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Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity

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ABSTRACT

We test the performance of a host of real and financial variables as early warning indicators for costly aggregate asset price boom/bust cycles, using data for 18 OECD countries.

A quasi real time signaling approach is used to predict asset price booms that have serious real economy consequences. We use a loss function to rank the indicators given policy makers' relative preferences with respect to missed crises and false alarms and suggest a new measure for assessing the usefulness of indicators.

Global measures of liquidity, in particular a global private credit gap, are the best performing indicators and display forecasting records, which are informative for policy makers interested in timely reactions to growing financial imbalances.

1. Introduction

The recent financial crisis has intensified the debate whether changes in regulatory policy and/or monetary policy should be actively used in the building up phase of financial imbalances in order to contain asset price booms and bubbles. With respect to monetary policy, the pertinent question is whether central banks should 'lean against the wind' of a sustained and swift upward movement in asset prices, which is considered unsustainable and bears the risk of a possibly abrupt future correction. An asset price bust can have serious negative consequences for the real economy and in case of financial instability it will complicate the central bank's task to maintain price stability. Indeed, in such a situation, uncertainty about the prevailing transmission mechanism would increase and in the worst case transmission could get seriously impaired. It is also an open question to which degree the reluctance to sufficiently 'lean against the wind' has played a role in accommodating the buildup of imbalances leading to the recent financial crisis.[1]

With respect to macro-prudential regulatory policy the potential benefits of some sort of counter-cyclical policies are much less controversial among economists. The problem is that macro-prudential policy is a relatively new field and clear advice on the precise tools to be used and their calibration is still in its infancy.[2]

In any case, the availability of real time information, which can be used to warn against imminent costly boom/bust cycles – i.e. those boom/bust cycles which have serious consequences for the real economy – is a necessary condition for the feasibility of any

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[1] See e.g. Taylor (2009) and Assenmacher-Wesche and Gerlach (2008) for opposite views.
[2] Brunnermeier et al. (2009).

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of the two types of counter-cyclical policies mentioned above. For example, the unavailability of this information has been a traditional argument against 'leaning against the wind' policies. Therefore, this paper addresses the real time availability of warning signals.[3] We aim to answer four questions. First, do we have indicators, which when used in the simplest early warning indicator (signaling) approach, provide useful information to decision makers in a timely manner? We attempt to answer this question using historical data but in a quasi real time experiment. Second, are financial or real indicators more useful in predicting costly asset price cycles? Third, considering the information content in financial variables, are global or domestic indicators better suited to provide early warning signals? And fourth, do money or credit based liquidity indicators show a superior performance in predicting costly asset price boom/bust cycles?

With respect to deciding on what is an acceptable performance for an indicator we go beyond the standard way of searching for indicators with noise to signal ratios below 1, but take into account the preferences of policy makers, i.e. their relative aversion with respect to missed crises and false alarms.[4] Our novel approach, requiring an indicator to provide positive utility compared to a benchmark in which the indicator is ignored, results in a much tougher criterion to assess the usefulness of indicators.

In order to see where this paper fits in the current discussion, it is worth highlighting three major knowledge gaps with respect to the current debate on 'leaning against the wind' with monetary policy.

First, it is not exactly clear through which channel tightening monetary policy in times of excessively low risk aversion would be successful in dampening an asset price boom and to which degree central bank communication could matter. Recently though more and more empirical evidence as well as theoretical arguments have been produced directly or indirectly supporting the 'leaning against the wind' proposition. There is growing empirical evidence on the existence of a risk-taking channel.[5] Banks seem to take on more risk in times of persistently low interest rates even after controlling for the cyclical net worth of borrowers and the endogeneity of monetary policy (Jiménez et al., 2007). Furthermore, it has been shown that possibly even small increases of the policy rate could be effective in containing exuberant behavior, as interest rate hikes could a) break herding behavior of private investors (Loisel et al., 2009), b) be interpreted as a credible signal revealing the central bank's analysis of current financial imbalances (Hoerova et al., 2009) and c) affect the profitability of intermediaries' business models relying on extreme leverage and maturity transformation (Adrian and Shin, 2008a). Another potentially important channel in favor of a 'leaning against the wind' policy is the increased symmetry in central banks' responses with respect to boom and bust periods, which would reduce moral hazard (Diamond and Rajan, 2009).

An issue very much related to the transmission channels is the central bank communication concerning 'leaning against the wind'. The above mentioned transmission mechanisms, namely risk taking, herd breaking, signaling and moral hazard (reduction), are likely to become much more effective when the central bank is transparent about why it is moving interest rates. Furthermore, Baltensperger et al. (2007) mention that especially goal independent central banks – as opposed to only instrument independent (e.g. pure inflation targeting) central banks – can only reap the benefits of increased flexibility, when their policies are clearly understood.[6] Of course, transparent communication requires policy makers to feel comfortable with the risks associated with type II errors, i.e. the likelihood of calling a false alarm.

Second, it has not yet been convincingly shown that asset price boom and bust cycles are under all conditions bad for the long run growth path of the economy. There is some evidence that the increase in collateral value during asset price booms alleviates financing constraints as long as the boom lasts, which could more than compensate for the recession during the bust phase. However, this evidence has only been provided for middle income countries and is unlikely to hold for countries with well developed financial markets (Rancière et al., 2008). But the general issue how much financial instability should be accepted in order to best exploit the long run growth potential remains an open question. The answer is likely to be country and time dependent. Furthermore, in quite a few micro-based theoretical models of bubbles, pricking bubbles is bad for investment and growth due to the resulting collateral shortage (Farhi and Tirole, 2009). However, these micro-models tend to abstract from several features, which make boom/bust cycles costly in the real world.[7]

Third, there is the above mentioned skepticism in the academic and central banking community whether asset price bubbles can be identified in real time in order to allow policy makers to react.[8] On the other hand, this theoretically well founded skepticism might, for the practical purpose of identifying warning signs, be overrated. It might not always be necessary to come to a firm conclusion whether particular asset price movements are justified by current and future expected fundamentals (Adrian and Shin, 2008a). Adalid and Detken (2007) pursue a more agnostic approach and derive characteristics of costly asset price booms, where booms are simply defined as unusually swift and persistent asset price increases compared to trend.[9] We follow this approach here and the results are encouraging.

[3] Strictly speaking, our approach is only a quasi real time approach, as described in Section 2. However, the crucial point here is that no use of future information is made at each point in time to predict costly boom-bust cycles.

[4] Demirgüc-Kunt and Detragiache (1999) introduced the loss function approach to the early warning literature. See also Bussière and Fratzscher (2008) and Borio and Drehmann (2009b) for more recent applications.

[5] While Rajan (2005) and Borio and Lowe (2002) introduced the channel, Borio and Zhu (2008) coined the term 'risk-taking'.

[6] More specifically Baltensperger et al. (2007) state: "...the goal independent central bank must demonstrate consistently its unwillingness to sacrifice long-run macro performance for the benefit of better short-run performance". Transparent communication on 'leaning against the wind' would also be compatible with the three reasons for central bank communication to matter, provided by de Haan et al. (2007), namely non-rational expectations, asymmetric information and absence of policy rules.

[7] See e.g. Reinhart and Rogoff (2009) on the typical government debt explosion following banking crises (on average 86 percentage points of debt/GDP increase in the three post crises years for the major post 1945 episodes).

[8] Kohn (2008) mentions this as one of the key challenges casting doubt on the feasibility of 'leaning against the wind'.

[9] Borio and Lowe (2002, 2004) and Borio and Drehmann (2009a) provide evidence that detrended asset prices can serve as indicators for banking crises.

