

Early Warning Indicators for Asset Price Booms

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Abstract: The recent financial crisis has demonstrated in an impressive way that boom/bust cycles can have devastating effects on the real economy. This paper aims at contributing to the literature on early warning indicator exercises for asset price booms. Using a sample of 17 industrialized OECD countries and the euro area over the period 1969 Q1 – 2010 Q2, an asset price composite indicator incorporating developments in both stock and house price markets is constructed. The latter is then further developed in order to identify periods that can be characterized as asset price booms. The subsequent empirical analysis is based on a probit-type approach incorporating several monetary, financial and real variables. Following some statistical tests, credit aggregates, the investment-to-GDP ratio, the interest rate spread together with the house price growth gap and stock price developments appear to be useful indicators for the prediction of asset price booms up to two years ahead.

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1. Introduction

The recent financial crisis has demonstrated in an impressive way that boom/bust cycles can have devastating effects on the real economy. At least since the Great Depression, economists and policy-makers have become aware of the potentially damaging effects of large fluctuations in asset prices, such as equity and property prices. The recent experiences in the 1970s-1990s in Japan and other countries have confirmed that, in some circumstances, boom and bust cycles in asset prices can be very damaging as they may lead to financial and, ultimately, to macroeconomic instability.

Against this background, for central banks it is important to have early indicators to assess the possible implications of large asset price movements and the building up of financial imbalances in the economy. In this respect, several recent studies have shown that the analysis of monetary and credit developments may be very useful. There are, in fact, several reasons why monetary and asset price developments tend to be positively correlated. One reason is that both sets of variables may react in the same direction to monetary policy or cyclical shocks to the economy. For example, strong money and credit growth may be indicative of a too lax monetary policy which leads to the creation of excessive liquidity in the economy and fuels excessive price changes 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 the banking credit for investment which may reinforce the increase in asset prices. The opposite mechanism can sometimes be observed during asset price downward adjustments.

This paper contributes to the literature on the properties of money and credit indicators for detecting asset price misalignments by using a “composite” asset price indicator which takes into account developments in both stock and house prices to define asset price booms. This indicator has already been used in a previous paper by Gerdesmeier, Reimers and Roffia (2009) to identify busts. The method is tailored to predict booms up to eight quarters ahead. The paper is structured as follows. Section 2 briefly summarizes the available evidence on the indicator properties of money and credit for detecting asset price imbalances, with a focus on the most recent contributions. Section 3 briefly describes the data used for the empirical analysis and describes the criterion to define an asset price boom. It also presents some results based on a probit-type approach, using the pooled estimation procedure. In Section 4 we present some robustness checks of the model, and Section 5 draws some conclusions.

2. Literature Review on Money, Credit and Asset Price

The idea that money and credit could be important for the analysis of asset price developments is not new. Already at the beginning of the 20th century, Fisher (1932) had investigated the reasons for various booms and depressions, emphasising, among other things, the role of the debt structure and, in particular, the debt contracted to leverage the acquisition of speculative assets for subsequent resale as possible sources of financial instabilities. Moreover, he stressed the role of monetary factors by pointing to the fact that, basically, in all cases, real interest rates had been too low and thus monetary factors had been “fuelling the flames”. Forty years later, Kindleberger (1978) provided a comprehensive history of financial crises, stretching back to before the South Sea bubble (1717-1720), to illustrate common threads that may have linked these different periods of turbulence over the centuries in almost all corners of the financial world. His work is illustrative of the idea that historically booms and bursts in asset markets had been strongly associated with large movements in monetary and, especially, credit aggregates.

The view that credit developments may contain useful indications in times of sharp asset price fluctuations was further explored by Borio, Kennedy and Prowse (1994). On the basis of an aggregate asset price index for several industrialized countries (based on the combination of residential property, commercial property and share prices), the authors investigated the factors (*inter alia* credit and money) behind the observed movements in the index over the 1970s and 1980s. The results suggested that the ratio of private credit-to-nominal GDP contains useful incremental information to predict movements in the real asset price index, in addition to more standard determinants such as real profits, nominal GDP growth and the long-term nominal interest rates, possibly reflecting the impact of the relaxation of credit constraints on the aggregate price index developments during the 1980s.

A summary of the results of some analyses regarding bubbles that emerged in past three centuries is presented by Vogel (2010). According to this, it seems that, first, the availability of money and credit beyond what is needed to finance real GDP growth tends to stimulate speculative activity, which might end into an asset price bubble. Second, crashes seem to occur when there is an insufficient amount of cash or additional credit available to service the debt incurred. Third, crashes are characterized by relatively rapid price changes whereas a bubble, from a behavioural perspective, seems to be characterised by a longer build-up period. More precisely, a bubble coincides with a period of euphoria while a crash is linked to fears. Prechter (1999) states that hope tends to build slowly while fear often crystalizes swiftly. This argumentation is also put forward by Greenspan (2009). In particular, the latter states that bubbles seem to be connected with periods of prosperity,

moderate inflation and moderate long-term interest rates which feed euphoria, thereby driving a bubble. By contrast, a contraction phase of credit and business cycles, driven by fear, have historically been far shorter and for more abrupt than expansion phases.

Regarding the definition of bubbles, Brunnermeier (2008) defines them as episodes when asset prices exceed an asset's fundamental value due to the fact that current owners believe that they can resell the asset at an even higher price in the future, whereas Grantham (2008) states that bubbles are definable events when the prices exceed a threshold marked by a two standard deviations away from a long-term trend.

More recently, a new strand of the literature (including work by several international organisations such as the BIS, the ECB and the IMF) has started investigating in a systematic manner episodes of asset price misalignments and/or financial crises with the aim to derive common stylized facts across the different episodes and, more specifically, to identify possible early indicators that could provide warning signals to policy-makers. For example, Borio and Lowe (2002, 2004) conducted a comprehensive analysis of the performance of various indicators in predicting episodes of financial crises in some industrial and emerging countries since the 1960s.¹

In the meantime, some studies were also produced aiming at drawing out by simple visual inspection common patterns in macroeconomic and financial developments in many countries which could characterize periods of equity and property prices boom/bust episodes.² For example, Helbling and Terrones (2003), by considering industrial countries in the post-war period, found that in the three-year period before the bust private credit growth expanded in the case of both stock market and housing prices booms, with the increase being more evident in the latter case. For broad monetary aggregates, the behaviour looks similar with the only difference that stronger signals are sent to equity prices.³

The analysis of booms and busts gets further refined in a study by Detken and Smets (2004) who, starting from the observation that not all booms lead to large output losses, focused on “high-cost” asset price booms (as high-cost booms usually entail huge drops in real estate prices and investment crashes in the post-boom periods):⁴ The analysis shows that during high-cost boom periods real estate prices rise stronger, real credit and monetary growth is larger and, in particular, the difference is significant in the first boom year, while differences in economic developments across types of booms during the pre-boom periods are less significant. The more robust result is that real money growth is

¹ More precisely, the analysis is based on a sample of 34 countries – including all G10 – and on annual data over the period 1960 to 1999.

² The authors first identify peaks and troughs in assets prices and then define a bust as a peak-to-trough decline for which the price change is in the top quartile of all declines during bear markets. The average contraction is a decline of above 37% (from peak to trough), and the average duration is 10 quarters. As for housing prices, to be qualified as a bust the contraction has to exceed a decline of 14%. The average contraction is 27%, while the average duration is 16 quarters. The association between booms and busts is stronger for housing than for equity prices.

