D TOOLS TO DETECT ASSET PRICE MISALIGNMENTS[1]

Asset markets seem to have been playing an increasingly important role in many economies, and policy-makers have become far more aware that the sizeable changes and, sometimes, significant corrections of asset prices may lead to financial and, ultimately, macroeconomic instability. Not least against the background of the recent financial turmoil, many international institutions and academics have focussed on the development of early warning indicator models for asset price misalignments.

After providing a short review of the literature and the methodologies used in this context, this special feature presents some empirical results related to defining and predicting asset price misalignments. An asset price composite indicator is constructed which incorporates developments in both the stock price and house price markets, and a method for identifying asset price busts is presented. An empirical analysis carried out on the basis of a panel probit-type approach finds that credit aggregates, nominal long-term interest rates and the investment-to-GDP ratio, together with developments in either house or stock prices, are the best indicators that help to predict busts up to eight quarters ahead.

INTRODUCTION

Over the past decade, asset markets seem to have played an increasingly important role in many economies, and policy-makers have become increasingly more aware that the sizeable changes and, sometimes, significant corrections of asset prices may lead to financial and, ultimately, macroeconomic instability. For example, the bursting of an asset price bubble (i.e. a bust) could lead to a sharp drop in aggregate demand, and thus to deflationary risks, both via direct wealth effects and, if the stability of the financial sector is affected, via a credit crunch. A zero lower bound on nominal interest rates could then make it more difficult for the central bank to maintain price stability.

Against this background, movements in equity values and prices of real assets – such as residential and commercial property – have also been in the focus of interest of central banks insofar as they pose many challenges. On the one hand, it is clearly important for central banks to be able to understand the underlying sources of asset price changes. This also implies the necessity of distinguishing whether asset price changes are driven by changes in current and expected future "fundamentals" (e.g. an improved productivity which would justify an increase in equity prices) or by deviations from those fundamentals (e.g. over-optimistic expectations of future earnings). The latter case is generally referred to as an "asset price bubble", the subsequent bursting of which can be destabilising for the financial system and the real economy. On the other hand, at a more practical level, it is also recognised that distinguishing fundamentals from non-fundamental sources of asset price movements in real time is an extremely difficult task, as estimates of the equilibrium value of asset prices are usually surrounded by a high degree of uncertainty.

History has shown that boom-bust cycles in asset prices can harm the entire economy. Whenever the building-up of a bubble is associated with excess credit and liquidity creation – which is very often the case – asset price crashes can become the cause of deflationary trends, as observed in some economies in the past.[2] It is also important to stress that monetary stability and financial stability are all closely interlinked, insofar as a monetary policy regime that guarantees aggregate price stability tends, as a by-product, to promote the stability of the financial system.

1 The empirical analysis in this special feature draws heavily on D. Gerdesmeier, H.-E. Reimers and B. Roffia, "Asset price misalignments and the role of money and credit", *ECB Working Paper Series*, No 1068, ECB, 2009.
2 See ECB, "Asset prices and monetary policy", *Monthly Bulletin*, April 2005.

This special feature analyses the different approaches that can be used to detect asset price misalignments and summarises the available evidence on the indicator properties of money and credit for detecting these misalignments. Finally, it reports some results based on an empirical analysis aimed at detecting asset price busts for some euro area and industrialised countries.

APPROACHES TO IDENTIFYING ASSET PRICE MISALIGNMENTS

Detecting asset price misalignments is a difficult exercise even if done ex post. This is due to the episodic nature of such events and the coincidence of very different factors and constellations that can give rise to such episodes. Against this background, empirical analysis typically uses samples constructed from different countries, with the latter usually being restricted to a set of countries considered to be relatively homogeneous. This allows the extraction of common features across countries that can explain the underlying forces of such episodes in a robust manner.