The paper is also directly relevant for the discussions about a new international monetary and financial architecture. The Report of the High-Level Group on Financial Supervision in the EU (de Larosière Report, published 25 February 2009) has argued that "it is crucial that there is an effective early warning mechanism as soon as signs of weakness are detected in the financial system". The new European supervisory framework will be established in January 2011 and comprises the European Systemic Risk Board (ESRB). The ESRB has the mandate to identify systemic risk in the EU financial sector at an early stage and to suggest policy recommendations to contain these risks. A model, like the one presented in this paper, could potentially be a useful input to ESRB proceedings.

This paper provides no further arguments with respect to the debate to which degree monetary policy or macro-prudential regulatory and supervisory measures are suitable to address growing financial imbalances—most likely they will have to complement each other in the sense that monetary policy will be the backup-solution to lacking or inefficient regulatory and supervisory actions. But in both cases, reliable and timely warning signals are a necessary requirement for any policy aiming at tightening the screws during pre-boom and early boom periods.

Section 2 introduces the signaling approach as in Kaminsky et al. (1998) and applied to banking crises in Borio and Lowe (2002, 2004) and Borio and Drehmann (2009a, 2009b) but adds some further elements of quasi real time evaluation and an alternative measure evaluating the usefulness of indicators.

In Section 3 we outline the method to define the events to be predicted, which are costly aggregate asset price booms. The asset price index consists of weighted real private property, commercial property, and equity prices for 18 OECD countries using quarterly data between 1970 and 2007 provided by the Bank for International Settlements.[10]

Section 4 describes the data set, i.e. 18 real and financial variables and the transformations we apply to derive overall 89 indicators, which we evaluate with respect to their forecasting performance. In particular, we include variables which have previously been found to explain real effects following asset price boom/bust cycles (Adalid and Detken, 2007).

Section 5 presents the results of the forecast evaluation and addresses the four questions raised above. We also investigate to which degree twin indicators improve the performance over single indicators as in Borio and Lowe (2002).

Section 6 uses the best indicators to analyze out-of-sample whether the most recent wave of asset price booms in the 2005–2007 period would have been predicted to be high cost.[11]

Section 7 concludes. The results reveal that over the average of all countries and for a wide range of preference parameters the global private credit gap and the global M1 gap are the best early warning indicators.[12] The forecast performance is such that the approach should provide value added to policy makers contemplating leaning against growing financial imbalances – either by means of monetary or macro-prudential policies – as long as their preferences are relatively balanced between missed crises and false alarms. With respect to the latest boom wave around 2005–2007, the global private credit gap has been sending persistent warning signals while the global money (M1) gap has not.

2. Quasi real time signaling approach and risk aversion

We use the signaling approach as described in Kaminsky et al. (1998) and Kaminsky and Reinhart (1999), which has frequently been employed to predict foreign exchange and banking crises, but to our knowledge not for predicting asset price boom episodes. While most banking crises are preceded by asset price cycles, not all asset price cycles lead to banking crises. The definition of a banking crisis is also less straight-forward as it might appear at first sight. For example, one could argue whether a banking crisis should be characterized by the failure of at least one bank or already by the provision of central bank emergency liquidity assistance and/or a government bail-out or the provision of government guarantees for at least one bank. Some banking crises have large, some low GDP costs, but most importantly there are relatively few banking crises around. The advantage of studying asset price cycles is that there are a sufficient number of them and one can also explore the characteristics of the group of relatively more costly compared to the less costly cycles.

The signaling approach is one of the two threshold approaches using a binary dependent variable. The other approach is the discrete-choice (probit/logit) model.[13] The choice between signaling and discrete choice models mainly depends on the degree of expected non-linearity between the indicator and the event variable. In the signaling approach a warning signal is issued when an indicator exceeds a threshold, here defined by a particular percentile of an indicator's own distribution. This approach assumes an extreme non-linear relationship between the indicator and the event to be predicted. Furthermore, as the theoretical guidance on the determinants of eventually costly exuberance in financial markets is not very concise, we prefer to test a large variety of potential indicator variables. Inference from regression based analysis might be easily misleading in case a large number of regressions are run. We therefore consider the signaling approach as a reasonable first step to detect indicators worth to be investigated further also using other approaches.

[10] The fact that we only focus on aggregate asset price booms and not equity and housing market booms separately, reveals that our primary motivation is to find information for a 'leaning against the wind' type of monetary policy. Due to the possible bluntness of interest rate changes, reasonable warning signals should refer to as large a share of the financial sector as possible. For ESRB purposes, one should also analyze risks in financial market segments separately, as they might be addressed with sector specific regulatory policy measures. This is left for further research.

[11] Borio and Drehmann (2009a) evaluate the performance of their indicators with respect to the 2007–09 banking crisis and show how results depend on the definition of a banking crisis.

[12] Global gaps refer to detrended ratios to GDP with country weights derived from PPP adjusted GDP shares.

[13] See Chui and Gai (2005) for a survey and Edison (2003) for relevant discussions. Recently Gerdesmeier et al. (2009) have used a probit approach to predict asset price busts.

Each quarter of the evaluation sample for each indicator falls into one of the quadrants of the following matrix.

	Costly boom/bust cycle (Within 6 quarters)	No costly boom/bust cycle (Within 6 quarters)
Signal issued	A	B
No signal issued	C	D

A is the number of quarters in which an indicator provides a correct signal, B the number of quarters in which a wrong signal is issued. Correspondingly, C is the number of quarters the indicator does not issue a signal despite a costly boom/bust cycle starting within the following six quarters. D is the number of quarters in which the indicator does not provide any warning signal, and rightly so.

$A/(A+C)$ is the number of good signals as a ratio to all quarters in which a costly boom/bust cycle followed within six quarters. $B/(B+D)$ represents the share of bad signals as a ratio of all quarters in which no such booms followed. $B/(B+D)$ can be considered the share of type II errors (event not occurring but signal issued, as share of $B+D$) or simply the share of false alarms. Correspondingly $C/(A+C)$ is labeled the share of type I errors (event occurring but no signal issued, as share of $A+C$) or simply the share of missed costly boom/bust cycles.

Kaminsky et al. (1998) and the literature following their seminal contribution assess the usefulness of an indicator by computing the adjusted noise to signal ratio (aNtS) defined as $[B/(B+D)]/[A/(A+C)]$. A useful indicator is supposed to have an aNtS of less than 1. A value of 1 would result if an indicator provides purely random signals.

However, the criterium of aNtS<1 is only a necessary condition for an indicators' usefulness in practice, as a) the resulting type I and type II errors might be unacceptable to policy makers given their preferences and b) the gain associated with receiving signals from an indicator as compared to ignoring it, which also depends on preferences, might be irrelevant.

We define a loss function for the policy maker, a central banker in this case, to analyze the usefulness and to rank indicators.[14] The loss function is defined as

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

θ is the parameter revealing the policy maker's relative risk aversion between type I and type II errors. The loss can be easily interpreted. It is the preference weighted sum of type I and type II errors. A θ lower than 0.5 reveals that the central banker is less averse towards missing a signal for a costly asset price boom/bust cycle than towards receiving a false alarm.[15]

The usefulness of an indicator can then be defined as

$$\text{Usefulness} = \min[\theta; 1-\theta] - L \tag{2}$$

A central banker can always realize a loss of $\min[\theta; 1-\theta]$ by disregarding the indicator. If θ is smaller than 0.5, the benchmark is obtained by ignoring the indicator, and never having any signals issued, so that $A=B=0$. The resulting loss according to Eq. (1) is θ. If θ exceeds 0.5, the benchmark for the central bank is assuming there is always a costly boom developing, i.e. assuming a signal is always issued so that $C=D=0$. The resulting loss is $1-\theta$. An indicator is then useful to the extent that it produces a loss lower than $\min[\theta; 1-\theta]$ for a given θ, i.e. relying on the indicator reduces the loss compared to a situation in which the indicator is ignored.

