08]*
Noise	*0.06 [0.14]*	*0.19 [0.03]*	*0.22 [0.01]*
QPS	*0.15*	*0.13*	*0.11*
LPS	*0.26*	*0.23*	*0.18*
No. of obs		937	

Deviations from trend are calculated via recursive Christiano-Fitzgerald filter.

The results of the models' out-of-sample performance are promising. Both models display acceptable "usefulness" and noise-to-signal indicators even in unmodified form, although Specification A seems to perform better. In fact the NtS indicators are very close to those reported by Gerdesmeier et al. (2010) for the original sample, while the QPS and LPS measures are actually lower (better fits). Using partially modified type (2) models leads to even lower QPS and LPS indicators but not necessarily to better performance in terms of other indicators. The "usefulness" of the models is not huge when assessed under benchmark threshold probability (0.5) due to the small number of signals issued (as pointed out in Roy and Kemme (2012), such an outcome is typical for this approach), although it is still positive. As could be expected, re-estimating all the coefficients substantially improves the models' performance. We will however concentrate on fully re-estimated models for emerging markets in the next section.

5.3 Discrete choice models: emerging markets model

As the final step in our empirical analysis we construct a discrete choice model fitted to predict asset price boom/busts on purely a cross-section of emerging market economies. We however try not to deviate from the model setup outlined above.

We design two separate models for predicting boom and bust occurrences. Accordingly, we construct our binary dependent variables to equal one in the period one to six quarters prior to the boom/bust occurrence (identified as described in Section 4) and to equal zero in all other periods.

We consider four categories of explanatory variables: asset price indicators (aggregate and housing price indices), real sector indicators (GDP, consumption and investment), financial variables (money and credit) and capital inflows (total and non-FDI). The variables in the first three categories are in real terms (asset price and financial variables are deflated via GDP deflator), in either annual growth rates or deviations from trend[11] (for money and credit, the ratios to GDP were de-trended). Additionally, we consider the investment to GDP ratio. Capital inflows are summed over four quarters and are in ratios to GDP. All variables that are not in deviations from trend are de-meaned.

Our empirical strategy is as follows. We combine the variables (one from each category) and their bivariate interactions in the pooled probit regression framework. The aim is to find a parsimonious model with only statistically significant[12] variables or corresponding interaction terms but with preference given to models that include indicators from all four categories. When several such models were found we selected the one with the best "usefulness" indicator under optimized threshold probability. Thus we arrive at two preferred models for boom and bust prediction. As in the previous section we assess model performance via the standard set of indicators under optimized and benchmark threshold probability.

[11] Deviations from trend are calculated via applying recursive Hodrick-Prescott filter (λ=100000) to series in logarithms.
[12] We assumed the criteria of test statistic>1.5.

Table 8 Emerging market booms prediction probit model

Variable	Coefficient	P-value
Real housing prices (y-o-y growth)	0.025	0.00
Real credit (y-o-y growth)	0.014	0.00
Total capital inflows	0.694	0.06
Investment to GDP ratio	-0.591	0.00
Real credit (y-o-y growth) * Investment to GDP ratio	0.002	0.01
constant	-1.312	0.00

Performance indicators
[performance under benchmark threshold probability=0.5 in brackets]

Number of observations: 853 McFadden R^2: 0.125 QPS: 0.09 LPS: 0.14

Threshold probability:0.15 U:0.19[0.02] NtS:0.37[0.21] Signal:0.68[0.07] Noise:0.25[0.01]

The boom prediction model includes annual growth of housing prices, total capital inflows and the credit growth variable, which is significant and has the correct sign both as a linear term and in interaction with the investment to GDP ratio[13].

Table 9 Emerging market busts prediction probit model

Variable	Coefficient	P-value
Real aggregate asset prices (de-trended)	-2.239	0.00
Real credit (y-o-y growth)	0.014	0.00
Total capital inflows	2.622	0.00
Investment to GDP ratio	0.054	0.00
Real aggregate asset prices (de-trended) * Investment to GDP ratio	0.092	0.13
constant	-1.34	0.00

Performance indicators
[performance under benchmark threshold probability=0.5 in brackets]

Number of observations: 818 McFadden R^2: 0.17 QPS: 0.08 LPS: 0.13

Threshold probability:0.3 U:0.2[0.08] NtS:0.13[0.06] Signal:0.47[0.16] Noise:0.06[0.01]

[13] The fact that the linear term of the variable in the interaction (in this case investment to GDP ratio) is negative does not imply that the overall effect of this variable is negative.