³ In terms of the quantification of the costs of asset price busts, the analysis shows that housing prices busts are associated with substantial output losses. In the case of asset prices, the decline in output is delayed to three quarters after the busts, but is shorter than in the case of housing busts.

⁴ The authors define as high-cost booms those booms that were followed by a drop of more than 3 percentage points in the average real growth (comparing the three years following the boom with the average growth during the boom) as long as the average post-boom growth is below 2.5%. Generally speaking, an asset price boom is a period in which the aggregate asset price index is continuously more than 10% above its trend, calculated recursively using a one-sided Hodrick-Prescott (HP) filter.

significantly higher for the high-cost booms during the pre boom period, which suggests that money and credit growth could be useful to distinguish high- from low-cost booms at a relatively early stage.

Along the same lines of analysis other studies can be cited. For instance, Adalid and Detken (2007) find that residential property prices developments and money growth shocks accumulated over the boom periods turn out to be able to well explain the depth of post-boom recessions. This stresses the major importance of housing prices boom-bust cycles and money growth for the real economy.⁵ Besides, liquidity shocks turn out to be driving factors for real estate prices during boom episodes. In a similar vein, the most recent paper by Alessi and Detken (2009) also tests for high-cost boom/bust cycles the performance of a variety of real and financial variables as early warning indicators using data for 18 OECD countries between 1970 and 2007. Overall, the authors find global measures of liquidity (narrow money — M1 — and credit) to be among the best performing indicators.

Using an alternative definition of asset price misalignments based on the use of quantile regressions, Machado and Sousa (2006) relate the booms and busts for the stock price index in the euro area both to growth rates of money and credit aggregates and to money overhangs. While the link between real money growth and asset price booms seems to be weak, asset price booms occur if credit growth is high. Focusing instead on the housing market, Goodhart and Hofmann (2007, 2008) find evidence of a significant multidirectional link between house prices, monetary variables and the macroeconomy, while the effects of shocks to money and credit are stronger when house prices are booming (see also Hofmann 2003). Finally, Carboni et al. (2010) provides a very brief survey of some studies analyzing the links between monetary aggregates and asset price.

Overall, the identification and quantification of asset price imbalances represents an extremely difficult task, both *ex ante* and *ex post*. Many studies also confirm that – among other variables – monetary and credit developments represent useful leading indicators of financial imbalances. In particular, one robust finding across the different studies is that measures of excessive credit creation are very good leading indicators of the building up of financial imbalances in the economy.

3. Results from a Probit Model Analysis

3.1 General set-up and data used

The present study complements the analysis of Gerdesmeier, Reimers and Roffia (2009, 2010) which focused on predicting asset price busts. This necessitates, as a first step, a precise definition of booms. Given that this study's focus is on deriving a combined signal derived from several individual asset markets, a composite indicator combining stock and house price development is used.

Once the respective boom periods are selected, as a second step, we try to explain them by use of leading indicators represented by various financial, monetary and real indicators. As for the financial variables, we consider historical series of the short-term (three-month money market) and long-term (ten-year government bond yield) interest rates and their spreads. Monetary indicators comprise broad money and credit to the private sector (or loans to the private sector whenever available). As for the real indicators, we consider real GDP and the investment-to-GDP ratio. In sum, the dataset contains quarterly data⁶ for 17 main industrial OECD countries (additionally, the euro area as a whole is included in the descriptive analysis) for the period 1969 Q1 – 2010 Q2.⁷

⁵ The study shows that real broad money growth seems to be a better indicator than real private credit growth to determine whether the current asset price boom will be followed by a period of low real growth.

⁶ All series are seasonally adjusted; whenever possible, quarterly series are calculated as averages of monthly series. For a detailed description of the series used and their sources see Gerdesmeier, Reimers and Roffia (2009), Annex 3.

⁷ For a few variables in some countries the starting point may be slightly later.

3.2 Defining an asset price boom

It is a crucial fact that a boom cannot simply be denoted as the inverse of a bust. Quite generally, busts and crashes can be seen as sudden and rather abrupt downward adjustments in asset markets. By contrast, a boom seems to be more related to a somewhat prolonged period of prosperity. Such a concept might be better represented by means of a gap variable, i.e. a positive deviation of actual developments from the trend development of a specific indicator variable. This statement is in line with Vogel (2010).⁸ Based on a behavioural interpretation of price developments of financial markets he develops a model incorporating behavioural risk premium. This premium in essence represents an equity risk premium which can be split up into a financial and a behavioural component. The former may incorporate quantifiable elements of discount rates, money supply changes, dividends and price-earning-ratios. By contrast, the latter component is based on herding, fear and other high-anxiety psychological factors. This premium could be visualised in form of a smile curve depending on the price-earning-ratio. As a consequence, high premia can stem from the perception or presence of large risks and/or from an increase in risk aversion. These fears tend to characterize a crash, whereas a bubble is more connected to a period of euphoria that tends to build up slowly.

In order to identify booms we use an indicator which combines two different market indices, namely a: stock market index and a housing market index. The method used to combine these two indices dates back to the methodology developed by Berg and Pattillo (1999) and Andreou et al. (2007), and is along the lines used in Gerdesmeier, Reimers and Roffia (2009). The main features are the following. A currency crisis is defined as a period when a weighted average of monthly percentage depreciations in the exchange rate and monthly percentage declines in reserves exceeds its mean by more than a multiple of the standard deviations, where means, standard deviations and weights are country-specific. In line with this, our composite asset price indicator has been calculated by combining the stock price index with the house price index as follows:⁹

$$\Delta C = \phi_1 \cdot \Delta \text{Stock prices} + \phi_2 \cdot \Delta \text{House prices} \quad (1)$$

where ϕ_1 is normalised to 1 and $\phi_2 = \sigma_{\Delta SP} / \sigma_{\Delta HP}$ (that is the ratio of the standard deviations of the two variables) and the weights are calculated recursively throughout the sample period.¹⁰ The quarterly changes are then cumulated to calculate the composite level variable. Following this, the indicator variable is used to select the boom periods.

In the literature, several approaches to identify asset price booms have been used. For instance, Borio and Drehmann (2009) define a boom as a period in which the three-year moving average of the annual growth rate of asset prices is greater than the average growth rate (i.e. its mean) plus a multiple (1.3 in this specific case) of the standard deviation of the growth rates. By contrast, Alessi and Detken (2009) follow a different approach. In essence, they calculate the trend of the price variable using the one-sided Hodrick Prescott filter and then derive the gap between the actual values of the price variable and its trend measure. If the gap is greater than 1.75 times of the recursively determined standard deviation a boom will be identified. With respect to such a procedure, Detken, Gerdesmeier and Roffia (2010) note that these methods rest on some critical assumptions. First, there is an implicit

⁸ See Vogel (2010), esp. Chapter 9.

⁹ This approach is a standard practice in the literature on currency crises, whereby the crisis indicators are usually obtained by statistical analysis of the exchange rate and official international reserve series. The weighting scheme used between the two series is generally inversely proportional to their conditional variance. When the pressure indicator goes above a certain threshold, it is deemed that there is a currency crisis. The threshold used is generally two or three standard deviations above the mean. The greater the number of the standard deviations, the smaller the number of identified crises.