Fig. 1 visualizes one particular example (global M1 gap, see Section 4) of how the optimal trade-off of policy makers depends on relative preferences. Policy makers' preferences, i.e. the aversion to missing a boom/bust cycle relative to receiving false alarms as measured by θ, is depicted on the X-axis. Type I errors (missed high-cost boom as percentage of periods in which a high-cost boom followed within 6 quarters, $C/(A+C)$) and type II errors (false alarms as percentage of periods in which no high-cost boom followed within 6 quarters, $B/(B+D)$) are depicted on the Y-axis. The boxes between the two error lines show the threshold (in terms of percentile of own past distribution) minimizing the loss function for the indicator. The optimal percentile of the distribution of the M1 gap – which when exceeded triggers a warning signal – declines in discontinuous steps with rising θ. Correspondingly, type I errors fall and type II errors increase. Another way to use the information provided in Fig. 1 is to choose the threshold, which would produce acceptable type I and II errors for the decision maker. In this particular example, a percentile of 85% looks like a reasonable choice. The (time varying) thresholds associated with an 85% percentile did not allow issuing a warning signal in 40% of quarters followed by a costly boom/bust cycle and provided false alarms in 20% of quarters not followed by a costly boom/bust cycle.

Another difference to the standard literature using the signaling approach is that the performance of the indicators reported here is based on a quasi real time analysis. Indeed, at each point in time we set the thresholds for the indicators on the basis of past

[14] See for comparison variations in Demirgüc-Kunt and Detragiache (1999) and Bussière and Fratzscher (2008).

[15] We believe a θ smaller than 0.5 is a realistic description of central bankers' loss functions, although the recent financial crisis might have increased the average θ. If asset price booms are not discovered as such in a timely manner or the monetary policy strategy does not foresee reacting to asset price developments beyond the impact of asset prices on consumer price inflation at traditional forecast horizons, there always remains the possibility to smooth the bust phase by means of a very accommodative monetary policy stance and by providing liquidity (to the market or individual banks). On the other hand, a central banker would certainly have to cope with serious public pressure when being found out to have spoiled the party while relying on a false alarm. Furthermore, even if the indicator performed well and provided a correct signal and the central banker successfully ‘leaned against the wind’, he might be criticized for too tight monetary policy as the counterfactual is unavailable. See also Borio and Lowe (2002) for a discussion of relative preferences.

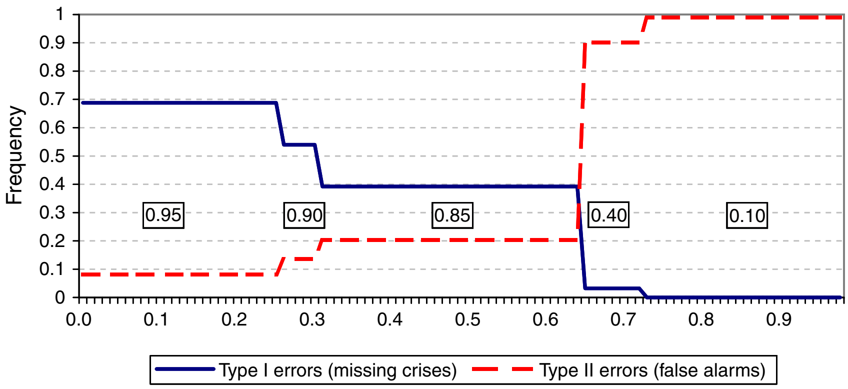

Fig. 1. The central banker's trade-off between missing crises and false alarms for the global M1 gap. X-axis: θ. Numbers in boxes refer to optimal percentiles of the distribution corresponding to different values of θ, which are used to set the optimal threshold.

observations. Trends are calculated recursively only using available data up to each point in time. Therefore we obtain signals as they would have been obtained in the period they refer to. However, there is one notable exception and one caveat. The percentiles of the distribution, beyond which a warning signal is issued, are optimized ex-post for each indicator using all relevant boom/bust cycles in the evaluation sample between 1979 and 2002. Unfortunately, choosing the optimal percentile of the distribution at each point in time is not feasible. Indeed, we would need to have, at each point in time, at least one past costly asset price boom/bust cycle, in order to evaluate the indicator's performance. In our approach, the specific indicator thresholds for each quarter are derived by applying the fixed optimal percentile to the distribution of the data available up to each specific point in time. Thresholds for each indicator are thus time and country dependent. The caveat is that we use the most recent vintage of data and not a true real time data set with unrevised data. Nevertheless, we use conservative lags to proxy for standard publication lags and thus real time data availability. Publication lags are particularly important for housing prices and vary across countries, as will be discussed in Section 4. Overall, our main conclusion, i.e. the good performance of money and credit variables for predicting costly asset price boom/bust cycles, should not be affected by the use of current vintage data instead of real time data, as financial variables are generally revised only slightly. On the other hand, the performance of real variables could possibly be worse in a true real time setting compared to a quasi real time setting, as real variables can be heavily revised (i.e., the quality of current vintage data can be much better than the quality of real time vintages).

3. Identification of asset price booms

We start by mechanically defining asset price boom episodes for 18 OECD countries[16] between 1970:Q1 and 2007:Q4. The real aggregate asset price indices have been provided by the Bank for International Settlements and are weighted averages of equity prices, residential and commercial real estate prices, and are deflated with the national consumption deflators. We use an aggregate asset price index as the primary objective has been to identify imbalances, which could potentially be addressed by monetary policy. As a change in the monetary policy stance will affect the whole range of asset prices, it is more useful to focus on episodes when a weighted average of domestic asset prices is booming. For other purposes, i.e. financial stability surveillance in the context of the to be created European Systemic Risk Board, it would be more appropriate to focus on individual asset classes and derive early risk warnings for specific segments of the market.

An aggregate asset price boom is defined as a period of at least three consecutive quarters, in which the real value of the index exceeds the recursive trend plus 1.75 times the recursive standard deviation of the series. The recursive trend is calculated with a very slowly adjusting Hodrick–Prescott filter ($\lambda = 100{,}000$) taking into account only data up to the respective quarter.[17]

Boom if for 3 consecutive quarters:

$$Asset\ \ price\ \ index > recursive\ \ HP\ \ trend + 1.75 * recursive\ \ stdev$$

The value of 1.75 is the one preferred by Mendoza and Terrones (2008) in identifying credit booms. 1.75 also provides results which are relatively comparable to the boom identification reported in Adalid and Detken (2007).[18]

[16] The countries are Australia, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, the United Kingdom, Ireland, Japan, Netherlands, Norway, New Zealand, Sweden, and the United States.

[17] A similar method has previously been used in Gourinchas et al. (2001) and Borio and Lowe (2002). Also in Detken and Smets (2004) and Adalid and Detken (2007) the price index needs to exceed 10% of its slowly adjusting recursive trend in order for a quarter to qualify as potential boom quarter. In this paper instead, we identify booms using country specific information with respect to the volatility of asset prices, which should give a better picture of what can be considered unusually swift asset price developments for each country. See also Mendoza and Terrones (2008) for a discussion of alternative methods.

[18] We also experimented with 1.5 and 2 times the recursive standard deviation. This did not have significant effects on the boom identification, except from delivering marginally longer and shorter boom episodes, respectively. The examples in Mendoza and Terrones (2008), their Figs. 4 and 5, show that the main difference in this class of boom identification methods derives from the choice of country specific standard deviations versus fixed percentage thresholds to compute deviations from trends, rather than the choice of λ to compute the recursive trend. Nevertheless, we also derived all results of the paper when defining booms by a fixed, not country-specific, larger than 10 percentage point deviation from trend without obtaining major qualitative changes.