The bust prediction model includes similar variables: credit growth, investment to GDP ratio and total capital inflows. In the busts model, the investment to GDP indicator is also included in the form of interaction with the aggregate asset prices indicator. Considering the results presented in Sections 5.1 and 5.2, we conclude that credit and investment are evident candidate variables for boom/bust prediction in emerging markets.

As could be expected, these models have the highest formal performance indicators (U=0.19 and U=0.2) among those assessed in this paper (although the composite index of stand-alone indicators' signals calculated in Section 5.1 is not far behind with U=0.18). There is no clear indication that boom prediction works better than bust prediction (or vice versa), although the busts model is notably less noisy (which is reflected in the low Noise and NtS indicators).

6 Conclusions

This paper contributes to the literature by investigating whether early warning indicator models can be used for predicting asset price boom/bust occurrences in a cross-section of 29 emerging markets. We identify booms/busts using different approaches. The results are not fully synchronized but may still be regarded as cohesive. 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 booms/busts can be analyzed.

We employ two modeling approaches (stand-alone indicators and discrete choice models) that were previously applied to a cross-section of developed countries. The results seem promising. In fact even the out-of-sample performance of the unmodified developed countries' models is satisfactory on our emerging markets dataset. Naturally further enhancement and re-estimation of these models increases their in-sample predictive performance, although these modifications need not be extensive.

Our results are generally inconclusive as to which approach to predicting asset price boom/bust is superior. But we argue that the concept that relies on monitoring the combined set of asset prices, real activity and financial indicators is widely applicable to emerging markets and its efficiency is confirmed under the different model setups. According to our estimates credit growth and investment (in either growth rates or ratio to GDP) turned out to be particularly reliable indicators for forecasting asset prices cycle. We also find that, in addition to this set of variables, early warning indicator systems for emerging countries may be augmented with capital flows indicators.

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Appendix

Table 10 Data sources

Indicators	*Sources*
Housing prices	- BIS property price statistics database; - Stepanyan et al. (2010) database; - Global Property Guide (www.globalpropertguide.com); - National statistical agencies
Equity prices	- Stock exchange websites; - Yahoo! Finance
GDP, investment, consumption	- IMF-IFS; - National statistical agencies' websites
Money, credit	- IMF-IFS; - Central banks' websites
Capital flows	- National statistical agencies' websites - Central banks' websites

Table 11 Descriptive statistics of variables used in Section 5

Variable	*Mean*	*Std Deviation*	*Min*	*Max*
Real aggregate asset prices (y-o-y growth)	7.4	28.9	-100	206
Real aggregate asset prices (de-trended with HP-filter)	-0.02	0.16	-1.07	0.46
Real housing prices (de-trended with HP-filter)	0.02	0.14	-0.81	0.59
Real housing prices (y-o-y growth)	4.35	15.8	-59.4	80.8
Nominal housing prices (y-o-y growth de-trended with CF-filter)	-0.7	7.2	-26.6	41
Real equity prices (de-trended with HP-filter)	0.00	0.34	-1.7	1.44
Nominal equity prices (y-o-y growth)	19.7	49.1	-79.1	670.7
GDP (de-trended with HP-filter)	0.00	0.08	-0.44	0.29
Investment (y-o-y growth)	4.5	18.5	-84.7	228.7
Investment/GDP ratio	24.1	7	9.7	58.6
Consumption (y-o-y growth)	4.5	7.5	-45.4	88.7
Real money (y-o-y growth)	9.2	12.7	-68.1	125.9
Real credit (y-o-y growth)	11.8	22.1	-81.1	162.9
Nominal credit (y-o-y growth)	26.3	42.4	680.9	-61.2
Nominal credit (y-o-y growth de-trended with CF-filter)	-0.4	7.6	-47.4	71.6
Long term interest rate (de-trended with HP-filter)	2	21.1	-248.6	512.4
Annual changes in long term interest rate	-1.5	30.1	-721.6	682.5
Total capital inflows	0.13	0.2	-0.33	1.35
Non-FDI capital inflows	0.08	0.15	-0.5	1.22