¹⁰ An alternative weighting scheme is the one applied by the Bank for International Settlements, which combines equity and property prices by their respective share of private wealth.

acknowledgement that it is difficult to derive equilibrium asset prices with reference to the respective underlying fundamental variables. Second, the method relies on the use of a time-varying trend as a proxy for those underlying fundamentals. Third, significant deviations from the trend are then considered excessive and expected to be reversed at some point in future. Following these assumptions, a boom occurs when the “composite” asset market indicator development is greater than a pre-defined threshold.¹¹ In this study, the trend is calculated by making use of the Christiano-Fitzgerald filter (2003), since the Hodrick-Prescott filter is well-known to suffer from an end-of-sample problem.

$$G_t = C_t - C_t^{CF} \quad (2)$$

The emergence of a boom (i.e. a value of 1 of the “boom dummy” variable) is defined as a situation in which the gap between the actual composite indicator and the indicator’s trend has been greater than its mean (\bar{G}) plus a factor δ (equal to 1.75 and fixed across the sample period) multiplied by the standard deviation of the same indicator (σ_G), which are calculated over a rolling period of 60 quarters:

$$Dum_t = 1 \quad \text{iff} \quad G_t \geq (\bar{G}|_s^t + \delta \sigma_G|_s^t) \quad (3)$$

where $s = t-60$ for $t > 60$ or 1 for $0 < t < 60$. At the same time, we are interested in predicting asset price booms several quarters ($T=8$ quarters) ahead. In line with this, we define a new “boom dummy” $C8$ by making use of Dum as follows:

$$C8_t = 1 \quad \text{iff} \quad \sum_{k=1}^8 Dum_{t+k} > 0, \quad (4)$$

where the signaling horizon is defined as the period within which the indicator would be expected to be able to signal an asset price boom up to 8 quarters ahead. Thus, a signal that is followed by a boom within two years is labeled as a “good” signal, while a signal not followed by a boom within that interval of time is called a “false” signal. In this respect, it is important to note that, contrary to Alessi and Detken (2009), we do not discriminate between high and low-cost booms.

Figure 1 summaries the behavior of the composite asset price indicator gap and the corresponding boom episodes for all selected countries, defined using the criterion illustrated in equation (3).¹² The following observations seem worth noting. First, booms seem to be concentrated around three main periods. The first period is represented by the 1970s before the first oil price shock; the second period includes the end of the 1980s and the beginning of the 1990s, following the oil price trough in 1986, while the last cluster is around 2006-2007. As far as the euro area is concerned, only two booms can

¹¹ The intention of basing our analysis on a “composite” asset price index is that such an index would facilitate a comparison of broad asset price movements over time and across countries, give some empirical content to the notion of general asset price “inflation” and “deflation” and highlight patterns of behaviours that would otherwise remained undetected. Furthermore, Detken and Smets (2004) state that the bursting of bubbles will be more severe if more asset markets are involved, which would support the use of a composite indicator. For example, Zhang (2001) expresses his preference for individual market analyses. It should, however, 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 risk existing in one of the two markets.

¹² The calculation of the indicator is based on running the procedure recursively and in a rolling manner from the beginning of the sample onwards. Of course, the choice of $\delta = 1.75$ times the standard deviation is arbitrary.

be detected, the first one from 1988 Q4 to 1991 Q4, which may be connected to the introduction of the common market and the second one from 2006 Q2 to 2007 Q4. It seems, however, that, at the aggregate level, developments in some countries are counterbalanced by movements in other regions of the euro area. Second, the overall number of booms seems to vary across countries. Third, the length of the booms also varies across countries, lasting from a few quarters up to, broadly speaking, two-three years. In addition, when looking at individual country's experience, a few interesting issues also arise when considering the most recent developments in relation to the driving factors. For instance, it is interesting to note that in countries like Spain, Ireland and the United States booms in the composite asset price market are detected around 2006-2007, which is a period when all three countries experienced a strong house price boom which had started some years earlier.¹³ However, it is important to take into account that developments in the composite asset price indicator are also influenced by developments in stock prices, which can, in principle, counterbalance house prices developments over some periods of time. Therefore, opposite developments in the two individual asset markets may lead to a lack of a signal of a boom. This is, for instance, the case for Germany where no boom can be detected in the most recent episode, given the subdued developments in house prices.¹⁴ Taken together, these observations lead to the conclusion that an analysis taking into account heterogeneities across countries and time has to be adopted.