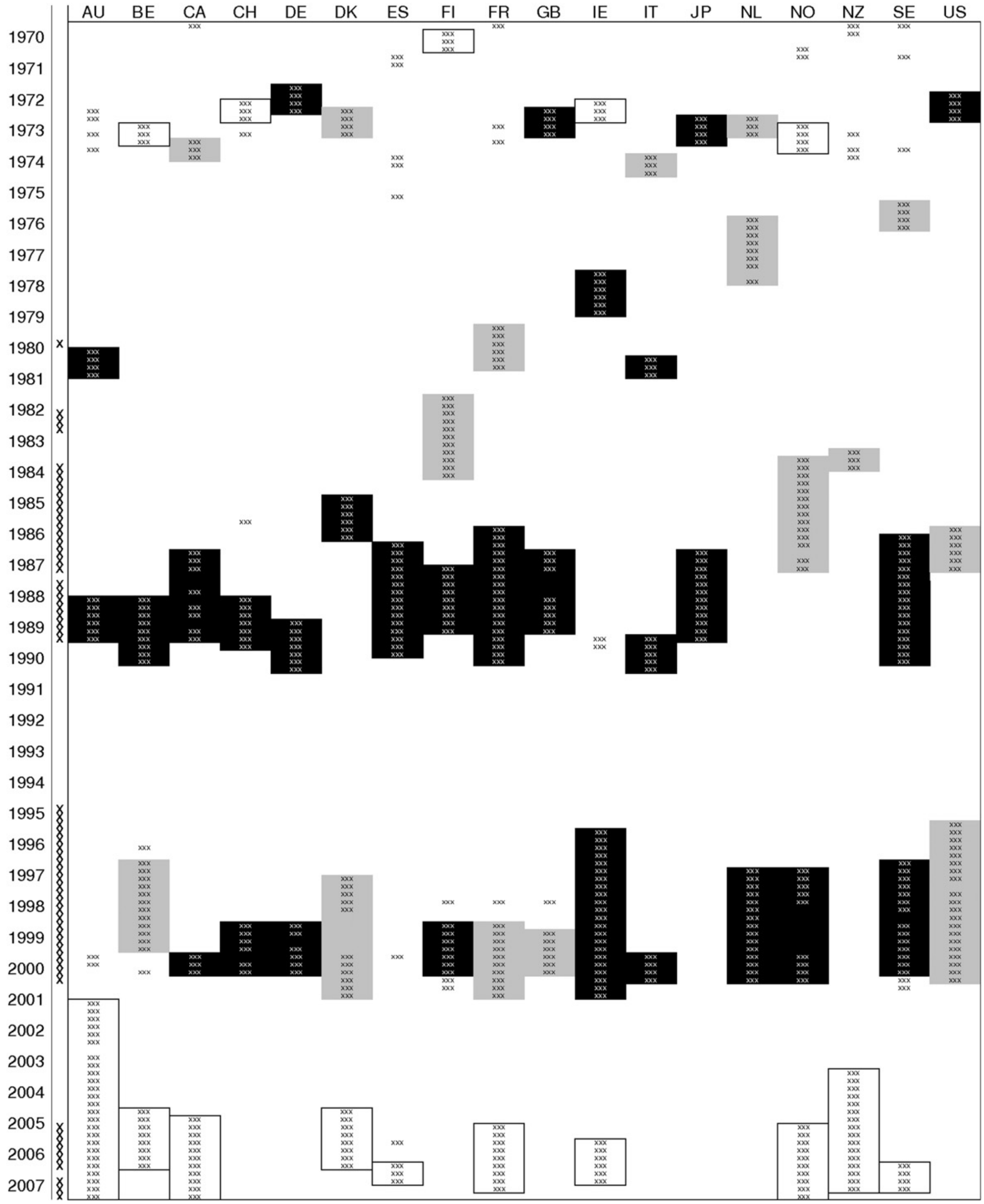

Fig. 2. Identified boom periods. In those periods highlighted with xxx the real value of the index exceeds the recursive trend plus 1.75 times its recursive standard deviation. Gray indicates low-cost booms, black indicates high-cost booms while the others are booms which do not fall into the evaluation period. The first column indicates with X those quarters in which the detrended global private credit to GDP ratio issues warning signals (with threshold at the 70th percentile).

We then differentiate between aggregate asset price booms, which have little consequences for the real economy and those that have significant effects. The definition of a high-cost boom (HCB) is chosen in a way to reasonably split our sample of 45 booms, i.e. the first two boom waves, into two groups so that the low-cost booms (LCB) can function as control group.[19] We define a high-cost boom as a boom, which is followed by a three year period in which overall real GDP growth has been at least three

[19] We exploit the last boom wave for an out-of-sample exercise, therefore we do not include it in the period we consider for the optimization of the indicators.

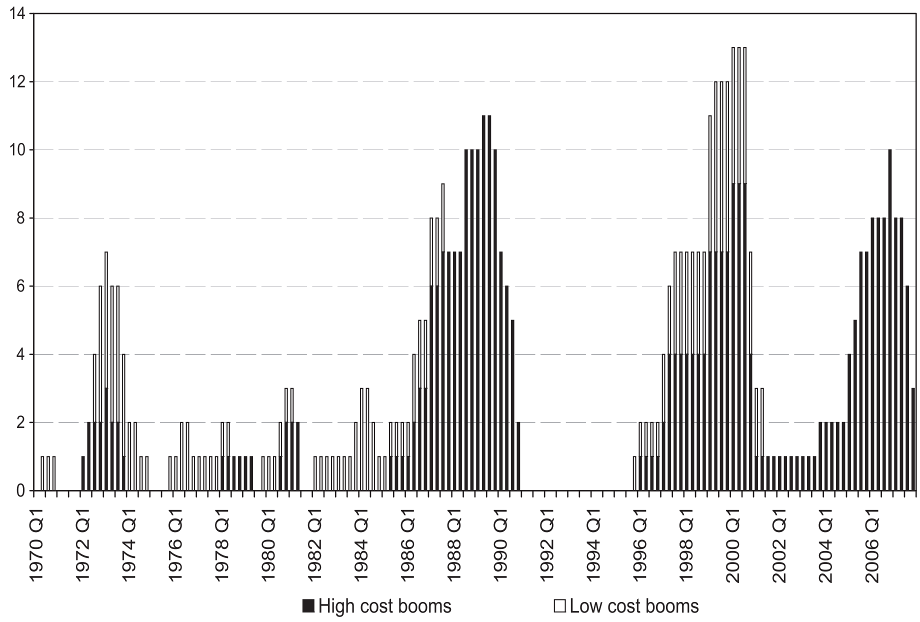

Fig. 3. Number of countries in an aggregate asset price boom each quarter.

percentage points lower than potential growth. The choice of 3 percentage points over three years lower than potential is close to the median of post boom losses, which is 3.5 percentage points. In this way we divide our sample of 45 booms into 29 high-cost and 16 low-cost booms. Fig. 2 shows the identified boom periods. High-cost boom quarters are depicted in black, low-cost booms are gray and framed periods are booms that do not fall into the evaluation period. The quarters marked by xxx in Fig. 2 are periods in which the asset price index breaches the boom threshold.[20] This reveals that in some cases we classified two boom episodes which closely followed each other as one boom and thus bridged a few periods of asset prices below the trend plus 1.75 standard deviations. Otherwise the post boom period of the earlier boom would have overlapped with the boom period of the later boom.[21] Furthermore, in two cases we artificially ended the boom periods (Finland and Sweden in 2000Q3) after the aggregate asset price gaps had been falling by more than 35 percentage points compared to their respective peaks. It is reassuring that all banking crises with significant GDP costs as identified by Honohan and Laeven (2005), i.e. Finland 1991–1994 (−21% of GDP), Italy 1990–1995 (−22% of GDP) and Sweden 1991–1994 (−11% of GDP), are following high-cost booms according to our identification scheme. Furthermore, 4 out of the 5 big banking crises identified by Reinhart and Rogoff (2008) are following our identified asset price booms (3 out of five are following high-cost booms). Also about half of the other banking crises mentioned by Reinhart and Rogoff are following high-cost asset price booms as identified here.