Empirical models for the detection of asset price booms/busts differ with regard to both the underlying methodologies and the indicator variables used. The way in which the indicators are set up and/or the way in which their threshold levels are chosen has a considerable impact on how clearly and/or early the indication of asset price bubbles/busts can be derived. In particular, while country-specific thresholds might, in principle, be desirable from a theoretical perspective, most studies make use of thresholds that are a priori uniform across a set of given countries. Country-specific characteristics are then taken into account indirectly, either by using loss functions of individual policy-makers (which weight policy-makers' preferences vis-à-vis certain policy outcomes) or, as in panel estimations, by introducing individual dummy variables.

In the literature, many different approaches have been used to anticipate asset price bubbles/busts of different types. A first approach, which could be characterised as a "signalling approach", looks for discrete thresholds for each indicator and calculates the respective noise-to-signal ratio, i.e. the ratio of the share of false alarms to the share of good signals. More precisely, the indicators are chosen such that they tend to exhibit an unusual behaviour prior to a boom/bust, whereby a boom/bust is defined to occur when certain developments in the variable of interest exceed/undershoot a threshold, e.g. their mean plus/minus a certain value.

Table D.1 Signal/event outcomes

	Bust (within 8 quarters)	No bust (within 8 quarters)
Signal was issued	A	B
No signal was issued	C	D

Table D.1 illustrates this concept. In the matrix, cell A represents the number of times that an indicator signals that a bust will occur in eight quarters (in this specific example) and that bust actually occurs.[3] Similarly, cell B gives the number of times that the indicator issues a bad signal, while cell C indicates the number of times that the indicator fails to issue a signal of the bust occurring. Finally, cell D contains the number of times that the indicator refrains from issuing a signal when there was in fact no bust. A perfect indicator would only produce observations that belong to cells A or D, or such that it would minimise the noise-to-signal ratio. In the course of such minimisation, several criteria could be adopted. For instance, one could assume that policy-makers assign more weight to the risk of missing busts (type I error) than calling those which do not occur (type II error) as the costs of the two differ. Alternatively, one could also take into account the minimisation of an implicit or explicit loss function of the policy-maker in relation to predicting at least some busts.

3 The choice of the "appropriate" time horizon represents a trade-off between achieving good predictability (with a shorter horizon) at the expenses of not having enough lead time for the policy-maker to react.

The signalling approach was used, for example, by Kaminsky et al. in the context of currency crises, and – more recently – by Alessi and Detken for asset prices.[4] In most of the studies adopting this approach, the threshold levels are chosen so as to strike a balance between type I and type II errors. In particular, if the threshold is set to too high a value, this leads to fewer signals and, therefore, to the possibility of missing some busts. Conversely, if the threshold is too low, small fluctuations in the variables would issue more frequent alarms, part of which would, however, turn into false alarms ex post. In the case of Alessi and Detken, the thresholds that would signal booms are set at each point in time using an optimisation procedure (i.e. one that minimises a particular loss function of the policy-maker) based on the fixed optimal percentile to the distribution of the data available up to each point in time. Thresholds for each indicator are thus time and country-dependent, and, as they are based on past observations, they are "quasi real-time".

An alternative approach used in the literature makes use of probit/logit regression techniques that test the occurrence of an asset price boom/ bust by, for example, using the dependent variable as a one/zero variable which takes a value of one if there is a boom/bust on the basis of a specific criterion chosen, and zero otherwise. As stressed by Berg and Pattillo, this approach has many advantages.[5] First, it allows a test of the usefulness of the threshold concept; second, it allows aggregating predictive variables more satisfactorily into one composite indicator index, taking into account correlations among different variables; and, third, it permits the testing of the statistical significance of individual variables and the constancy of coefficients across time and countries.

This methodology consists of running bivariate and multivariate probit regressions on the panel data set and comparing several specifications of the probit models, whereby an assessment of specifications is done in terms of the probability scores and goodness-of-fit. Overall, these two types of approach can be seen as being complementary and have been increasingly used in the literature, although there is no clear evidence of a superior performance of any of the two, also in the context of the most recent crisis.