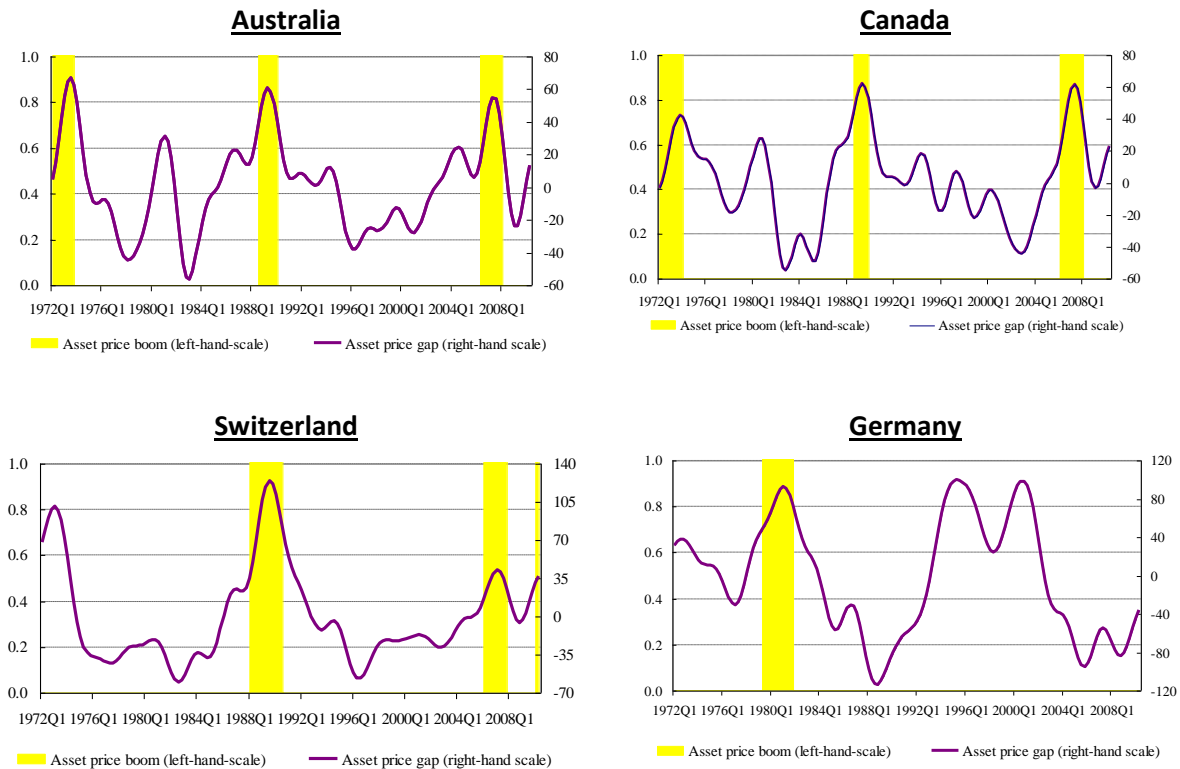
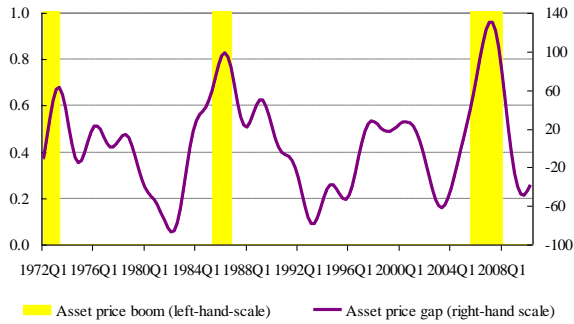
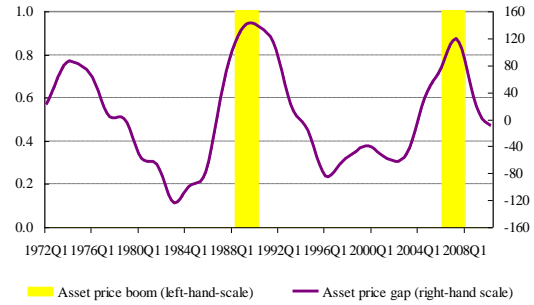
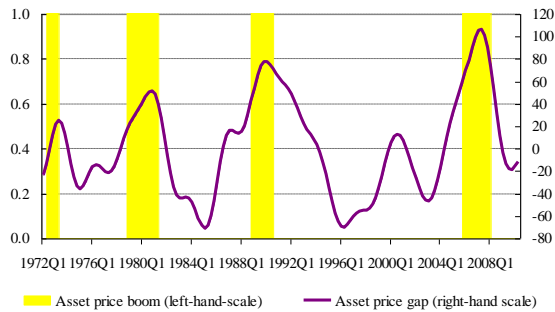
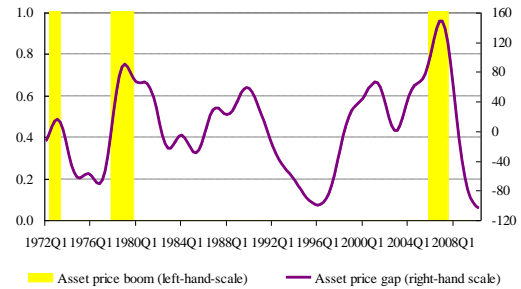
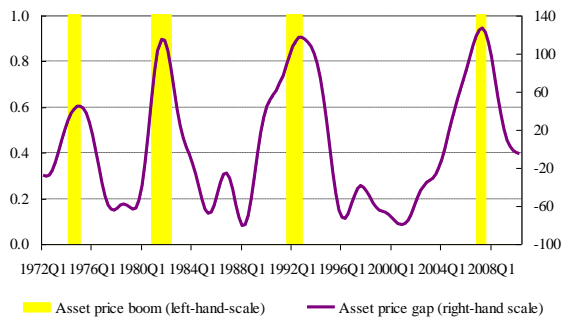
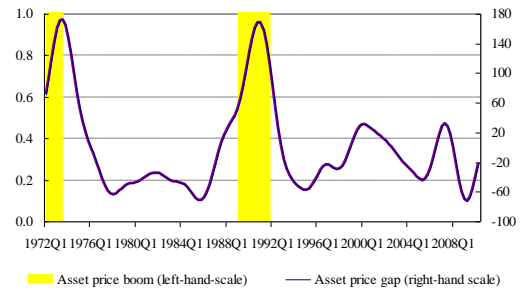
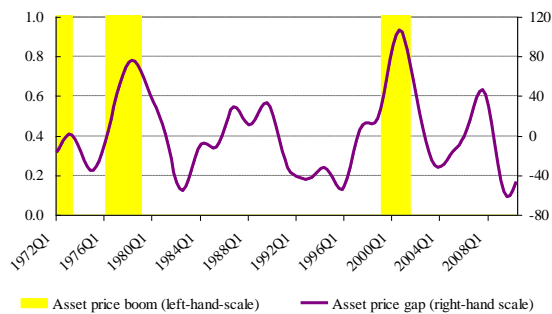
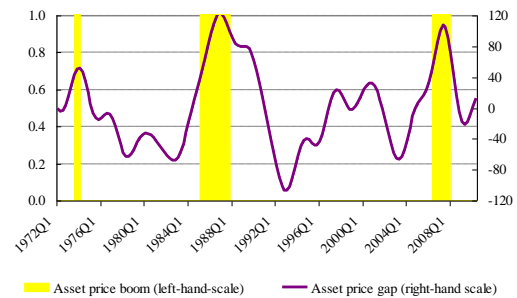


Figure 1 Developments in the composite indicator gaps and boom periods in the main OECD countries and the euro area (To be continued)

¹³ In particular, in Ireland (Spain and United States) the house price race began in 1996 (1999 and 2000, respectively).

¹⁴ It is also important to note that the boom definition applied in the analysis is based on the deviations of a form its trend. Therefore, in case of long-lasting but gradual deviations from the trend, it may take some time before a boom episode is actually detected.

Denmark**Spain****France****Ireland****Italy****Japan****Netherlands****Norway**

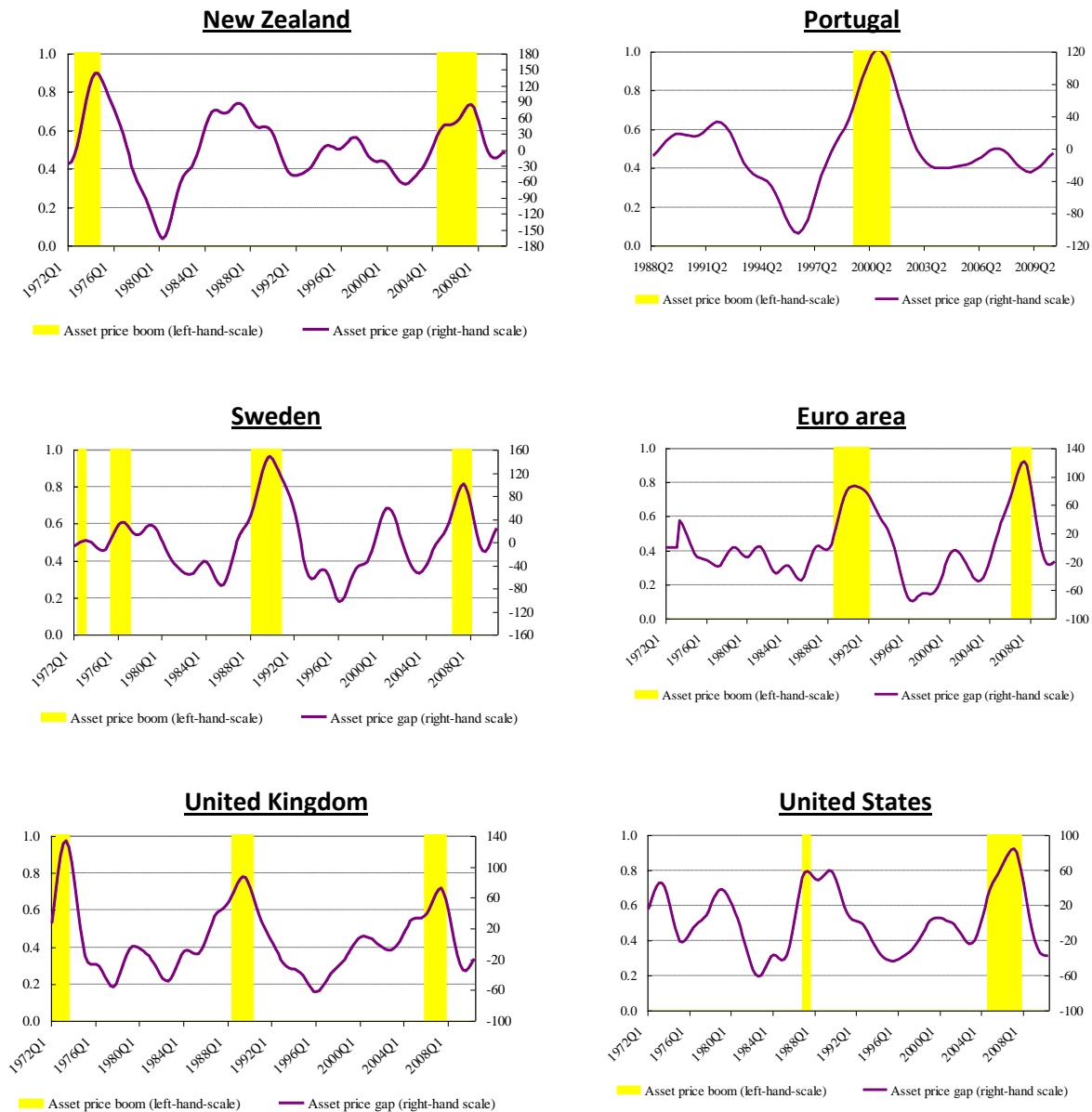


Figure 1 Developments in the composite indicator gaps and boom periods in the main OECD countries and the euro area

Note about the above figure: The solid line represents the composite indicator gap of each respective country, while the yellow shaded area represents the boom periods.