Fig. 3 provides a different perspective on the boom classification results. It shows the number of countries experiencing aggregate asset price booms at each point in time. There have been basically three major waves of asset price booms since the 1980s. In terms of the number of countries affected, the first wave peaked in 1989, the second in 2000 and the third in early 2007. While the first and last waves of cycles were all high-cost booms, only about 60% of the second wave has been classified as such.

4. Indicators

We test a set of 18 real and financial variables, and up to 6 different transformations of these variables – overall 89 indicators – on their suitability as early warning indicators for high-cost asset price boom/bust cycles within a 6 quarter forecasting horizon. The data set goes from 1970:Q1 to 2007:Q4. Variables related to the real side of the economy are GDP, consumption, investment and housing investment (all in real terms). Financial variables are consumer price deflated equity, housing and aggregate asset prices, the term spread, real effective exchange rates, real and nominal 3-month interest rates and 10 year bond yields, real M1, real M3, real private credit and real domestic credit. Furthermore we correct real money and credit growth rates from endogenous business cycle and asset price components by means of recursive VAR models.[22] In addition, we also evaluate consumer price

[20] There is one exception to the high/low-cost classification scheme, which is the boom identified for Japan between 1987 and 1989. According to our definition it would be a low cost boom with aggregate GDP growth 1.7 percentage points below potential over the following three years. But as this boom triggered the 'lost decade' with losses of 48% of GDP occurring after our reference period, we nevertheless classified this boom as high cost.

[21] The longest bridged period is 6 quarters, see Fig. 2.

[22] See Adalid and Detken (2007), for a description of the methodology to derive these shocks. Here we estimate the VARs recursively in order not to make use of future information at each point in time, and use six quarter moving averages of the derived shocks.

inflation. Furthermore, we test GDP (at PPP) weighted averages of the 18 countries of seven financial variables (private credit, M1, and M3 all as ratios to GDP, nominal short rates, and the VAR shocks for M1, M3 and private credit growth), which we label global financial variables.[23]

We compute several transformations of the variables in order to check for their forecasting performance. Variables are used (if applicable) as year on year growth rates, six quarter cumulated growth rates, deviations ('gaps') from a recursive HP trend, deviations from a recursive HP trend of the ratio to GDP, and levels.[24] For housing prices we use seasonally adjusted as well as non-seasonally adjusted data, taking into account the established seasonal patterns.[25] All other variables, except aggregate asset prices, equity prices, exchange rates and interest rates are seasonally adjusted.

In order to proxy for data availability at the time decisions have to be taken, we generally assume a publication lag of 1 quarter. This means that an indicator is calculated for each quarter with variables lagged by one quarter. This might bias the results against financial variables, as in reality the latter often have a much shorter publication lag if any at all, so that at least a reasonable approximation for the current quarter would usually be available. Housing price indices are different though. For some countries, private residential housing prices are available only annually or biannually and publication lags vary significantly. Given the country specific information we collected, the following lags are applied in the analysis: most country housing and aggregate asset price indices are applied with a one quarter lag, except France, Italy, Japan and Denmark for which we use two quarters and Germany which is lagged four quarters.

Comparing our set-up with the series of papers by Borio and coauthors, the following main differences should be highlighted. For the same set of countries, we are predicting costly asset price cycles and not banking crises, so that compared to Borio and Lowe (2004) and Borio and Drehmann (2009a) we evaluate 24 (plus a control group of additional 10) instead of 15 and 13 events, respectively. A distinction is also relevant with respect to the analyzed lead time, which is set up to 6 quarters in our case and varies between 1 and 5 years for the BIS papers. This makes sense noting that booms tend to precede banking crises. Also notice that only Borio and Lowe (2004) also use quarterly data (1974–1999) like in this paper, while otherwise annual data are employed. Only Borio and Drehmann (2009a) also use property prices. More generally, the main differences are the loss function criterium introduced in Section 2 to rank indicators, the broader set of reported indicators which also includes global variables and the choice to define thresholds in terms of percentiles rather than absolute values.

5. Results

In order to compare the forecasting performance for high-cost boom episodes within a six quarter horizon for our 89 indicators we proceed as follows. In a first step we optimize the percentile to calculate the thresholds for each indicator for each individual country by minimizing the loss function (1) by means of a grid search for the best percentile in the range of [0.05 − 0.95] in steps of 0.05. We compute a ranking of the 89 indicators for different values of θ (0.2, 0.3, 0.4, 0.5, 0.6 and 0.8). Note that the optimal percentile is derived ex-post by using all available high-cost booms per country, but the threshold varies in time as the percentile is applied to quarterly updated distributions of the indicator as time passes. This time variation of the threshold is taken into account during the optimization of the percentile. The evaluation period is 1979:Q1 to 2002:Q1. We begin the evaluation only in 1979 as we need some starting window in order to compute reasonable initial trends and to estimate the initial VARs. Furthermore, we exploit the last boom wave for an out-of-sample exercise in the next section. There are thus 24 high cost booms (and 10 low-cost booms) left in the evaluation window.

When we compute the resulting figures for A, B, C and D of the matrix shown in Section 2, we exclude boom periods as of the fourth consecutive quarter from the evaluation, as by then a warning signal is not really useful anymore and it might not be advisable to mix early warning signals with signals during an established boom episode.

Finally, we also test whether twin indicators can further improve the usefulness of the signaling approach. Twin indicators imply that a warning signal is issued only when both indicators exceed their respective optimal thresholds (Borio and Lowe, 2002).

5.1. Single indicators

At the country level, our indicators are able to achieve very good performances (e.g., for $\theta = 5$, the aNtS ratios for the best indicators range from 0.05 for Spain to 0.62 for Australia). Indeed, it is relatively easy to obtain very good results when the percentile is allowed to vary across countries and can be calibrated to one or two, maximum three high cost booms. It therefore seems more relevant to discuss the results obtained when the optimal threshold percentile is imposed to be the same for all

[23] The main data source is OECD Economic Outlook and Main Economic Indicators. Domestic and private credit are from the IMF's International Financial Statistics, lines 32 and 32D, respectively. The two latter series have been corrected for structural breaks as described in Adalid and Detken (2007). Asset price indices have been kindly provided by the BIS. Narrow monetary aggregates are from the BIS and ECB sources.

[24] All variables for each country were found to be stationary (augmented Dickey Fuller test with constant term). Exceptions were the domestic credit gap for two and the M1-gap for three of the 18 countries. However, stationarity is here not an issue for deriving a sensible warning signal, as the level of the threshold is time-varying (see Section 2).

[25] See Ngai and Tenreyro (2009).

Table 1
Five best indicator variables for different θs: average over all countries.

	θ=0.2				θ=0.3				θ=0.4			
	(Strong aversion against false alarms)											
		Usef.	Signal	Noise		Usef.	Signal	Noise		Usef.	Signal	Noise
1	Global M1 (d)	0.03	0.38	0.06	Global M1 (d)	0.07	0.38	0.06	Global pr. credit (d)	0.14	0.82	0.32
2	Global M1 (s)	0.01	0.09	0.01	Global pr. credit (d)	0.06	0.55	0.15	Global M1 (d)	0.12	0.48	0.12
3	M1 (c)	0.01	0.19	0.04	Equity prices (d)	0.04	0.47	0.14	Equity prices (d)	0.11	0.73	0.31
4	Investment/GDP (d)	0	0.21	0.05	GDP (d)	0.03	0.37	0.11	Investment (c)	0.11	0.67	0.27
5	Investment (c)	0	0.21	0.05	Investment (c)	0.03	0.36	0.11	Consumption (c)	0.11	0.64	0.25
	θ=0.5				θ=0.6				θ=0.8			
									(Strong aversion against missed crises)			
		Usef.	Signal	Noise		Usef.	Signal	Noise		Usef.	Signal	Noise
1	Global pr. credit (d)	0.25	0.82	0.32	Global pr. credit (d)	0.17	0.88	0.41	GDP (d)	0.07	0.99	0.63
2	Investment (c)	0.22	0.85	0.42	GDP (d)	0.16	0.94	0.51	Aggr. asset prices (c)	0.06	0.99	0.64
3	Aggr. asset prices (y)	0.21	0.9	0.47	Aggr. asset prices (c)	0.15	0.95	0.54	Global short rate (d)	0.06	0.98	0.63
4	Aggr. asset prices (d)	0.21	0.89	0.46	Aggr. asset prices (y)	0.15	0.9	0.47	Aggr. asset prices (d)	0.06	0.99	0.65
5	GDP (d)	0.21	0.91	0.49	Aggr. asset prices (d)	0.15	0.89	0.46	Investment (c)	0.06	0.99	0.68

