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Bubbles and crises: The role of house prices and credit

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Bubbles and crises: The role of house prices and credit*

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Abstract

This paper exploits a quarterly panel data set for 16 OECD countries over the period 1975q1–2013q2 to explore the importance of house prices and credit in affecting the likelihood of a financial crisis. Estimating a set of multivariate logit models, we find that booms in credit to both households and non-financial enterprises are important to account for when evaluating the stability of the financial system. In addition, we find that global housing market developments have predictive power for domestic financial stability. Finally, econometric measures of bubble-like behavior in housing and credit markets enter with positive and highly significant coefficients. Specifically, we find that the probability of a crisis increases markedly when bubble-like behavior coincides with high leverage.

Keywords: *Basel III; Countercyclical Capital Buffer; Early Warning Models; Exuberance Indicators; Financial Market Imbalances*

JEL classification: *G01; G18; G21; G28*

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1 Introduction

Although most countries have experienced relatively few banking and financial crises, they are usually very costly when they occur (see e.g. Reinhart and Rogoff (2009a), Boyd et al. (2005), Laeven and Valencia (2010), Cerra and Saxena (2008)). It has also been shown that crises preceded by credit booms are more costly than other crises, see Jorda et al. (2013).

Recently, the countercyclical capital buffer (CCB) was introduced as a new policy tool for regulating banks (see Basel Committee on Banking Supervision (2010a)). The objective of the CCB is to enable authorities to increase the resilience of banks during booms in order to withstand higher loan losses in the event of a bust. The idea is that the more capitalized banks are prior to a bust, the less likely it is that the supply of credit will be constrained by capital requirements from the authorities or market demands. With the introduction of the CCB, it seems imperative to develop an analytical framework for determining which factors contribute to the build-up of systemic risk in the financial system.

Against this background, this paper asks three main questions: first, are there differences in how booms in credit to households and non-financial enterprises affect the probability of a crisis? Second, is there a tendency that rapid developments in global house prices and credit transmit across countries and generate higher risk in the domestic financial system? Finally, how does bubble-like behavior in house prices and credit add to the build-up of systemic risk in the financial system?

While individual indicators may provide informative signals about the likelihood of a future crisis in their own right, the signalling properties may be improved by combining them in an econometric model. For this reason, we estimate multivariate logit models to explore to what extent the different factors alluded to above affect the probability that the financial system is in a vulnerable state.[1]

Using quarterly panel data for 16 OECD countries over the period 1975q1–2013q2, we make several contributions to the literature on early warning systems. While private sector credit-to-GDP as a deviation from its long-term trend (*the credit-to-GDP gap*) has been extensively used as an early warning indicator, we decompose this variable into separate measures for households and non-financial enterprises. Our results show that they both have positive and significant effects on the likelihood of a financial crisis. This result contrasts with Büyükkarabacak and Valev (2010), who only find a robust effect of household credit considering a sample that runs through the period 1990–2006. Performing a sample split, we find that the difference in results may be ascribed to the shorter sample used in their study. As a second contribution, we construct country-specific "global" variables to capture international spill-over effects. Inspired by the GVAR literature (see e.g. Pesaran et al. (2004), Dees et al. (2007a) and Dees et al. (2007b)), the global variables are constructed using time-varying trade weights. Our results demonstrate that global developments in house prices were of great importance in the build-up to the recent global financial crisis, while it had less influence prior to earlier crisis episodes. The final

[1] This is in line with the recommendations of the ESRB, see ESRB Recommendation on guidance for setting countercyclical buffer rates., and both LoDuca and Peltonen (2013) and Behn et al. (2013) have shown that multivariate models outperform stand-alone indicators when it comes to signalling future crises.

and main contribution of this paper is to construct country-specific and econometrically based measures of bubble-like behavior, or *exuberance*, in housing and credit markets. These measures are constructed by recursively testing whether a time series variable is in a regime characterized by explosive behavior or not, see Phillips et al. (2011), Phillips et al. (2012) and Phillips et al. (2013). We establish a positive and highly significant effect of exuberant behavior in any of these markets on the likelihood of a crisis. Specifically, the combination of a state of exuberance and a high credit-to-GDP gap (high leverage) seems to send a strong signal that risks are building up in the financial system.

In addition to these contributions, our results encompass a central finding in the early warning literature, namely that the domestic credit-to-GDP gap is an important predictor of financial crises. This suggests, as has also been highlighted in the guidelines from the Basel committee (Basel Committee on Banking Supervision, 2010b), that policymakers should keep a close eye on the credit cycle (as measured by the credit-to-GDP gap) when monitoring the soundness of the financial system. We also find that both a larger house price-to-income and non-core funding ratio gap increases the likelihood of a crisis. These results are in line with Borio and Lowe (2004), Alessi and Detken (2011), Drehmann et al. (2011), Schularick and Taylor (2012), Behn et al. (2013), LoDuca and Peltonen (2013) and Hahm et al. (2013). It is reassuring that similar results may be established using a different information set.