3.3 Empirical results

After having selected the boom periods, the next step consists in identifying which set of indicators can help to predict such periods. In this respect, a number of different approaches have been used in the literature to select the leading indicators. In theory, also considering the studies analyzing the crises, different types of approaches are possible. A first approach, which could be characterized as “indicators” or “signaling” methodology, looks for discrete thresholds and discriminates across the different indicators by checking some statistics, such as the noise-to-signal ratios. The indicators are chosen in such a way that they tend to exhibit unusual behavior prior to a boom. More precisely, an

indicator issues a signal whenever it moves above this level. In order to examine the effectiveness of individual indicators, one way to think about the performance of the set of indicators could be in terms of the matrix presented in Figure 2. In this matrix, A is the number of months/quarters (in the example 8 quarters, consistent with our analysis) in which the indicator issued a good signal, B is the number of months/quarters in which the indicator issued a bad signal, C is the number of months/quarters in which the indicator failed to issue a signal when the boom occurred and D is the number of months/quarters in which the indicator refrained from issuing a signal when in fact there was no boom. A perfect indicator would only produce observations that belong to A or D cells, or that is it would minimize the noise-to-signal ratio.

Seen from that angle, a set of indicators is said to issue a signal whenever it crosses a given threshold, which is chosen so as to strike a balance between the risks of having too many false signals (which would happen if a signal is issued with the smallest possibility of occurrence of a crisis/bust) and the risk of missing many crises/busts (which would happen if the signal is issued only when the evidence of a boom is overwhelming).¹⁵

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

Figure 2 Performance of indicators

An alternative approach makes use of probit or logit regression techniques which test the occurrence of an asset price boom by, for example, using the independent variable as a one/zero variable which takes a value of one if there is a boom on the basis of a specific criterion chosen and zero otherwise. As stressed by Berg and Pattillo (1999), this approach has many advantages. First, it allows to test directly the usefulness of the threshold concept; second, it allows to aggregate predictive variables more satisfactorily into one composite indicator index, taking into account correlations among different variables; and third, it permits to test the statistical significance of individual variables and the constancy of coefficients across time and countries.¹⁶

The empirical analysis in this paper will be based on the second approach and make use of probit techniques. As in the literature it has been pointed out that the standard errors of the panel probit estimates of early-warning-system models are often incorrect because of serial correlation problems, we apply the heteroscedasticity and autocorrelation corrected (HAC) procedure as proposed by Berg and Coke (2004) which produces accurate estimates.

The probit equation takes the following general form:

$$Prob(C_{it}=1)=\alpha_{it}+\beta_{it}\cdot X_{it}+\varepsilon_{it} \quad (5)$$

where X_t consists of the fundamental variables and ε_t stands for the error term. As already mentioned, the fundamental variables are grouped into monetary, real and financial variables

¹⁵ More recently, Alessi and Detken (2009) set the thresholds for the indicators for each quarter 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.

¹⁶ For details on the advantages of using panel data analysis, see Baltagi (1995).

categories, and specified in form of either annual growth rates and/or as deviations from a trend and/or as ratios to GDP.¹⁷

Applying probit techniques for our unbalanced data set enables us to estimate the probability of occurrence of an asset price boom in the next eight quarters. However, the assessment of whether a boom will occur or not depends on the subjective choice of a threshold, which, once crossed, would give a signal of an upcoming boom. Against this background, we make a subjective choice which, however, is in line with the literature.

Moreover, in order to compare the performance across the several probit models, besides looking at the significance of the coefficients and the McFadden R-squared, we apply the evaluation procedures suggested by Jacobs et al. (2005), i.e. the quadratic probability score (QPS), the log probability score (LPS) analysed by Diebold and Rudebusch (1989), as well as the Kuiper's score (KS) test considered in van der Berg et al. (2008). These scores are meant to give an indication of the average closeness of the predicted probabilities and the observed realizations which are measured by a binary variable (i.e. the "boom dummy" $C8$). Let P_t be the prediction probability of the occurrences of boom (or no boom) event by the model at time t and $C8_t$ the zero-one dummy derived in Section 3.2. The QPS, LPS and KS tests are then defined as follows:

$$QPS = \frac{1}{T} \sum_{t=1}^T 2(P_t - C8_t)^2 \quad (6)$$

$$LPS = -\frac{1}{T} \sum_{t=1}^T ((1 - C8_t) \ln(1 - P_t) + C8_t \ln(P_t)) \quad (7)$$

$$KS = \frac{A}{A + C} - \frac{B}{B + D} \quad (8)$$

where T is the sample size, A is the number of correctly predicted busts, B counts the number of false alarms, C are the missed busts and D stands for the correctly predicted tranquil periods.

The quality of a model increases when QPS and LPS move close to 0, and KS approaches 1. More precisely, the QPS ranges from 0 to 2 with a lower QPS implying a more accurate forecast. A value of 0 then corresponds to perfect accuracy.¹⁸ As for the next step regarding the probit estimations, we start off from the models selected in Gerdesmeier, Reimers and Roffia (2009) and test different lags for all the explanatory variables. In a subsequent step, we tested the inclusion of several measures of interest rates (spread, short and long-term interest rates) and finally we tested the significant of other variables, such as real GDP and stock prices.

¹⁷ To calculate the trend, we make use of the Christiano-Fitzgerald filter (2003), since the Hodrick-Prescott filter is known to suffer from an end-of-sample problem.

¹⁸ The implied loss function of the QPS is quadratic and symmetric which may be not appropriate as a forecaster may be penalized more heavily for missing a sign of a bust than for signalling a false alarm. The LPS has a logarithmic loss function and corresponds to the loss function used in the probit regression, so it has the advantage of coordinating the in-sample estimation criterion with the out-of-sample loss function (see Rudebusch and Williams, 2008). The LPS penalises large mistakes more heavily than QPS and takes value between zero and infinity, with 0 reflecting perfect accuracy. The advantage of the QPS and LPS is that they do not need an ad hoc threshold value.

Table 1 presents the results of the preferred specification which includes credit growth gap, house price growth gap, investment-to-GDP ratio, the interest rates spread and the stock price growth.¹⁹ All coefficients have the expected sign and are statistically significant. The signs of the coefficients should be interpreted as having an increasing or decreasing effect on the probability of a boom. This notwithstanding, the values are not as intuitive to interpret. In fact, eq.(5) shows that the coefficients are not constant marginal effects of the variable on boom probability since the variable's effect is conditional on the values of all other explanatory variables. Rather, the slope-coefficients represent the effects of X_i , the respective right-hand variables when all other variables are held at their sample means. The McFadden R-squared is 0.34.