MONEY AND CREDIT AGGREGATES AS INDICATORS OF ASSET PRICE MISALIGNMENTS

As pointed out by pioneering studies on the topic many years ago, boom and bust cycles in asset markets have historically been closely associated with large movements in monetary and credit aggregates.[6] There are, in fact, several reasons why monetary and asset price developments tend to be positively correlated. To start with, both sets of variables may react in the same direction to monetary policy or to cyclical shocks to the economy. For example, strong money and credit growth may be indicative of too lax a monetary policy, which leads to the creation of excessive liquidity in the economy and fuels excessive price increases in the asset markets.

Moreover, there can be self-reinforcing mechanisms at work. For example, during asset price booms, the balance sheet positions of the financial and non-financial sectors improve and the value of collateral increases, permitting a further extension of banking credit for investment, which may reinforce the increase in asset prices. The opposite mechanism can sometimes be observed during times of downward adjustments to asset prices.

4 See G. Kaminsky, S. Lizondo and C.M. Reinhart, "Leading indicators of currency crises", *IMF Staff Papers*, Vol. 45, No 1, International Monetary Fund, 1998. In this specific study, a crisis is identified (ex post) as a situation in which the monthly percentage change of the variable is above its mean by more than three times the standard deviation. For the identification of asset price bubbles, see L. Alessi and C. Detken, "'Real time early warning indicators for costly asset price boom/bust cycles: a role for global liquidity", *ECB Working Paper Series*, No 1039, ECB, 2009.

5 See A. Berg and C. Pattillo, "Predicting currency crises: the indicators approach and an alternative", *Journal of International Money and Finance*, Vol. 18, No 4, 1999. For a early warning signal model for predicting financial crises, based on a multinomial logit model, see, for example, M. Bussière and M. Fratzscher, "Towards a new early warning system of financial crises", *ECB Working Paper Series*, No 145, ECB, 2002.

6 See I. Fisher, *Booms and depressions,* New York, Adelphi, 1932, and C. Kindleberger, *Manias, panics and crashes: a history of financial crises,* John Wiley, New York, 1978.

All studies confirm that the identification and quantification of asset price and/or financial imbalances represent an extremely difficult task, in particular from an ex ante point of view. Even ex post, different criteria can be used, each involving some degree of arbitrariness. This also explains some differences in the findings across studies.

This notwithstanding, one robust finding across the different studies is that various measures of excessive credit creation (e.g. a deviation of the credit-to-GDP ratio from its trend, global credit growth detrended) are very good leading indicators of the build-up of asset price misalignments in the economy.[7] Among the contributing studies on this issue, Borio and Lowe have constructed indicators that provide a fairly good sense of the build-up of imbalances as they develop.[8] The basic idea is that the imbalances manifest themselves in the coexistence of unusually rapid cumulative growth in private sector credit and asset prices. The indicators are intended to capture the coexistence of asset price misalignments with a limited capacity of the system to withstand the asset price reversal. Both of these indicators are measured on the basis of deviations of variables from their trends ("gaps"), which are calculated so as to incorporate only information that is available at the time the assessments are made. Asset price misalignments are captured by asset price gaps, in inflation-adjusted terms, while the shock absorption capacity of the system is proxied by credit gaps, where credit is measured as the ratio of private sector debt to GDP – a broad measure of leverage for the economy as a whole. Signals of future crises are issued when these gaps exceed certain thresholds.

This notwithstanding, it cannot be ruled out that money, representing a "natural" summary indicator, also possesses good indicator properties for asset price bubbles and busts. Indeed, excessive money creation is likewise singled out by some studies in the literature, although evidence is more mixed in this regard, possibly because substitution effects between money and asset prices can sometimes be substantial, particularly in times of high financial turbulence and uncertainty.[9] However, high real money growth appears to be a useful indicator for a very early detection of the possible building-up of asset price misalignments that lead to financial distress and costly adjustments in the economy. As mentioned earlier, the observation that credit and money may be associated with asset price bubbles is often linked to the observation of very low interest rates, indicating that too loose monetary conditions are generally observed in the pre-crisis periods.