Notes: (d) = HP detrended, (s) = 6 quarter moving average of recursive VAR shocks, (c) = 6 quarter cumulated growth rates, (y) = year-on-year growth rate; Usefulness $= \min[\theta; 1-\theta]-\left(\theta\frac{C}{A+C}+(1-\theta)\frac{B}{B+D}\right)$, Signal $=\frac{A}{A+C}$, Noise $=\frac{B}{B+D}$.

countries, which resembles taking a pooled panel perspective. The common percentile chosen is the one which minimizes the aggregate loss over all countries.[26] We also average the evaluation statistics derived with the common θ.[27]

Table 1 summarizes the most important information for the 5 best indicators for different θ, imposing the same optimized percentiles for all countries.[28]

Constructing early warning indicators in this relatively simple way (i.e. using a single indicator in a signaling model) seems to provide useful information to predict costly asset price booms in case of relatively balanced preferences of the policy maker. For example, Table 1 reveals that taking the average over all countries with a balanced risk aversion between type I and type II errors ($\theta = 0.5$), using the global private credit gap, defined as the PPP-GDP weighted average of detrended private credit to GDP ratios, would reduce the preference weighted errors, i.e. the loss, by 25 percentage points compared to a situation in which the policymaker would ignore the indicator. The private credit gap would signal a costly asset price boom in 82% of quarters which are actually followed by a costly boom within 6 quarters. The private credit gap would issue a false alarm in 32% of cases in which no costly boom follows. The optimal percentile to derive the threshold is 70% while it varies across countries between 40% and 85% (65–85% for euro area countries), which results in a relatively low coefficient of variation of 0.17. The average lead time is 5.5 quarters. Most importantly, 95% of booms are signaled in at least one of the 6 preceding quarters (or one of the first three boom quarters), and the difference in the conditional and unconditional probabilities of a boom following a signal is 16%.[29]

Table 1 also reveals that the usefulness of the approach chosen here is not breathtaking when policy makers have a clear preference for either type I or type II errors. Overall losses are lowest for very low and very high θ, but the gain in computing an early warning indicator in comparison to disregarding it, is only marginal for θ equal to 0.2, 0.3 and 0.8. In the case of rather unbalanced preferences, the aversion to one or the other type of errors is so high that it is hard to beat the benchmark, which is disregarding the indicator. This is the case despite the fact the aNtS is excellent by the standards of the literature, i.e. much closer to zero than to one (e.g. as low as 0.12 for $\theta = 0.2$). In this respect we believe our indicator of usefulness adds value to the literature in providing a more appropriate measure to communicate the benefits to be expected from early warning models.

An additional argument suggesting that the mentioned indicators are useful can be derived when the 10 low-cost booms in our evaluation period are used as control group. The best five indicators for the overall average as well as the best three indicators for the euro area average are transformations of the real aggregate asset price index which is used to define the boom episodes. It is not surprising that the aggregate asset prices themselves are at some threshold able to predict a boom. The interesting point is that with respect to low-cost booms, there is no other variable which contains more information, in contrast to the high-cost boom

[26] We carried out the same analysis optimizing the common threshold percentile over the 8 euro area countries included in our sample, i.e. by minimizing the GDP-weighted average loss. Results are broadly in line with those obtained by optimizing over all countries.

[27] For simplicity we impose a common θ, i.e. we assume that preferences are the same across all central banks. However, it would be possible to derive aggregate results by assigning country-specific preference parameters. Moreover, this framework does not require preferences to be constant over time: indeed, what matters for the choice of the best indicator are only *current* preferences.

[28] Detailed results can be found in the working paper version of this article, ECB WP No. 1039 (2009).

[29] The crosses in the very left column of Fig. 2 show as an example the exact periods in which the global private credit gap provides warning signals, i.e. the periods in which the indicator breaches the 70th percentile threshold.

exercises.[30] This seems to suggest that there is genuine information in e.g. private credit gaps to predict costly asset price boom episodes.

With respect to the question whether real or financial variables contain more information to predict costly asset price boom/bust cycles, Table 1 suggests that financial indicators perform better, except for $\theta = 0.8$, i.e. a very strong aversion against missing a crisis. Indeed, only 3 indicators based on investment and real GDP make it into the top five considering 6 different values of θ. Global private credit gaps and for the three lower θ also the global M1 gap dominate. For the euro area countries, the dominance of financial variables is even more evident. This is perhaps surprising, as the ECB's monetary policy strategy implicitly includes some element of 'leaning against the wind' of asset price cycles due to its second pillar, the monetary analysis. As there is evidence that asset price boom/bust cycles are associated with money and credit cycles (Adalid and Detken, 2007; Goodhart and Hofmann, 2008) one could expect the observable leading indicator properties of money and credit aggregates to be reduced over time to the extent that 'leaning against the wind' is effectively pursued. In any case, this would bias our results against finding a good forecast performance for financial variables for euro area countries.[31]

Concerning the question whether the more useful financial variables are global or domestic variables, the verdict is very clear. Global credit and global money are the best indicators. This result is certainly linked to the strong international correlation of asset price booms as depicted in Fig. 3.[32] Nevertheless, even if one believes that what matters for asset price booms is global liquidity, the dominance of global measures for domestic booms is not obvious, at least for the indicators based on broad monetary aggregates. One could expect that global liquidity will affect domestic asset prices once foreign capital is invested in a particular country. In this case global liquidity would usually show up in domestic monetary aggregates in case the foreign investment is settled through the banking system. This is not the case for (domestic) credit based indicators, which is why Adalid and Detken (2007) suggest that foreign capital flows driving a wedge between money and credit aggregates might have been one reason to explain their result that M3 based liquidity shocks are more relevant for asset price booms than credit based measures. Indeed, we do not find any dominance of global M3 versus domestic M3 indicators.

There remains the question whether money or credit based liquidity measures perform better. Borio and Lowe (2004) argue that credit is the better indicator for banking crises. Recently Schularick and Taylor (2009) confirm this view and argue that financial regulation and regulatory ease have delinked monetary from credit aggregates and only the latter would warn against banking crises. Adalid and Detken (2007) present evidence that M3 growth corrected for endogenous components is a more robust determinant of post asset price boom recessions than any credit based measure. Adrian and Shin (2008b) argue that money could be the better indicator of growing financial imbalances as it might be a more comprehensive measure of banks' balance sheets.[33] The results in this paper suggest that the differences between money (M1) and private credit are not very large, but that the global credit gap is overall the best early warning indicator. The fact that M1 performs better than M3 requires further investigation with respect to the underlying reason for the indicator property of money. M1 focuses on the monetary policy stance while M3 would suggest the role of money as a summary statistic of banks' balance sheets.

5.2. Twin indicators

We focused on the two best indicators, the global private credit gap and the global M1 gap, and combined them with 16 indicators we were relatively more interested in and/or which were among the best indicators in the single indicator analysis.[34]

The matrix grid search is performed and all percentile combinations of two joint indicators each in the range [0.05–0.95] with 0.05 steps are tested in order to find the combination minimizing the loss function for six different values of θ. The average results over all countries are derived by imposing that all countries adopt the same threshold percentiles per indicator.