The paper proceeds as follows. In the next section, we describe the methodological approach we use to identify the main determinants of financial crises. The data are presented in Section 3. We discuss our econometric results in Section 4, while Section 5 evaluates the out-of-sample properties of the models, and their temporal and cross-sectional stability. The final section concludes the paper.

2 Estimation and evaluation

2.1 Econometric approach

Systemic risk is a product of two components: the probability and the cost of a crisis. While it is clear that all crises differ in terms of depth and duration, the interest of this paper is to develop econometric models to estimate the probability of a crisis. For this reason, we follow the burgeoning literature on early warning systems and make use of a multivariate binary choice model.

More specifically, the aim of our empirical analysis is to assess the likelihood that the economy is in a pre-crisis state – defined as 1-3 years prior to the outbreak of a crisis. This gives policymakers some time to put in place measures to counteract the increased vulnerability of the economy. This is particularly relevant in the context of the CCB due to the 12 month implementation lag.[2] For this reason, we follow Bussiere and Fratzscher (2006) and define our dependent variable, $Y_{i,t}$, as a forward-looking variable

$$Y_{i,t} = \begin{cases} 1 & \text{if } FC_{i,t+k} = 1 \text{ for } k \in [5, 12] \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

[2]As specified in the CRD IV (EU, 2013), an increase in the CCB should normally be announced 12 months in advance before it becomes effective for banks.

where $FC_{i,t+k}$ signifies that country i experienced a financial crisis at time $t+k$. Thus, our dependent variable takes the value one during the 5 to 12 quarter period preceding a financial crisis. We follow Behn et al. (2013) and omit all observations in which a country is classified to have experienced a financial crisis, as well as the 6 quarters succeeding a crisis. This is done to avoid the post-crisis bias, as discussed in e.g. Bussiere and Fratzscher (2006).[3]

Given the definition of our dependent variable in (1), and considering a logit specification, the probability of a financial crisis in country i over the specified horizon is given by

$$p_i = Pr\left(Y_{i,t}=1\right) = \Phi\left(\alpha_i + \boldsymbol{\beta}'\mathbf{x}_{i,t}\right) = \frac{\exp(\alpha_i + \boldsymbol{\beta}'\mathbf{x}_{i,t})}{1+\exp(\alpha_i + \boldsymbol{\beta}'\mathbf{x}_{i,t})} \tag{2}$$

where $\mathbf{x}_{i,t}$ is a vector of explanatory variables and $\boldsymbol{\beta}$ is the corresponding coefficient vector. The α_i's measure country fixed effects and are included to account for unobserved heterogeneity.

2.2 Model evaluation

For a given model, m, a crisis signal is issued whenever the estimated probability of a crisis from that model, $\hat{p}_m$, exceeds some threshold level τ, i.e. a crisis signal is issued whenever $\hat{p}_m > \tau$. There are two types of errors that can be made; the model fails to predict a crisis (Type I error), or the model issues a false crisis signal (Type II error). Clearly, there are costs attached to both errors, which give rise to a trade-off between missing crises and issuing false alarms. In the following, we will discuss some ways in which alternative models can be evaluated against each other taking this trade-off into account.

Let the true positive rate ($TPR_m(\tau)$) denote the share of all crises where a correct signal is issued, i.e., one minus the share of Type I errors. Further, let the false positive rate ($FPR_m(\tau)$) be the fraction of all non-crisis events where a false signal is issued (the share of Type II errors). Lowering the value of the threshold parameter will in general imply that the model issues more signals. While this increases the share of correctly predicted crises, it comes at the cost of issuing more false alarms. The opposite is true if the value of the threshold parameter is increased. Determining the optimal threshold requires knowledge of the policymaker's preferences regarding the trade-off between Type I and Type II errors, which depends (among other things) on the relative cost of the different outcomes, as well as the frequency at which financial crises occur. One way of formalizing this trade-off is by formulating a loss function. For model m, a linear loss function takes the following form (see e.g. Sarlin (2013))

$$L_m(\theta,\tau) = \theta p(1 - TPR_m(\tau)) + (1-\theta)(1-p)FPR_m(\tau) \tag{3}$$

where p is the unconditional probability of a crisis, or the frequency of financial crises in the sample under consideration. θ is the relative weight that the policymaker attaches to missing a crisis. A reasonable assumption is that $\theta \in [0.5; 1]$, i.e. the policymaker is at

[3]For most countries in our sample, we only use data up to the financial crisis of 2007/08. The reason is that there is as yet no general consensus on – or (at least for most countries) the official dating of – when the crisis ended.