Overall, given the fact that the interactions between monetary and asset price developments are rather complex and as no mechanical link can be assumed, the overall results point to a need for a close monitoring of the nature of movements in money, credit and asset prices, complemented by a broader analysis of monetary conditions.[10]

AN APPLIED METHOD FOR IDENTIFYING ASSET PRICE BUSTS

This section focuses on the selection of periods of asset price busts, while another strand of the literature focuses on asset price bubbles.[11] This choice is justified on the basis that the former

7 For currency crises see, for example, M. Bussière and M. Fratzscher (2002), op. cit.; for asset price misalignments, see C. Borio and P. Lowe, "Securing sustainable price stability: should credit come back from the wilderness?", *BIS Working Papers*, No 157, Bank for International Settlements, 2004; Alessi and Detken (2009), op. cit.; C. Borio and M. Drehmann, "Assessing the risk of banking crises - revisited", *BIS Quarterly Review*, Bank for International Settlements, March 2009; D. Gerdesmeier et al., (2009), op. cit.

8 See, C. Borio and P. Lowe, "Asset prices, financial and monetary stability: exploring the nexus", *BIS Working Papers*, No 114, Bank for International Settlements, July 2002; and C. Borio and P. Lowe, "Assessing the risk of banking crises", *BIS Quarterly Review*, Bank for International Settlements, December 2002.

9 See, for example, C. Detken and F. Smets, "Asset price booms and monetary policy", in Horst Siebert (ed.), *Macroeconomic Policies in the World Economy*, Springer, Berlin, 2004; and R. Adalid and C. Detken, "Liquidity shocks and asset price boom/bust cycles", *ECB Working Paper Series*, No 732, ECB, 2007.

10 See, for instance, Borio and Lowe (2002, 2004), op. cit.; M.D. Bordo and O. Jeanne, "Monetary policy and asset prices: does 'benign neglect' make sense?", *International Finance*, Vol. 5, No 2, 2002.

11 See, for instance, Detken and Smets (2004), op. cit.; and Adalid and Detken (2007), op. cit.

are widely recognised as being more damaging for the economy, whereas booms/bubbles do not necessarily end in busts.[12]

A variety of approaches has been used in the literature to identify asset price busts. Bordo and Jeanne, for instance, define a bust as a period in which the three-year moving average of the growth rate of asset prices is smaller than the average growth rate less a multiple (1.3 in this specific case) of the standard deviation of growth rates.[13] In a similar vein, the IMF defines busts as periods when the four-quarter trailing moving average of the annual growth rate of asset prices, in real terms, falls below a particular threshold, which is set at -5% for house prices and -20% for stock prices.[14] These thresholds are roughly equal to the average growth rate of the respective asset prices across the whole sample less one times the standard deviation of the growth rates.

The selection of episodes of asset price busts, as is illustrated in this section, is based on a combination of the methodologies presented in the literature.[15] In particular, several studies have focussed separately on stock prices or on house prices. In other cases, the composite asset price indicator constructed at the Bank for International Settlements (BIS) has been used, which is calculated as the weighted average of equity prices, residential and commercial property prices, deflated with the national consumption deflators.[16] This indicator was developed for several of the major industrialised countries, thereby summarising the information contained in the separate movements of the three asset prices, i.e. equities and residential and commercial property. The intention was that such an index would facilitate the comparison of the broad asset price movements over time and across countries, give some empirical content to notions of general asset price inflation and deflation, and highlight patterns of behaviour that would otherwise remain undetected.[17]

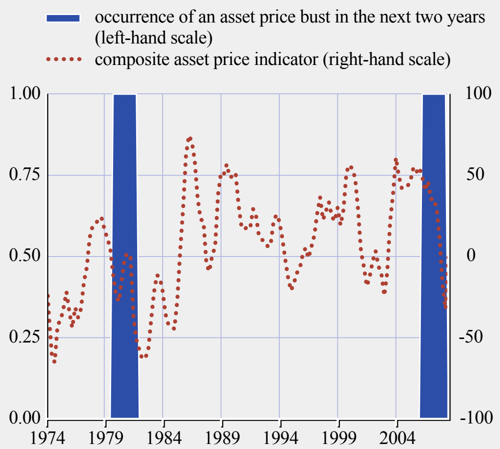
Along these lines, a more recent paper presents the construction of a composite asset price indicator that combines the stock price index and the house price index (both in quarter-on-quarter growth rates) and that can be easily updated in real time.[18] The two growth rates are weighted and calculated recursively throughout the sample period, and the weighting scheme used for the two series is generally inversely proportional to their conditional variance.