The best twin indicators for $\theta = 0.4$ attain a usefulness for the policy maker, as defined in Eq. (2), of 0.14. This is only a slight improvement over the single best indicator, by 1 percentage point. In Table 2 we follow Kaminsky et al. (1998) and present also a few other standard evaluation measures like the aNtS ratio and its two components $A/(A+C)$ (signal) and $B/(B+D)$ (noise). The *booms* column reveals the percent of booms which is predicted in one of the six quarters preceding the boom or during the first three quarters of the boom. The probability of the event conditional on a signal being issued is $A/(A+B)$. The *diffprob* column shows the difference between the conditional (on a signal being issued) and unconditional probabilities of the event, i.e. $A/(A+B) - (A+C)/(A+B+C+D)$. The larger this probability difference the better the indicator, but it must at least be positive for an indicator to be potentially valuable. We also report the average lead time of an indicator in the *ALT* column, which is the average

[30] An interesting observation, which is compatible with the previous argument, is that the higher θ the more prominent the aggregate asset price index appears in the ranking of indicators, which is also visible in Table 1. This shows that the more averse the policy maker is against missing a boom, the more difficult it is for any other indicator to provide relatively more useful warning signals than the asset price index itself.

[31] Borio and Lowe (2004) find no evidence for 'leaning against the wind' type of behavior in Australia, Germany, Japan and the US using Taylor rules as a benchmark for a neutral policy stance. Adalid and Detken (2007) show that on average over 22 high-cost boom episodes across 18 OECD countries, Taylor rule gaps indicate a loosening of monetary policy in pre-high-cost and during high-cost boom periods. As the samples of both studies correspond with our evaluation window, the absence of 'leaning against the wind' behavior might explain the benign statistics of our financial indicators.

[32] See also Ciccarelli and Mojon (2010) who find evidence for a large global component in domestic consumer price inflation.

[33] Adrian and Shin (2008a) instead argue that most likely neither money nor private credit is a good indicator as one should focus on investment banks' balance sheets and disregard traditional Monetary and Financial Institutions (MFI) balance sheets.

[34] The indicators combined with the global private credit gap and the global M1 gap are the aggregate asset price index (detrended and in yoy growth rates), real property prices (detrended), equity prices (detrended), real and nominal long term rates (detrended), nominal short term rates (detrended), global short term rate (detrended), shock to global private credit, shock to global M3, real exchange rate (detrended), real GDP (detrended), real investment and housing investment (in yoy growth rates), real consumption (six quarter cumulated growth rates), and CPI inflation (yoy).

Table 2
Best twin indicators for $\theta = 0.4$: average over all countries.

Twin indicators	Usefulness	Optimal percentile	Coefficient variation	% booms called	Signal	Noise	aNtS	Condprob	Diffprob	ALT	Pers.
Global pr. credit (d)	0.14	90	0.76	0.59	0.55	0.13	0.23	0.45	0.31	5.8	4.4
GDP (d)		20	0.67								
Global M1 (d)	0.14	85	0.59	0.67	0.55	0.13	0.23	0.43	0.29	5.2	4.3
Aggr. asset prices (d)		30	0.58								
Global M1 (d)	0.14	85	0.48	0.67	0.55	0.13	0.24	0.42	0.28	5.2	4.2
GDP (d)		25	0.64								
Global pr. credit (d)	0.14	90	0.75	0.59	0.54	0.13	0.23	0.48	0.34	5.8	4.3
Nominal long rates (d)		35	0.49								
Global pr. credit (d)	0.14	90	0.69	0.59	0.54	0.12	0.23	0.46	0.32	5.7	4.3
Aggr. asset prices (d)		30	0.47								
Global pr. credit (d)	0.14	90	0.68	0.59	0.53	0.12	0.23	0.49	0.35	5.7	4.4
Nominal short rates (d)		30	0.56								
Global M1 (d)	0.14	85	0.46	0.67	0.56	0.14	0.25	0.42	0.28	5.2	4.0
Global short rate(d)		30	0.52								
Global pr. credit (d)	0.14	90	0.50	0.59	0.52	0.12	0.22	0.46	0.32	5.7	4.5
Real long rates (d)		40	0.66								
Global M1 (d)	0.14	90	0.57	0.58	0.48	0.08	0.18	0.53	0.39	5.4	5.6
Nominal long rates (d)		40	0.56								
Global M1 (d)	0.14	85	0.46	0.67	0.55	0.13	0.24	0.43	0.29	5.1	4.1
Aggr. asset prices(y)		30	0.61								
Global pr. credit (d)	0.14	90	0.32	0.59	0.54	0.13	0.25	0.44	0.30	5.7	4.1
Real exch. rate(d)		10	0.77								
Global M1 (d)	0.14	85	0.48	0.66	0.51	0.11	0.22	0.44	0.30	5.2	4.6
Investment (y)		40	0.73								
Global pr. credit (d)	0.14	90	0.57	0.59	0.51	0.12	0.23	0.45	0.31	5.7	4.4
Investment (y)		35	0.71								

Notes: Indicators either detrended (d) or in yoy growth rates (y).
Signal is $\frac{A}{A+C}$, noise is $\frac{B}{B+D}$, aNtS is the adjusted noise to signal ratio, condprob is the probability of a crisis conditional on a signal being issued ($\frac{A}{A+B}$), diffprob is the difference between conditional and unconditional crisis probability, ALT is the average lead time in quarters, and pers. is the persistence of the signal compared to tranquil times.

number of leading quarters by which an indicator has been signaling an event for the first time. And finally, we report the persistence of the signal, which is nothing else than the inverse of the aNtS ratio, labeled *pers*. This number can be interpreted as the factor by which a signal is issued more persistently in times of growing imbalances (i.e. costly boom/bust cycle starting within 6 quarters) compared to tranquil times. A persistence value larger than 1 is a necessary condition for an indicator to be useful.

When comparing Table 2 with the results for the single indicators (not shown) a few patterns emerge. The coefficients of variation across the group of countries increase strongly in the twin indicator exercises, possibly signaling that the optimal thresholds from the twin indicator exercise are less robust and less easily generalized to e.g. the euro area as a whole. Improvements of the aNtS are more sizable (reductions up to 50%), which are achieved by eliminating a large number of false alarms. Thus the overall best indicator (at $\theta = 0.4$) would set a simultaneous 90th percentile threshold for the global private credit gap and a 20th percentile threshold for the real GDP gap. 55% of periods in which a costly boom followed within six quarters have been correctly signaled. False alarms are issued in only 13% of periods not followed by a costly boom. The aNtS is 0.23 and the average lead time 5.8 quarters. It should be noted that several combinations of indicators in Table 2 have practically the same performance. Many of these combinations involve besides the global credit and global money gaps, the aggregate asset price gap, which confirms earlier findings (e.g. Borio and Lowe, 2002).

6. Predicting the recent boom/bust episode

Finally, we are interested to see whether the asset price booms which started in the mid 2000s are predicted to be high-cost booms by our best indicators. In order to do so, we first counted the warning signals in the 11 quarters between the first quarter of 2005 and the third quarter of 2007 (the start of the financial turmoil) for the two best indicators. With respect to the global private credit gap, the threshold has been breached in 7 of the 11 quarters. The optimal threshold of the global private credit gap is the 70th percentile (for $\theta = 0.3$). Using the global M1 gap instead provided no warning signals at the optimal 90th percentile threshold. This shows how the result can depend on whether money or credit is used as an indicator (despite the fact that both performed well historically).[35] From a global perspective, the

[35] The ECB working paper version of this article also shows how the results can furthermore depend on the particular method used to set the threshold for detrended indicators.

Table 3
Number of quarters where warning signals were issued in specified (pre-boom) period ($\theta = 0.3$).