least as concerned with missing a crisis as issuing false alarms (see also Sarlin (2013) and Behn et al. (2013)). In evaluating the models considered in this paper, we set θ to 0.9 and 0.95, which are realistic values for this preference parameter for authorities that give considerable emphasis to not missing a crisis, and report the so-called *relative usefulness*, which is defined as

$$U_r(\tau) = \frac{min\{\theta p, (1-\theta)(1-p)\} - L(\theta,\tau)}{min\{\theta p, (1-\theta)(1-p)\}} \tag{4}$$

where $min\{\theta p, (1-\theta)(1-p)\}$ is the loss that is always achievable.[4] The model is said to be useful if the numerator (defined as the *absolute usefulness*) is positive, i.e. if the loss associated with the model is lower than what we can achieve without using a model. The denominator is the absolute usefulness associated with a perfect model (where $L(\theta,\tau)=0$). By calculating the relative usefulness of several competing models, we can rank their performance, where a higher relative usefulness indicates a better model.[5]

A complementary tool that has been used extensively to compare alternative early warning models is the *Receiver Operating Characteristic* (ROC), which plots the full mapping of the false positive rate, $FPR_m(\tau)$, and the true positive rate, $TPR_m(\tau) = TPR_m(FPR_m(\tau))$, across different values of the threshold parameter τ (see Drehmann and Juselius (2014) for further details). We will report the *Area Under Receiver Operating Characteristic* (AUROC), which takes into account every point on the ROC curve. More formally, AUROC is defined as

$$AUROC_m = \int_{\tau=0}^{1} TPR(FPR_m(\tau))FPR'_m(\tau)d\tau \tag{5}$$

The advantage of AUROC is that it is independent of the policymaker's preferences and it covers all possible preference parameters (see Elliot and Lieli (2013)). When comparing the performance of model m relative to model c, model m is preferred to model c if $AUROC_m > AUROC_c$, i.e., on average (across preference constellations), model m has a higher TPR for a given FPR than model c.[6]

[4] If a signal is always issued, the loss in (3) is $(1-\theta)(1-p)$. If a signal is never issued, the loss in (3) is θp.

[5] Note that the relative usefulness is bounded between zero and one; a perfect model has $U_r(\tau)=1$, while a useless model (same as always issuing a signal) has $U_r(\tau)=0$. The reader is referred to Sarlin (2013) for a more comprehensive discussion of the loss function and related evaluation criteria.

[6] A perfect model has $AUROC = 1$, while a completely uninformative model has $AUROC = 0.5$. Pepe et al. (2009) and Janes et al. (2009) suggest the following Wald type test statistic to compare model m to model c (see Berge and Jorda (2011) for an economic application)

$$W_{\text{AUROC}} = \frac{\text{AUROC}_m - \text{AUROC}_c}{se\left(\text{AUROC}_m - \text{AUROC}_c\right)}$$

W_{AUROC} follows a standard normal distribution under the null hypothesis of no difference. Thus, when formally testing whether model m is preferred to model c, we compare W_{AUROC} to the relevant critical value from a standard normal distribution.

3 Data description and temporal properties

Our panel includes quarterly data for 16 OECD countries on various macroeconomic and financial variables over the period 1975q1 - 2013q2. The countries included in our data set are: Australia, Belgium, Canada, Finland, France, Germany, Italy, Japan, Korea, Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom and the United States, and the data have been collected from numerous sources.[7] In the following, we will describe how we operationalize the dependent variable and the explanatory variables, the sources of our data, as well as their temporal properties and how they behave around crisis periods.

3.1 Financial crises

Our operationalization of the dependent variable relies on, among others, Laeven and Valencia (2008, 2010, 2012) and Reinhart and Rogoff (2008, 2009a,b).[8]

Table 1 shows the identified crisis episodes in our sample. In addition to the global financial crisis of 2007-09, it includes what Reinhart and Rogoff (2009a) have labeled the *"big five"*: Spain (1977/1978), Norway (1988), Finland (1991), Sweden (1991) and Japan (1992), as well as other banking and financial crises.

Table 1: Dating of financial crises

Country	Start of Crisis	Country	Start of Crisis
Australia	1989q4	Korea	1997q3
Belgium	2008q3	Netherlands	2002q1, 2008q3
Canada	1983q1	Norway	1988q2, 2008q3
Finland	1991q1	Spain	1978q1, 2008q3
France	1993q3, 2008q3	Sweden	1991q3, 2008q3
Germany	1977q1, 2008q3	Switzerland	1991q1, 2008q3
Italy	1994q1, 2008q3	UK	1973q4, 1990q3, 2007q3
Japan	1992q1	USA	1988q1, 2007q4

Notes: The table reports the periods at which the different countries in our sample experienced a financial crisis. The reported dates concern the start of the crisis and have been determined by relying on the crisis classifications suggested by Laeven and Valencia (2008, 2010, 2012), Reinhart and Rogoff (2008, 2009a,b) and Babecky et al. (2012).

3.2 Explanatory variables

The indicators we consider seek to capture vulnerabilities stemming from both the asset side and the liability side of banks' balance sheets. Risks on the asset side of banks' balance sheets are related to developments in aggregate credit to households and non-financial enterprises, as well as the development in residential house prices. Risks on the

[7]The number of countries in our study was limited by the availability of consistent data.