An asset price bust is defined on the basis of this composite indicator, and is denoted as a situation in which the composite asset price indicator declines with respect to its peak by a certain amount at the end of a certain period.[19] In this special feature, the occurrence of a bust (i.e. a value of 1 for the "dummy bust" variable) is denoted as a situation in which at the end of the rolling period (specifically, 12 quarters) the composite indicator has declined to below its mean minus a factor of 1.5 times the standard deviation in the period from 1 to 12 with respect to the maximum reached in the same period.[20]

12 In the signalling approach, this issue is usually taken into account by differentiating between "high-cost" and "low-cost" booms (see, for instance, Detken and Smets (2004), op. cit.).
13 Bordo and Jeanne (2002), op. cit.
14 IMF, "Lessons for monetary policy from asset price fluctuations", *World Economic Outlook*, Chapter 3, International Monetary Fund, 2009.
15 See the methodologies developed by Berg and Pattillo (1999), op. cit.; I. Andreou, G. Dufrénot, A. Sand-Zantman and A. Zdzienicka-Durand, "A forewarning indicator system for financial crises: the case of six central and eastern European countries", *William Davidson Institute Working Paper*, University of Michigan, No 901, 2007. It could, of course, be envisaged to use, for robustness check, alternative approaches derived from theory to quantify the fundamental equilibrium values, such as the price-earning ratio adjusted for the cyclical position.
16 C. Borio, N. Kennedy and S.D. Prowse, "Exploring aggregate asset price fluctuations across counties, measurement, determinants, and monetary policy implications", *BIS Economic Papers*, No 40, Bank for International Settlements, 1994; and S.V. Arthur, "Experience with constructing composite asset price indices", *BIS Working Papers*, No 21, Bank for International Settlements, 2005.
17 However, it should also be noted that combining two different markets (such as the housing and equity markets) in a single indicator can, in some cases, be misleading. This happens, for instance, when the two markets move sharply in opposite directions, so that the developments in the composite indicator would mask diverging trends and may not flag the true risks existing in that respective market. This problem may become more pronounced if house and equity price cycles tend to exhibit different dynamics.
18 See Gerdesmeier et al. (2009), op. cit.
19 See Andreou et al. (2007), op. cit.
20 The threshold used generally comprises between 1.5 and 3 standard deviations above the mean. The greater the number of the standard deviation, the smaller the number of identified crises.

Chart D.1 Asset price misalignments in the euro area

(Q1 1974 – Q3 2008; percentage change per annum; (0.1) probability range)



Sources: ECB, BIS, Thomson Reuters Datastream, Reuters, national sources and ECB calculations.

Table D.2 Asset price busts detected by the composite indicator

(Q1 1970 – Q3 2008; based on a sample of 17 countries)

Country	No of busts
Australia	6
Canada	7
Denmark	4
France	3
Germany	6
Ireland	6
Italy	2
Japan	6
Netherlands	6
New Zealand	5
Norway	9
Portugal	4
Spain	6
Sweden	6
Switzerland	6
United Kingdom	3
United States	6

Sources: ECB, BIS, Thomson Reuters Datastream, Global Financial Data, OECD Main Economic Indicators, Reuters, national sources and ECB calculations.

However, in line with other studies, an attempt is made to predict busts several months ahead. In line with this, the "bust dummy" is defined such that the indicator is expected to be able to signal a bust up to eight quarters ahead, with this period being referred to as the "signalling horizon". Thus, a signal that is followed by a bust within two years is labelled a "good" signal, while a signal not followed by a bust within that interval of time is called a "false" signal. Chart D.1 shows the results obtained when applying such a procedure to the euro area.