Table 1 Results of the preferred specification

Variables	Coefficient	t-statistics ML	t-statistics GMM
Credit growth gap	0.71	13.1	6.8
Credit growth gap (-1)	-0.58	-11.2	-6.4
House price growth gap	0.11	15.1	6.6
Investment-to-GDP ratio	0.02	5.9	1.9
Stock price growth	0.01	5.2	3.0
Spread	0.06	4.4	1.9
Constant	-1.70	-16.4	-5.5
McFadden R ²	0.34		

Statistics	LPS	QPS	Threshold	KS	N-t-S ratio	Booms called (in %)	Missed booms (in %)	False alarms (in %)
Value	0.33	0.21	0.35	0.58	0.18	71.7	28.3	13.2
			0.25	0.62	0.26	83.4	16.6	21.9

As regards the threshold value of the probability, designing a good forecasting model requires balancing the number of false alarms and the number of failures. In general, the value depends on the costs related to the two different types of errors and their assessment by the policy maker. In our analysis, we checked the threshold values ranging from 0.10 and 0.40 (see Section 4 for the results). For instance, the value 0.35 implies a small proportion of errors for non-booms but a low proportion of booms called. By contrast, the lower threshold value of 0.25, which is more often selected in the literature²⁰, results in a higher proportion of booms called. The statistics related to these two thresholds are reported in Table 1. In both cases, however, it turns out that the number of false alarms is not very high, while the number of booms called is quite satisfactory.

Figure 3 provides an illustration for each country of how well the probit model predicts a possible boom in a forecasting horizon up to 8 quarters ahead (see eq.(4)), where the threshold is set at 0.35.²¹

¹⁹ The inclusion of the spread as indicator for asset price booms may reflect the fact that in the literature it has been shown that the term spread is a good measure to predict future output growth. See, for instance, Estrella and Hardouvelis (1991).

²⁰ For instance, in Berg and Pattillo (1999) the choice of a threshold of 25% leads to an accuracy of predicting crises of about 73%, while that of false alarms is at 41%.

²¹ It might, however, be argued that the assumption of restricting the constant and slope coefficients to the same value cannot be seen as particularly realistic. Therefore, a robustness check of the results

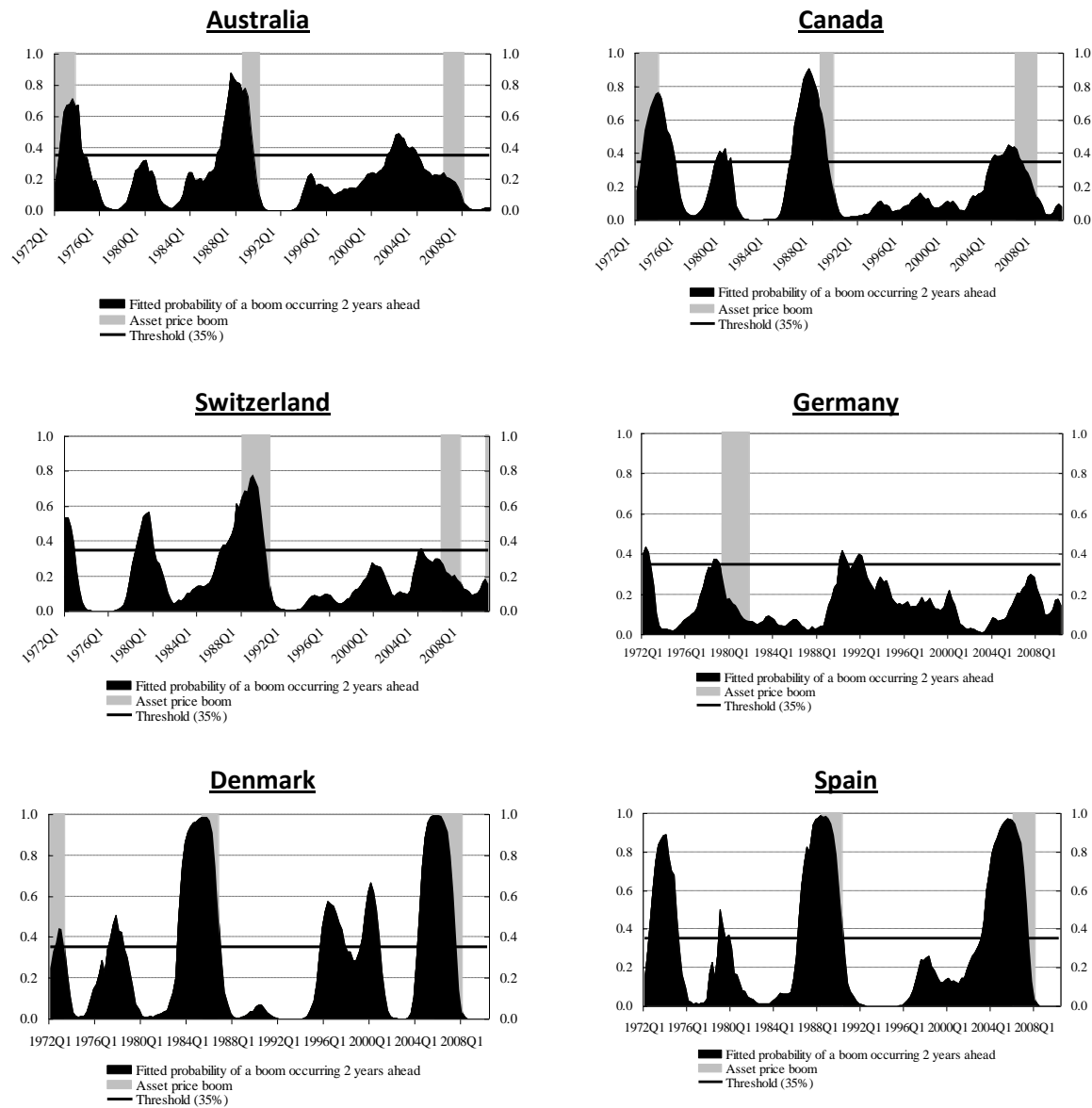
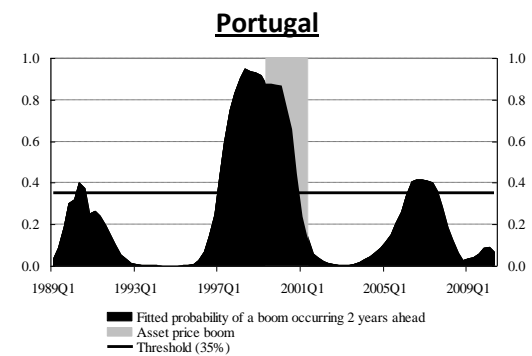
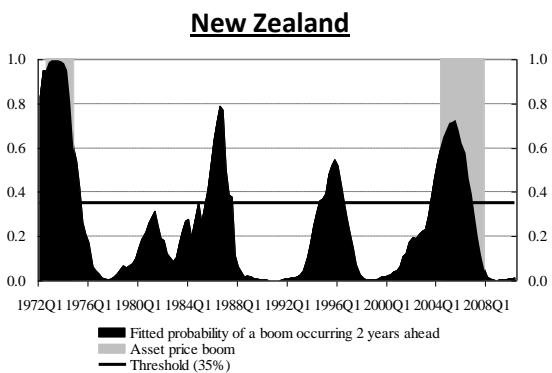
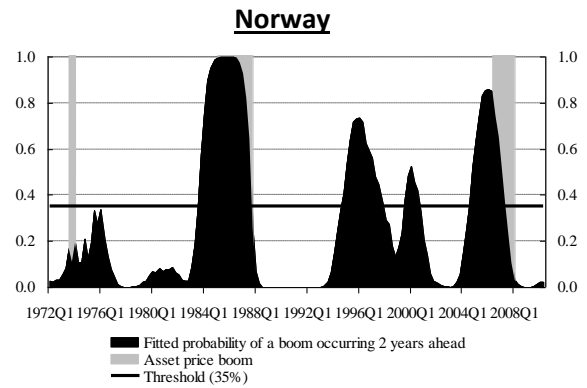
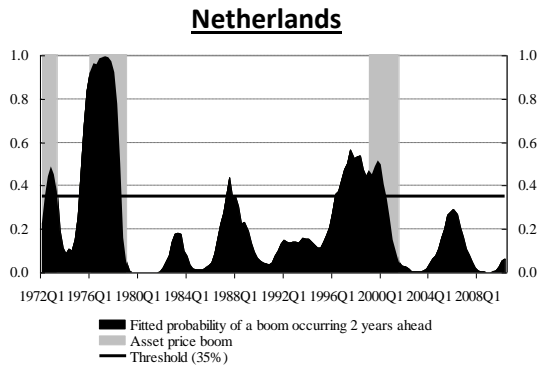
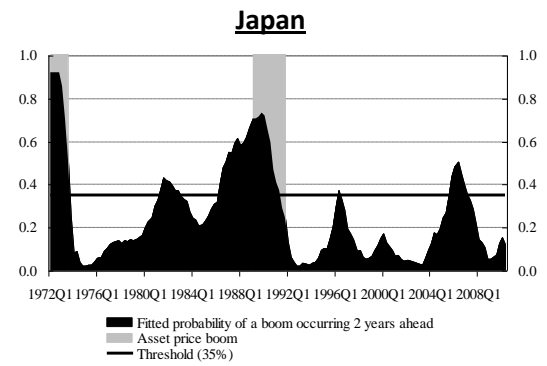
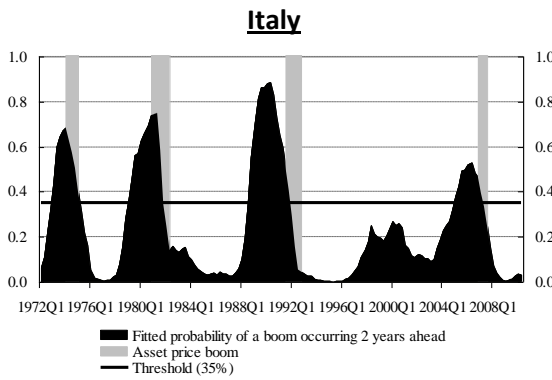
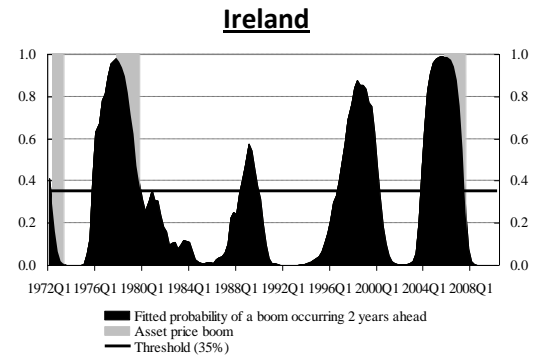
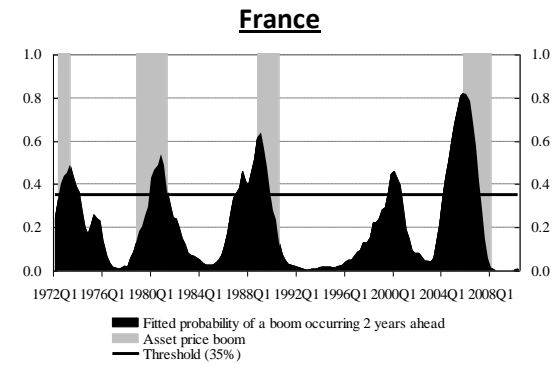