Indicator	AU	BE	CA	CH	DE	DK
	2000Q1–2002Q1	2003Q3–2005Q3	2003Q4–2005Q4	2006Q4–2008Q1	2006Q4–2008Q1	2003Q3–2005Q3
Global pr. credit (d)	5	0	1	5	5	0
Global M1 (d)	3	0	0	0	0	0
1st best	0	0	0	4	5	0
Country level	Equity/GDP (d)[90]	GDP (d)[95]	Global short rate (d)[80]*	House pr./GDP (d)[90]	Pr. credit/GDP (d)[95]	Agg. asset pr. (c)[80]
2nd best	0	0	0	3	0	0
Country level	Equity (d)[95]	Hous. inv./GDP (d)[80]	Global M1 (d)[75]	Cons. (c)[75]*	M1/GDP (d)[85]	Dom. credit/GDP (d)[90]
	ES	FI	FR	GB	IE	IT
	2005Q2–2007Q2	2006Q4–2008Q1	2004Q1–2006Q1	2006Q4–2008Q1	2004Q3–2006Q3	2006Q4–2008Q1
Global pr. credit (d)	6	5	2	5	4	5
Global M1 (d)	0	0	0	0	0	0
1st best	0	0	0	0	2	1
Country level	Nom. long rate (d)[95]	Equity (d)[95]	Nom. short rate (d)[85]	Global M1 (d)[95]	Hous. inv. (c)[70]	Hous. inv. (c)[75]*
2nd best	0	0	0	0	2	0
Country level	Agg. asset pr./GDP (d)[85]	Nom. long rate (l)[95]*	Global pr. credit (d)[90]	M1 (c)[90]	10 year–3 m spread (l)[60]	Hous. inv. (y)[85]*
	JP	NL	NO	NZ	SE	US
	2006Q4–2008Q1	2006Q4–2008Q1	2004Q1–2006Q1	2002Q2–2004Q2	2005Q2–2007Q2	2006Q4–2008Q1
Global pr. credit (d)	5	5	2	0	6	5
Global M1 (d)	0	0	0	0	0	0
1st best	0	0	9	na	7	na
Country level	Global M1 (d)[95]	10 year–3 m spread (l)[70]	Nom. short rate (l)[90]	na	House pr. (d)[70]	na
2nd best	0	2	5	na	4	na
Country level	Nom. long rate (d)[85]	Pr. credit (y)[65]	10 year–3 m spread (l)[85]	na	Agg. asset pr. (d)[90]*	na

Notes: (d) = HP detrended, (s) = 6 quarter moving average of recursive VAR shocks, (c) = 6 quarter cumulated growth rates, (y) = year-on-year growth rate, (l) = level, optimal threshold percentiles in square brackets, * threshold derived over a 20 quarter rolling window.

tightening of monetary policies during the second half of the 2000s has clearly been visible in developments of M1 during our evaluation window, while credit growth had still been strong enough to exceed the 70th percentile of its own past distribution.

In Table 3 we report the two global indicators, which are here applied to the country specific booms identified in the late 2000s. We also checked the three best indicators for predicting high-cost booms derived country by country and evaluated whether they would have predicted a high-cost boom in the 6 quarters preceding the boom and the first three boom quarters. The time window for which the number of warning signals is reported is mentioned for each country in Table 3. In case no boom has been identified for a particular country in the second half of this decade, we evaluate the signals for the last 9 quarters of our sample. In the lower part of Table 3, the country specific indicators as well as the optimal thresholds are shown below the number of quarters in which warning signals are issued.

Apart from Belgium, Denmark and New Zealand, the global private credit gap issued at least one warning signal for all countries, while the global M1 gap did not. The results for the country specific indicators certainly provide a very mixed picture. These results are similar to Borio and Drehmann (2009a) who find that the performance of their best indicator, i.e. a joint domestic private credit and property price gap, in the recent episode depends on the definition of a banking crisis. According to a restrictive definition of a crisis the indicator picks two out of three countries in crisis. With a less restrictive definition, it issues a warning signal in 9 out of 14 countries with banking crises.

7. Conclusions

We analyze the performance of a signaling approach to predict high cost aggregate asset price booms for 18 OECD countries since the 1970s. We deviate from the standard early warning indicator literature by carrying out a quasi real time exercise and by focusing on the usefulness of indicators from a policy maker's perspective.

The results show that some indicators perform very well on average over our 18 countries with regard to standard evaluation criteria like the adjusted noise to signal ratio.[36] However, the usefulness of the indicators for a policy maker crucially depends on

[36] These results confirm the findings in Borio and Lowe (2002, 2004) and Borio and Drehmann (2009a) for banking crises.

her relative preferences with respect to missed crises and false alarms. In case of relatively balanced preferences, the best indicator reduces the preference weighted sum of type I and type II errors by as much as 25 percentage points compared to a situation in which the indicator is ignored.

In our opinion central bankers on average tended to have a stronger preference for missing crises than for acting on noisy signals for various reasons. The recent financial crisis may have changed this to some degree. Preferences becoming more balanced might be another argument, besides the new macroprudential oversight structures being set up all over the world, to explain the growing interest in early warning systems with respect to financial imbalances.

The best indicator for a policy maker who is only slightly more averse against false alarms than missed crises, is the global private credit gap. In terms of the absolute performance using the optimal 70% percentile across countries predicted on average 95% of high-cost booms by issuing a signal in at least one of the six preceding quarters. The share of correct signals as a percentage of periods in which a high-cost boom actually developed within the following six quarters is 82%. The share of false alarms as a percentage of periods in which no high-cost boom followed is 32% and the average lead time for the first warning signal is 5.5 quarters.

Considering twin indicators is one way of significantly reducing the noisiness of signals (by close to 50%), though without noticeably improving the overall gain with respect to preference weighted errors. Furthermore, the optimal threshold percentiles of twin indicators reveal a much stronger cross-country variation than single indicators, which raises issues for extracting a common optimal percentile for a group of countries like the euro area by analyzing historical data for individual countries. It might also be more difficult to address country specific policy recommendations in the context of the European Systemic Risk Board, if optimal thresholds of the chosen indicator vary significantly across countries.

With respect to the other three questions mentioned upfront, the results of this paper would suggest that financial variables contain more information for predicting costly asset price booms than the real indicators we tested, that global financial indicators perform better than domestic ones and that global credit outperforms global money, though often by a very small margin.

The good performance of global financial indicators certainly reflects the large international simultaneity of the identified asset price cycles, which suggests to further reflect upon stability oriented macro and macro-prudential policies from an international perspective. From a theoretical perspective, various channels have been proposed, which could explain why money and credit perform well as early warning indicators for costly asset price booms. The literature has in this context referred to risk-taking behavior of financial market participants in times of abundant liquidity, banks' leverage targeting behavior and a portfolio real balance effect of other financial intermediaries.[37]

Nevertheless, as the exercise of predicting the most recent boom wave shows, historically nearly equally well performing indicators can provide different messages. Signals obtained by any of the suggested indicators should thus be interpreted very carefully and should only be considered one of several inputs to the information set of decision makers. In particular, reliance on any single or twin indicator is certainly not advisable at this stage. One way to proceed might be to consider weighted composite indicators as in Kaminsky et al. (1998) and Edison (2003).

The evidence presented in this paper – in our view – shows that the often claimed unavailability of timely warning indicators is unlikely to be a major hindrance for 'leaning against the wind' type of policies, if the latter would be deemed desirable by policy makers.

In terms of future research, conclusions suggested here should be cross-checked and qualified by discrete choice models in particular to better explore the degree of non-linearity and the co-dependence between variables to derive an operational early warning indicator system for costly asset price boom/bust cycles. Furthermore, other balance sheet items of (other) financial intermediaries should be analyzed with respect to their information content. Finally, a factor approach could be useful to summarize the relevant information into a few synthetic indicators, in particular in the case of a large number of potentially valuable indicators belonging to a few economic sectors.

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[37] For an overview see Detken et al. (2010).

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