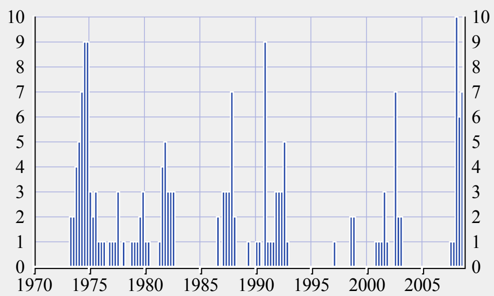
On the basis of this construction and using a sample comprising 17 OECD countries for the period from 1970 to 2008, the overall number of busts detected with this method totals 93 (see Table D.2). In geographical terms, the countries in the south and centre of Europe (i.e. France, Germany, Italy, Portugal, Spain and Switzerland) account for about 30% of the crises, while 16.5% of the crises seem to occur in the three largest currency areas excluding the euro area (i.e. Japan, the United Kingdom and the United States). The rest of the crises are distributed among the countries of northern Europe (i.e. Denmark, Ireland, the Netherlands, Norway and Sweden) (33%) and the remaining overseas countries (20%).

When looking at the occurrence of the busts over time, busts seem to be concentrated mainly in periods around the early/mid-1970s (oil crisis), the early and late 1980s (1987 stock market crashes), the mid-1990s (period of banking and currency crises), early 2000 (dot-com bubble) and, especially towards the end of the sample, in 2008 when a bust was experienced in 13 out of 16 countries, thus marking the most widespread cluster of busts in both house and stock prices (see Chart D.2).

Of course, it must be noted that, when looking at the disaggregated level of the developments in the composite indicator, the occurrence of a bust may be driven by specific developments in one of the two markets comprising the aggregate indicator. For instance, as regards the bursting of the dot-com bubble in 2000, not all countries experienced a bust. This was mainly due to the fact that in those countries in which the bust was not detected, the housing market was on an expansionary trend, thus partly counterbalancing the stock market developments.

Chart D.2 Number of euro area countries experiencing asset price busts

(Q1 1970 – Q3 2008; based on a sample of 17 countries)



Sources: ECB, BIS, Thomson Reuters Datastream, Global Financial Data, OECD Main Economic Indicators, Reuters, national sources and ECB calculations.

Finally, the length of the crises also varies across the countries, lasting either two quarters or more than one year. Overall, these observations lead to the conclusion that an analysis that takes into account heterogeneities across countries and time has to be adopted.

Seen from a financial stability perspective, it is worth noting that all major banking crises in industrial countries during the post-war period coincided with housing price busts, whereby the latter were less frequent than equity price busts, but more costly in terms of output losses.[21] In addition, when comparing the above composite asset price busts with the episodes of banking distress highlighted by Bordo et al., it appears that in many cases the two episodes were concomitant, while in few cases the banking distress periods followed the busts with a slight delay.[22]

SOME RESULTS OF A PROBIT-TYPE APPROACH

In this section, an analysis based on a panel probit-type approach is presented, whereby the conditional probability of a bust is evaluated directly on the basis of a given set of indicators. The idea is to separate time periods into a bust and a tranquil/normal period, and mapping a set of indicators, as suggested a priori by theory, into a known probability distribution of these episodes, in order to evaluate the likelihood of a bust using logit/probit models.

Panel data have the advantage of incorporating information across countries, as well as across time.[23] More formally, the probit equation takes a general form whereby the determinants consist of the fundamental variables that may, according to the theory, have some indicator properties, while the binary left-hand variable would indicate whether the event bust occurred. In line with some earlier literature, the fundamental variables (both in nominal and in real terms) are grouped into four categories.[24] The category of monetary variables comprises broad money and credit, the category of real variables comprises investment, consumption and GDP, the category of financial variables comprises the long-term and short-term interest rates, stock prices, the price/earnings ratio, the dividend yields and the (nominal and real) effective exchange rates, and the prices category includes all the deflators, consumer prices and house prices. The dataset used for the analysis consists of quarterly data collected for the countries mentioned in the previous section and spans more than three decades, starting in the first quarter of 1969 and ending in the third quarter of 2008.[25] The variables are measured in different ways, either as annual percentage changes or as a deviation from a trend or as a ratio to GDP.[26] Using probit techniques, the probability of the occurrence of a bust in the next eight quarters is

21 See T. Helbling and M. Terrones, "When bubbles burst", *World Economic Outlook*, Chapter 2, International Monetary Fund, Washington, 2003.