Figure 3 Predictive performance of the best specification for asset price booms up to 8 quarters ahead
(To be continued on next two pages)

with other methods is warranted. This notwithstanding, these findings turn out to be robust also to the use of the panel probit estimation with fixed effects. In terms of statistics, in the latter case they improve as the LPS and QPS tests turn out to be lower, while the McFadden R-squared is higher; at the same time, most of the fixed effects coefficients do not seem to be significant at conventional significance levels.



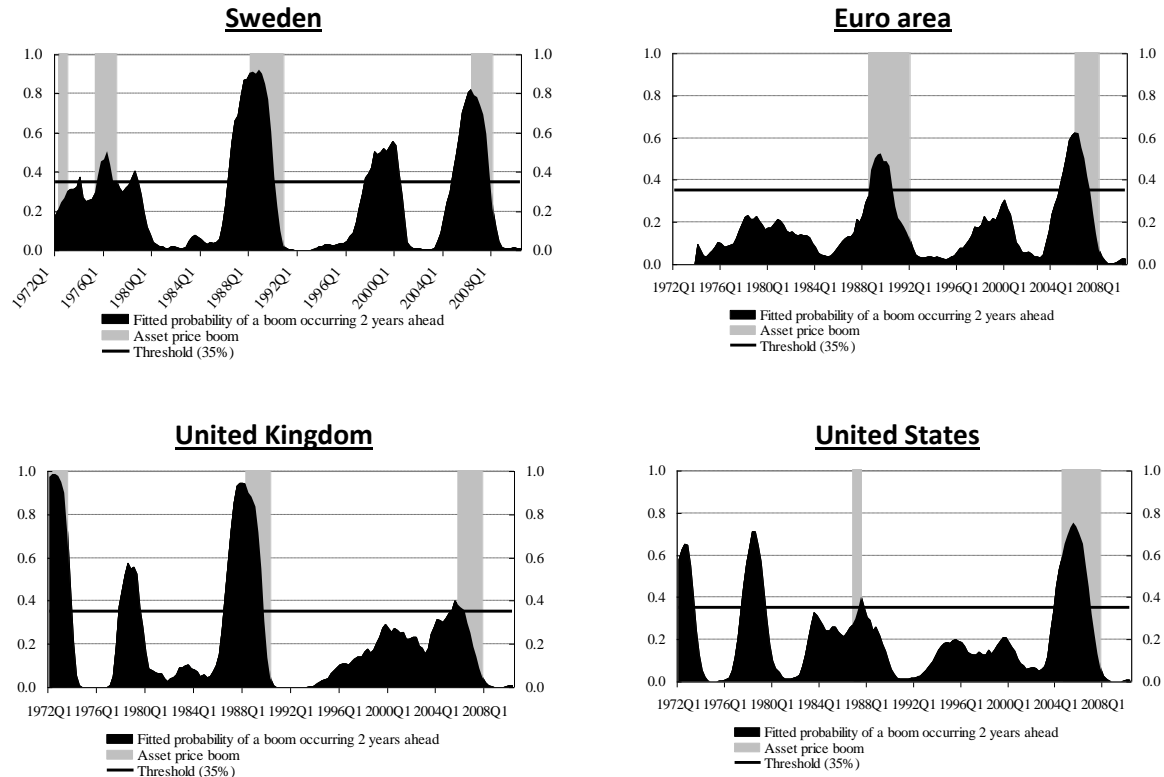


Figure 3 Predictive performance of the best specification for asset price booms up to 8 quarters ahead

Note about the above figure: The black shaded area represents the boom probability of an asset price boom occurring within two years ahead; the gray shaded area represents the boom periods and the solid black line represents the threshold value of 35%.