[8]For some EU countries, we include crisis dates from the European System of Central Banks (ESCB) Heads of Research Group, initially collected by Babecky et al. (2012), see also Behn et al. (2013).

liability side are related to how banks finance their assets. In the following, we present each of the explanatory variables that we include in our baseline model.

Credit

The consensus view in the early warning literature is that strong growth in credit is one of the most important drivers of financial crises (see e.g. Reinhart and Rogoff (2008), Schularick and Taylor (2012) and Mendoza and Terrones (2008)).[9]

We include both *four-quarter growth in private credit* and the *credit-to-GDP gap* as explanatory variables in our empirical exercise. The credit-to-GDP gap can be thought of as a measure of excessiveness, and it is constructed using a recursively estimated one-sided Hodrick-Prescott (HP) filter. Using a one-sided filter means that we calculate the trend that the authorities would have estimated in real time.[10] Subtracting the trend component from the actual series, we have a measure of the credit-to-GDP gap.[11]

Quarterly series on private credit were obtained from the Bank of International Settlements (2014).[12] The private sector includes non-financial enterprises (both privately and publicly owned), households and non-profit institutions serving households. We decompose the credit series into credit to non-financial enterprises and credit to households and non-profit institutions serving households. Credit covers both loans and debt securities and measures the amount of outstanding debt at the end of the quarter. The nominal GDP data, used to construct the credit-to-GDP gaps, were collected from the OECD.[13]

House prices

Developments in house prices (and other durable assets) are closely linked to the evolution of credit, since the amount of credit made available by lenders depends on the net worth of the prospective borrower.[14] Due to imperfections and informational asymmetries in the credit markets, most housing loans are collateralized by the value of the property itself, which may give rise to a self-reinforcing spiral, where higher house prices lead to more lending, which again drives house prices up etc. This financial accelerator effect may lead to both persistence and amplification of real economic shocks (see e.g. Bernanke and

[9]The idea that credit booms are important for our understanding of financial crisis goes back to the seminal work of Minsky (1977) and Kindleberger (1978), who – through a comprehensive study of financial crises – documented regular trends in the relationship between credit and financial imbalances.

[10]Historical trend estimates are therefore not revised when new data are added to the sample. We do, however, not take into account revisions in data, and use only the latest available data release/vintage.

[11]As suggested by the Basel Committee on Banking Supervision (2010b), we use a smoothing parameter for the HP filter, λ, of 400 000. To reduce end-point uncertainty (which is a well-known weakness of HP filters), the series were extended with a simple moving average forecast before applying the HP filter (see Gerdrup et al. (2013)).

[12]See also Dembiermont et al. (2013).

[13]The GDP series for *mainland* Norway, i.e., total production in Norway excluding extraction of oil and gas as well as other production related to this, was obtained from Statistics Norway.

[14]Development in equity prices closely mimic economic developments and are based on an assessment of future economic developments (profits, interest rates etc.). While equity prices are important for many decisions, we find that equity prices are too volatile and noisy to work as an early warning indicator of financial crises. For this reason, we purposefully omit equity prices from our analysis.

Gertler (1989), Bernanke et al. (1999) and Kiyotaki and Moore (1997)).[15] There is also a range of recent papers that confirm the empirical relevance of a financial accelerator effect in a housing context, see e.g. Fitzpatrick and McQuinn (2007); Berlinghieri (2010); Gimeno and Martinez-Carrascal (2010); Anundsen and Jansen (2013) for evidence from Ireland, the US, Spain and Norway, respectively.

We include house prices relative to households' disposable income as a deviation from the trend in this ratio (*the house price-to-income gap*) as an indicator of excessiveness in house prices.[16] Data for house prices and disposable income were gathered from the International House Price Database at the Federal Reserve Bank of Dallas (see Martínez-García and Mack (2013) for documentation).

Banking sector variables

Recent studies point out that high levels of non-core (wholesale) funding in banks are a major source of vulnerability in the financial system (see e.g. Shin (2009), Hanson et al. (2011) and Stein (2012)). Hahm et al. (2013) find empirical evidence suggesting that measures of non-core liabilities contain valuable information about financial vulnerabilities in both advanced and emerging market economies. Shin and Shin (2011) present similar evidence, suggesting that non-core liabilities may serve as a measure of the stage in the financial cycle and the vulnerability to systemic spillovers (contagion).

To operationalize this, we consider the ratio of non-core funding (defined as total assets less customer deposits and bank equity) to total assets. Since this ratio is non-stationary, we calculate the *non-core funding gap* by subtracting the medium-term trend from the ratio.[17]

We also include the *equity share*, defined as the end-of-year amount of capital and reserves in the banking sector as a share of total assets, which has been shown to be an important predictor of financial crises, see e.g. Barrell et al. (2010) and Behn et al. (2013).

Aggregate data on banks' balance sheets are obtained from the OECD Banking Statistics (now discontinued), which provides annual data on the different components in banks' assets and liabilities for most of the countries included in our sample.[18] The sample runs from 1979 to 2009 for most of the countries.