22 See M. Bordo, B. Eichengreen, D. Klingebiel and M.S. Martinez-Peria, "Is the crisis problem growing more severe?", *Economic Policy*, Vol. 32, Spring, 2001.

23 See B.H. Baltagi, *Econometric analysis of panel data*, John Wiley and Sons, New York, 1995.

24 See, for instance, M. Kumar, U. Moorthy and W. Perraudin, "Predicting emerging market currency crashes", *Journal of Empirical Finance*, Vol. 10, 2003.

25 For the main sources of the series, see Gerdesmeier et al. (2009), op. cit., Annex 3.

26 The trend is calculated using the Christiano-Fitzgerald filter, since the Hodrick-Prescott filter is known to suffer from an end-of-sample problem. The choice of using the ratio of credit to GDP is that it is a proxy for a leading indicator that captures the influence of banking crises, with credit expanding prior to a crisis and contracting afterwards.

estimated, whereby the bust is defined using the method outlined in the previous section. As regards the standard errors of the probit estimates, the heteroskedasticity and autocorrelation corrected (HAC) procedure as developed by Berg and Coke is applied, which produces accurate estimates, following the methodology proposed by Estrella and Rodrigues.[27]

The various probit models are compared in terms of performance on the basis of the significance of the coefficients, as well as other statistical tests, which also assess the predicted probabilities and the observed outcomes.[28] Generally speaking, the signs of the coefficients should be interpreted as having an increasing or decreasing effect on the probability of a bust. The credit variable seems to be a key driving factor. In order to verify this hypothesis, the main preferred specifications are run without this variable, but this leads to a substantial decrease in the explanatory power and the measures for the quality of the model. Across the equations with the best performance, the one that includes the credit gap, long-term nominal interest rates, the investment-to-GDP ratio and the house prices gap is singled out on the basis of some statistical tests.[29]

Overall, these results support the importance that credit aggregates have – together with monetary aggregates – in the context of the monetary analysis, insofar as they enable central banks to assess longer-term risks to price stability, including emerging financial imbalances, costly asset price misalignments or other threats to financial stability.

Viewed from a forward-looking perspective, designing a good forecasting model requires striking a balance between type I and type II errors. In the discrete choice approach used in this special feature, the expected value of crises, given a specific set of indicators, is a probability measure. As in the literature, there is no correct answer with respect to the value that should be assigned to the optimal threshold level of the probability; as a rule of thumb, a threshold level of 25% is usually selected.[30] Based on a more conservative approach, a 35% threshold is used for the most preferred specifications, on the basis of which those models are able to predict correctly around 66% to 70% of the crises, while the missed calls for crises are in the range of 25% to 30%. The false alarms are of a similar size as the missed calls, while the noise-to-signal ratio is in the range of 36% to 41%.[31]

A "PSEUDO REAL-TIME" EXERCISE: A EURO AREA APPLICATION

The results so far might be criticised on the basis that the model has proven to have a good fit from an ex post perspective. This, however, does not necessarily imply that the model also has good forecasting abilities in real time. In order to address this issue, a real-time exercise for the euro area is carried out. More precisely, the model is estimated up to the fourth quarter of 2006 and – on the basis of the coefficients and the actual values of the explanatory variables – the probability that the model would have predicted a bust to occur over the subsequent two years in the euro area is estimated.

Chart D.3 shows the results of this exercise. Two periods of busts are detected for the euro area (one being the most recent period), which suggests that, at the euro area aggregate

27 See A. Berg and R.N. Coke, "Autocorrelation-corrected standard errors in panel probits: an application to currency crisis prediction", *IMF Working Paper*, WP/04/39, International Monetary Fund, 2004; and A. Estrella and A.P. Rodrigues, "Consistent covariance matrix estimation in probit models with autocorrelated errors", *Staff Report*, No 39, Federal Reserve Bank of New York, 1989.