Figure 2 “Triangular approach” identification of booms/busts: Russian case

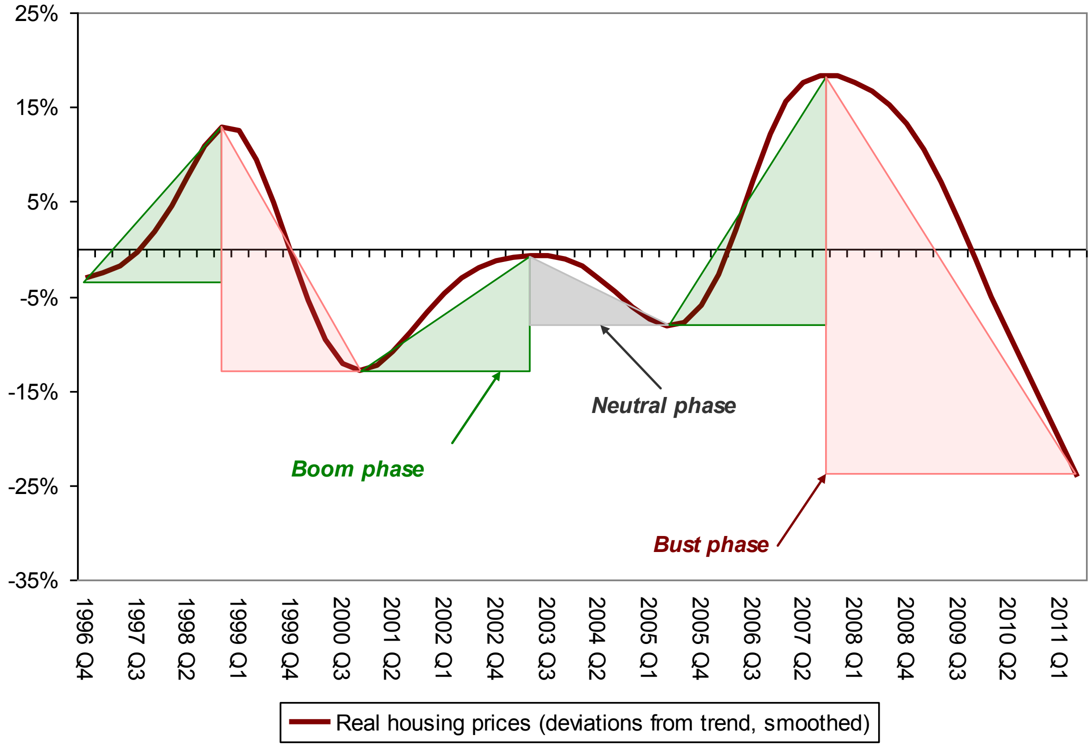
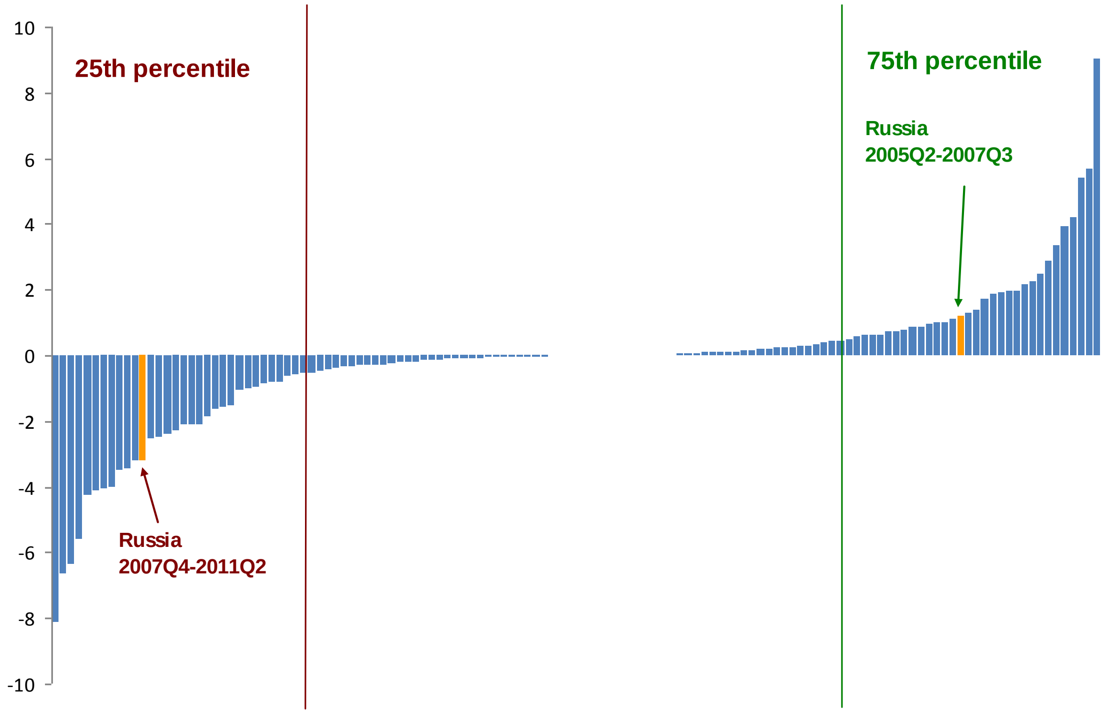


Figure 3 Distribution of “severity” measures (triangular squares) of boom/bust phases



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