Economic activity

In the econometric analysis, we include *the output gap* as an indicator of economic activity.[19] Measures of developments in real activity are included to control for the state of

[15] Collateral constraints are also viewed as a source of "overborrowing" (see e.g. Lorenzoni (2008) and Bianchi (2011)).

[16] This measure is constructed in the same way as the credit-to-GDP gap with a λ of 400 000.

[17] Again, the trend is extracted using an HP filter with a λ of 400 000.

[18] The OECD provides data for all the countries in our sample, with the UK and Australia being the only exceptions. All banking sector variables have been converted into quarterly series using linear interpolation methods.

[19] The output gap is calculated as the deviation of the log of real GDP from a one-sided HP trend using a smoothing parameter of $\lambda = 3000$.

the business cycle.[20]

3.3 Temporal properties of the data

It is by now well known that standard inference theory, in general, ceases to be valid if there are stochastic non-stationarities in the data, see e.g. the seminal paper by Granger and Newbold (1974). A similar problem can arise in binary choice models, see Park and Phillips (2000). Thus, for the reliability of the inference, it is important to establish the temporal properties of the data series considered in the empirical analysis. To explore this, we consider both country-specific unit-root tests using an ordinary Augmented Dickey-Fuller test (Dickey and Fuller, 1979) for each variable in each country, as well as the Im-Pesaran-Shin test (see Im et al. (2003)) and a Fisher-type test (see Choi (2001) for a discussion). The latter two are suitable for testing for unit roots in unbalanced panels. Results from the unit root tests are presented in Table B.1 in Appendix B. While the results are not unambiguous for all the series, we follow the literature and continue our analysis under the modeling assumption that all series are stationary.

3.4 Behavior around crisis episodes: Any signs of excessiveness?

Before turning to the econometric analysis of the determinants of macro-financial vulnerabilities, we analyze how key economic and financial variables behave around crisis episodes. We follow Gourinchas and Obstfeld (2012) and estimate a linear regression model to determine how an economic variable's conditional expectation depends on the temporal distance from a crisis.[21]

Let $x_{j,i,t} \in \boldsymbol{x}_{i,t}$ represent the variable of interest (e.g. the growth in credit, house prices etc.), where i indicates country and t refers to the time period. Now, consider the following specification

$$x_{j,i,t} = \alpha_{j,i} + \beta_{j,s}\delta_{j,i,s} + \varepsilon_{j,i,t} \tag{6}$$

where $\delta_{j,i,s}$ is a dummy variable taking the value one when variable j in country i is s quarters away from a banking crisis, and a value of zero otherwise. In our analysis, we let s run from -16 to 16, i.e. we evaluate the behavior of some key variables in the 4 years preceding and the 4 years succeeding a crisis. The parameter $\alpha_{j,i}$ is a country fixed effect, while $\varepsilon_{j,i,t}$ is an error term, with $\varepsilon_{j,i,t} \sim IIN(0, \sigma^2_{x_j})$. The coefficient $\beta_{j,s}$ is our parameter of interest, and it measures the conditional effect of being s quarters away from a financial crisis on the mean of the variable $x_{j,i,t}$ relative to "normal times".

[20] Real interest rates may also be important in shaping financial cycles, e.g. through the risk-taking channel. However, we do not expect that real interest rates will increase the predictive power of the models significantly when we already include measures of real economic activity and financial variables. Strong co-movement between, e.g., real interest rates and economic activity may make it difficult to decouple the effects in our empirical exercise, and real interest rates are for that reason omitted from the econometric models.

[21] An alternative approach is to investigate the average cross-country development of a given variable close to a financial crisis (see e.g. Kaminsky and Reinhart (1999) and Drehmann and Juselius (2014)). A drawback with this approach is that it is not possible to evaluate whether the average behavior displays signs of excessiveness, i.e. whether the variables behave significantly differently relative to "normal" times.

Normal times are defined as all country-quarter observations that do not fall within the event window.