28 See J.P.A.M. Jacobs, G.H. Kuper and L. Lestano (2005), "Currency crises in Asia: a multivariate logit approach", *CCSO Working Papers* 2005/06, University of Groningen; and F.X. Diebold and G. Rudebusch, "Scoring the leading indicators", *Journal of Business*, Vol. 62, No 3, 1989.

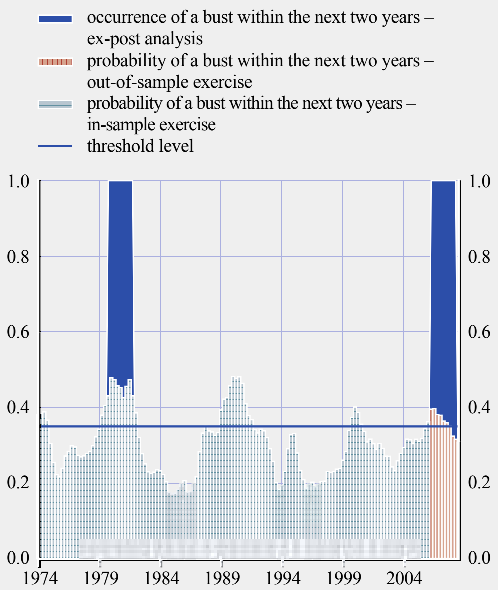
29 In IMF (2009), op. cit., the same variables are found to be of relevance in the run-up to costly house price busts.

30 For instance, in Berg and Pattillo (1999), op. cit., the choice of a threshold of 25% leads to an accuracy of predicting crises of about 73%, while that of false alarms is 41%.

31 In a number of cases, the noise-to-signal ratio could be made arbitrarily small by tightening the selectivity of the threshold. Of course, the choice of the threshold could be carried out more formally by assigning specific weights to the costs of type I and type II errors.

Chart D.3 Out-of-sample forecast of the probability of asset price busts in the euro area

(Q1 1974 – Q3 2008)



Sources: ECB, BIS, Thomson Reuters Datastream, national sources and ECB calculations.

level, developments in some countries are counterbalanced by movements in others.

As can be seen from the chart, the model would have predicted the most recent bust to occur within a two-year-ahead horizon with a probability higher than 40%, clearly above the selected threshold level. At the same time – abstracting from the initial few years that are needed for the initialisation of the model – the model would also have predicted the bust in 1979-1982, but it would likewise have predicted two other crises that are not included in the set of busts. However, at least as regards the first bust, a plausible explanation may be attributable to the fact that that bust period predicted by the model (1989-1992) was more related to the period of German reunification (driving up house prices in Germany) and the crisis of the European Monetary system (EMS), so that it cannot be labelled as a bust according to the criterion chosen. Finally, it should be noted that, while the model predicts a bust to occur within the following two years, it does not provide any information on the length of the busts and on when the bust period will be over and normal conditions are re-established.

CONCLUDING REMARKS

This special feature presents a composite asset price indicator that incorporates developments in both the stock and the housing markets. In addition, asset price busts are defined and an empirical analysis is carried out on the basis of a probit-type approach. According to statistical tests, credit aggregates, nominal long-term interest rates and the investment-to-GDP ratio, together with developments in either house prices or stock prices, turn out to be the best indicators that help to predict asset price busts up to eight quarters ahead.

Putting these results into perspective, the ECB's analysis of monetary and credit developments with the aim of identifying longer-term inflation risks can also provide signals of growing financial imbalances. By exploiting the link between monetary and credit developments and evolving imbalances in asset and credit markets, the ECB's monetary analysis (consisting of a comprehensive assessment of liquidity and credit conditions) may provide early information on developing asset price imbalances and, therefore, allow a timely response to the implied risks to price and financial stability. In this respect, it should be noted that the approaches illustrated in this analysis could be used as input into several areas, including, for instance, financial supervision and systemic risk analysis in addition to the regular monetary analysis.