4. Assessing the Robustness of the Model

4.1 Cross-checking the results from the probit model vis-à-vis a logit variant

In order to check the robustness of our results, we compare the probit model outcomes vis-à-vis the results obtained by using a logit-model. The results of this comparison are reported in Table 2. While the size of the coefficients is larger compared to the probit model, the significance of the coefficients is in line with the earlier results and thus support the validity of the latter. The LPS- and QPS-statistic as well as the number of the booms correctly called are found to be similar to those for the probit model. Therefore, the logit approach does not represent an improvement in comparison to the probit approach.

4.2 Testing for the impact of different forecasting horizons

It can be argued that the variable $C8$ is a comprehensive indicator of a boom which occurs from 1 to 8 quarters ahead, and that the model might perform differently across different horizons. As a matter of fact, in constructing the variable $C8$ we followed the suggestions of Berg and Pattillo (1999) and Andreou et al. (2007) to simplify our model search procedure. Furthermore, 8 quarters represent a compromise with the empirical results from the transmission mechanism literature. Indeed, it is possible that the specification would change according to the forecast horizon, a result which is well known from the literature of inflation forecasting. Although the derivation of an optimal forecasting horizon is beyond the scope of this analysis, we cross-check our results using forecast horizon periods

ranging from 1 to 8. The results are reported in Table 3. It can be noticed that, for the shortest horizon, the information content of the credit gaps is lower, while the size of the coefficient of the house price gap is slightly higher. However, for a forecast horizon of three quarters or more the stock price growth has no significant effects, while the investment-to-GDP ratio loses its influence after 4 quarters. By contrast, the credit and house gaps are significant for most all horizons.

Table 2 Results from a logit-model

Variables	Coefficient	t-statistics ML	t-statistics GMM
Credit growth gap	1.24	12.8	6.8
Credit growth gap (-1)	-1.01	-11.0	-6.4
House price growth gap	0.20	14.5	6.6
Investment-to-GDP ratio	0.04	5.5	1.9
Stock price growth	0.02	5.7	3.0
Spread	0.12	4.8	1.9
Constant	-3.01	-15.4	-5.5
Mcfadden R ²	0.35		

Statistics	LPS	QPS	Threshold	KS	N-t-S ratio	Booms called (in %)	Missed booms (in %)	False alarms (in %)
Value	0.33	0.2	0.35	0.6	0.17	71.0	29.0	12.2
			0.25	0.6	0.24	82.0	18.0	20.1

Table 3 Coefficients and statistics of the preferred specification for different forecast horizons

Variables	Horizon							
	1	2	3	4	5	6	7	8
Credit growth gap	0.22 2.44	0.45 5.07	0.63 6.85	0.76 7.46	0.82 7.70	0.83 7.66	0.79 7.46	0.72 6.95
Credit growth gap (-1)	-0.07 -0.68	-0.31 -3.49	-0.52 -5.95	-0.67 -7.15	-0.76 -7.54	-0.79 -7.55	-0.77 -7.41	-0.71 -7.00
House price growth gap	0.11 6.30	0.11 6.02	0.12 5.94	0.11 5.88	0.11 5.85	0.10 5.61	0.08 5.14	0.07 4.58
Investment-to-GDP ratio	0.01 1.82	0.01 1.89	0.01 1.88	0.01 1.74	0.01 1.63	0.01 1.56	0.01 1.46	0.01 1.38
Stock price growth	0.01 3.75	0.01 2.29	0.00 1.10	0.00 0.10	0.00 -0.33	0.00 -0.04	0.00 0.72	0.00 1.68
Spread	0.05 1.71	0.07 2.48	0.07 2.70	0.07 2.70	0.07 2.70	0.07 2.65	0.06 2.35	0.05 1.92
Constant	-2.07 -10.04	-2.06 -10.22	-2.01 -10.28	-1.93 -10.15	-1.89 -10.03	-1.87 -9.58	-1.82 -9.00	-1.79 -8.34

Note about the above table: For the different horizons each column contains the estimates of the coefficients while the row below contains the HAC corrected t-statistics.

4.3 Determining the threshold

In the previous analyses we used, in line with the literature, threshold value of 0.25 and 0.35. In this subsection, we cross-checked the results obtained by the use of different threshold values, starting from a threshold of 0.50 and reducing it stepwise down to 0.10. The results are given in Table 4. It is apparent that when the threshold increases from 0 to higher values, the KS statistic increases and

achieves its maximum in correspondence of a threshold of 0.25-0.29. As regard the signals, it seems that lowering the threshold values leads to a higher number of booms correctly called and to a reduced number of missed booms. By contrast, it strengthens the number of false alarms (i.e. the non-booms which were called). In light of these results, the optimal threshold value between 0.28-0.35 seems to be a good and plausible choice.

Table 4 Optimizing across different threshold values

Threshold	0.50	0.45	0.40	0.35	0.32	0.31	0.30	0.29	0.28
KS	0.49	0.53	0.55	0.58	0.59	0.60	0.60	0.62	0.62
N-t-S ratio	0.10	0.12	0.15	0.18	0.21	0.21	0.22	0.22	0.23
Booms called (in %)	54.23	59.64	64.32	71.71	74.05	75.50	76.76	79.10	80.18
Missed booms (in %)	45.77	40.36	35.68	28.29	25.95	24.50	23.24	20.90	19.82
False alarms (in %)	5.43	7.13	9.77	13.23	15.35	15.87	16.54	17.31	18.40

Threshold	0.27	0.26	0.25	0.24	0.22	0.20	0.15	0.10
KS	0.61	0.61	0.62	0.61	0.62	0.61	0.57	0.47
N-t-S ratio	0.24	0.26	0.26	0.28	0.30	0.32	0.39	0.51
Booms called (in %)	80.90	81.62	83.42	84.86	87.93	89.55	92.79	95.68
Missed booms (in %)	19.10	18.38	16.58	15.14	12.07	10.45	7.21	4.32
False alarms (in %)	19.43	20.83	21.91	23.82	26.10	28.48	36.07	48.73

5. Conclusions

For central banks it is important to use early warning indicators to assess the possible implications of large asset price movements and the building up of financial imbalances in the economy. In this respect, several studies have shown that the analysis of monetary and credit developments may be very useful in this respect. This paper contributes to this literature for investigating whether money and credit indicators can play an important role in detecting asset price booms by looking at the evidence stemming from a sample of 17 OECD industrialized countries and the euro area over the period 1969 Q1 – 2010 Q2.

By using an asset price composite indicator (which incorporates developments in both the stock price and house price markets) and following the methodology illustrated in Gerdesmeier, Reimers and Roffia (2009), an empirical analysis is carried out based on a pooled probit-type approach, which considers several macroeconomic variables. According to statistical tests, credit aggregates (growth gap), house price growth gap and the investment-to-GDP ratio jointly with developments in stock prices and the interest rate spread turn out to be the best indicators which help to forecast asset price booms up to 8 quarters ahead. The model is cross-checked vis-à-vis the estimation methods, forecasting horizon and probability thresholds and it turns out to be quite robust.

Overall, while differing with respect to the precise quantification and identification of asset price booms, the results of this paper are in line with the theoretical findings and a number of studies in the literature, and confirm that it is useful to look at monetary and credit developments as early indicators of the building up of financial imbalances.

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