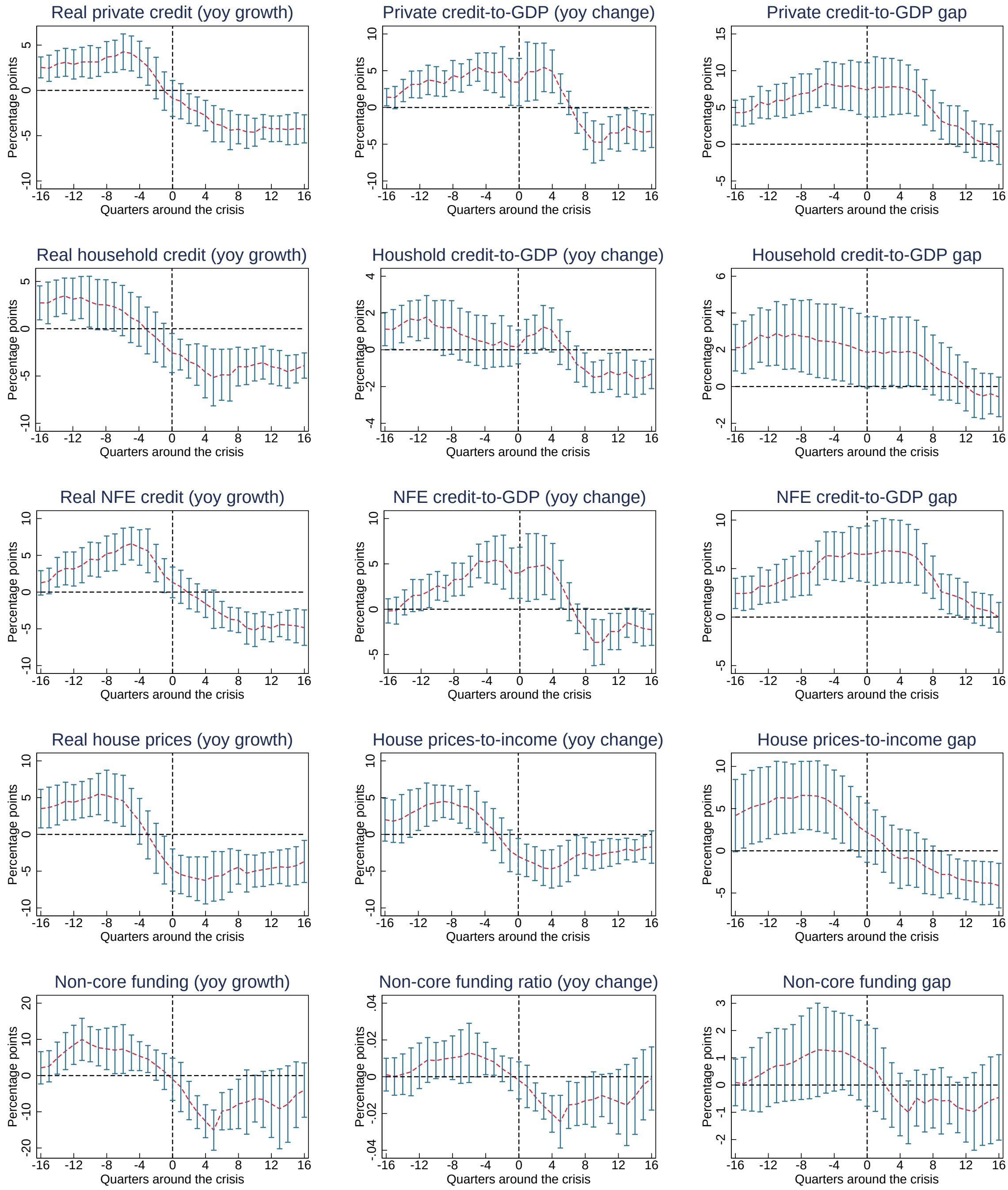
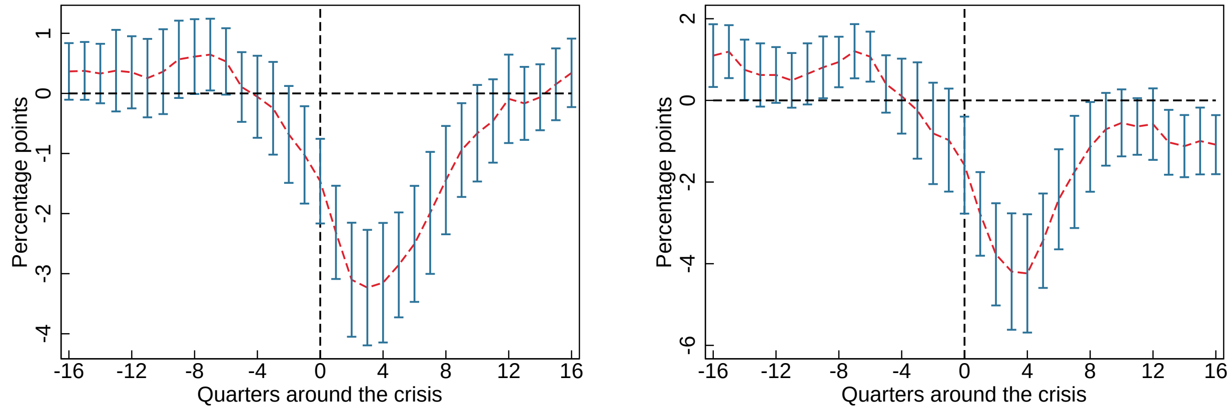


Figure 1: *The behavior of key indicators around crises episodes. The dashed red lines are the conditional effects of being $s \in [-16; 16]$ quarters away from a crisis (the parameter $\beta_{j,s}$ in equation (6)), while the blue bars show the corresponding 95% confidence intervals. A value different from zero means that the variable takes values that deviate from those in "normal times", defined as all country-quarters outside the event window.*



(a) Output gap

(b) Year-on-year growth in output

Figure 2: *Behavior of economic activity around crises episodes. The dashed red lines are the conditional effects of being $s \in [-16; 16]$ quarters away from a crisis (the parameter $\beta_{j,s}$ in equation (6)), while the blue bars show the corresponding 95% confidence intervals. A value different from zero means that the variable takes values that deviate from those in "normal times", defined as all country-quarters outside the event window.*

Figure 1 presents the behavior of credit, house prices and non-core funding in the banking sector. In the four-year period preceding a crisis, variables related to credit and house prices (the first four rows in the figure) tend to be significantly higher than in normal times, which is consistent with the view that banking crises often are preceded by unsustainable developments in credit and house prices (see e.g. Reinhart and Rogoff (2009b) and Schularick and Taylor (2012)). At its peak (4 to 5 quarters preceding the crisis), real credit growth is about 5 percentage points higher than in normal times. The excessivness in the change in credit relative to GDP and the credit-to-GDP gap are of a similar magnitude.[22]

The second and third row show the behavior of credit to households and non-financial enterprises (NFEs), respectively. Credit to households peaks already 3-4 years prior to a crisis. Credit to non-financial enterprises reaches its peak somewhat later, around 1-2 years before the onset of the crisis, but is significantly higher than in normal times already 3-4 years before the crisis.

It is clear that house price inflation is significantly higher than normal in the run-up to a crisis, and the evolution of house prices closely follows developments in household credit, peaking around 2-3 years prior to a crisis.[23] It is also evident that financial crises are associated with a significant decline in both credit and house price growth. Growth in

[22] Growth in credit-to-GDP peaks at about 2.5-3%, corresponding to an average growth rate of about 5%. The credit-to-GDP gap is highly persistent, increasing all the way up to the crisis, peaking at nearly 10 percentage points on average.

[23] Both growth in house prices, house prices relative to disposable income and the house prices relative to disposable income gap are around 5 percentage points higher than normal at their peak. This corresponds to an average growth rate of 10% in real house prices, 7% in house prices to income and a house price-to-income gap of 8%.

real credit is significantly below the growth rate in normal times throughout the post-crisis period (5 percentage points below the normal times baseline).

Growth in non-core funding (the fifth row in Figure 1) is significantly higher before a crisis than during normal times (around 10 percentage points higher at its peak). While the change in non-core funding relative to total assets and the non-core funding gap both display a similar pattern, they are not (always) significant.

Figure 2 shows the behavior of two measures of real economic activity. Neither year-on-year growth in real GDP nor the output gap display any clear signs of excessiveness in the period preceding a financial crisis. Financial crises are, however, associated with a significant decline in real economic activity, as would be expected. The decline in the output gap from peak to trough is 3.5%, and the level of real activity remains depressed for a prolonged period of time, reaching "normal" levels almost 3 years after the crisis.

4 The determinants of financial market imbalances

4.1 Econometric Results

Credit, house prices and non-core funding

We start by considering a model including four-quarter growth in total credit to the private sector, the credit-to-GDP gap, and the house price-to-income gap as explanatory variables. The results from this specification are reported in Column (1) in Table 2. It is evident that all variables exercise a positive and highly significant effect on the likelihood of a crisis. The finding of a strong role of credit is in line with earlier literature on the determinants of financial crises (see e.g. Borio and Lowe (2004), Alessi and Detken (2011), Drehmann et al. (2011), Schularick and Taylor (2012), Behn et al. (2013) and LoDuca and Peltonen (2013)), and it also supports the Basel Committee's focus on monitoring movements in the credit-to-GDP gap when setting the countercyclical capital buffer (see Basel Committee on Banking Supervision (2010b)).[24]

In the next three columns, we gradually extend the information set by adding the non-core funding gap, banks' capitalization (as measured by the equity ratio) and the output gap.

The coefficients on the credit-to-GDP gap and the house price-to-income gap remain relatively stable across the different specifications, and the additional variables all have the expected signs and are statistically significant at conventional significance levels. Note that the sample size drops when we include the banking sector variables, since these are available for only 14 of the 16 countries in our sample. The fact that the coefficient for banking sector capitalization (confer Column (3)) is negative and highly significant is in line with Barrell et al. (2010) and Behn et al. (2013). This is a reassuring finding for authorities deciding on countercyclical capital buffer rates or other capital requirements. The estimated coefficient on the non-core funding gap is positive, implying that it provides information on the state of the financial cycle in addition to that contained in the other measures. Furthermore, it may provide evidence that non-core funding is more vulnerable and risky than other types of funding.

[24] For a more critical view on the relevance of the credit-to-GDP gap, see Gadea Rivas and Perez-Quiros (2012).

Table 2: Results from baseline models

	(1)	(2)	(2')	(3)
Private credit growth (yoy)	10.61***	10.58***	4.787	3.370
	(2.621)	(2.579)	(3.569)	(3.890)
Private credit-to-GDP gap	18.14***	18.70***	27.88***	29.84***
	(2.082)	(2.104)	(3.067)	(2.972)
House price-to-income gap	7.260***	7.659***	5.564***	4.950**
	(2.651)	(2.585)	(2.127)	(2.449)
Non-core funding gap				23.84***
				(5.878)
Equity ratio				-30.32***
				(11.23)
Output gap		26.32***	57.33***	53.89***
		(5.871)	(11.92)	(11.90)
Pseudo R-Squared	0.258	0.276	0.356	0.374
AUROC	0.829	0.838	0.815	0.883
$U_r(\theta = 0.9/0.95)$	0.49/0.26	0.51/0.32	0.44/0.32	0.52/0.41
$TPR(\theta = 0.9/0.95)$	0.80/0.82	0.71/0.95	0.69/0.93	0.89/0.92
$FPR(\theta = 0.9/0.95)$	0.29/0.34	0.19/0.58	0.23/0.52	0.36/0.40
Country fixed effects	Yes	Yes	Yes	Yes
Countries	16	16	14	14
Crisis	26	26	20	20
Observations	1880	1880	1049	1049

Notes: The table shows results from our baseline specifications when estimating the logit model in (2) on a panel of 16 OECD countries over the period 1975q1–2013q2. Column (1) reports results from a model including the four-quarter growth in total private credit, the credit-to-GDP gap, and the house price-to-income gap. In Column (2), the output gap is added, while Column (3) reports results from a model where also the non-core funding gap and the equity ratio of banks enter. Column (2') reproduces the results from Column (2) using only data for countries where banking data are available. Clustered standard errors are reported in parenthesis below the point estimates, and the asterisks' denote significance level; * = 10%, ** = 5% and *** = 1%.

The fit of the model, measured both in terms of the pseudo R^2 and the AUROC, increases as additional variables are included in the information set. For all models, the relative usefulness is above zero, which suggests that there are indeed benefits of having a model relative to either always issuing a signal or never issuing a signal. The true positive rates are generally high, meaning that the models are able to correctly predict a large fraction of crises.

Credit to households vs. non-financial enterprises

We will now explore whether credit to households and credit to non-financial enterprises contributes differently to the likelihood of a crisis – a question that has received little attention in the literature. One notable exception is Büyükkarabacak and Valev (2010), who argue that authorities should keep a close eye on expansions in household credit for two main reasons: first, because the share of household credit has increased substantially over time in most countries. Second, because growth in household credit raises debt levels without significantly affecting long-term growth prospects. For this reason, we have partitioned the private credit variable into its two sub-components.[25]

Similar to the specific-to-general approach we followed in the previous section, we start by considering a model where only these two gaps, along with private sector credit growth and the house price-to-income gap, are included in the model. Then, we sequentially augment the specification by additional variables. Results are displayed in Table 3.

Table 3: Results from models distinguishing between credit to households and to non-financial enterprises

	(1)	(2)	(2')	(3)
Private credit growth (yoy)	12.63***	11.44***	7.979**	7.172*
	(2.541)	(2.133)	(3.425)	(3.728)
Household credit-to-GDP gap	23.86***	21.70***	42.38***	45.12***
	(3.644)	(3.604)	(5.494)	(5.770)
NFE credit-to-GDP gap	26.08***	29.45***	24.62***	24.85***
	(3.891)	(3.839)	(4.024)	(3.951)
House price-to-income gap	9.064**	10.75***	3.664*	2.846
	(3.520)	(3.574)	(2.191)	(2.392)
Non-core funding gap				16.06***
				(6.009)
Equity ratio				-22.72**
				(10.34)
Output gap		39.67***	55.33***	51.36***
		(7.083)	(13.96)	(14.43)
Pseudo R-Squared	0.332	0.368	0.392	0.400
AUROC	0.873	0.888	0.859	0.892
$U_r(\theta = 0.9/0.95)$	0.51/0.27	0.52/0.33	0.47/0.40	0.56/0.35
$TPR(\theta = 0.9/0.95)$	0.70/0.89	0.84/0.84	0.89/0.96	0.76/0.92
$FPR(\theta = 0.9/0.95)$	0.18/0.48	0.32/0.32	0.41/0.51	0.18/0.46
Country fixed effects	Yes	Yes	Yes	Yes
Countries	16	16	14	14
Crisis	24	24	19	19
Observations	1691	1691	948	948

Notes: The table shows the results after decomposing total private credit into credit to households and non-financial enterprises. All models are estimated using a logit model of the type represented by (2), and the data set cover a panel of 16 OECD countries over the period 1975q1–2013q2. Column (1) reports results from a model including the four-quarter growth in total private credit, the household credit-to-GDP gap, the credit-to-GDP-gap for non-financial enterprises and the house price-to-income gap. In Column (2), the output gap is added, while Column (3) reports results from a model where also the non-core funding gap and the equity ratio of banks enter. Column (2') reproduces the results from Column (2) using only data for countries where banking data are available. Clustered standard errors are reported in parenthesis below the point estimates, and the asterisks' denote significance level; * = 10%, ** = 5% and *** = 1%.

[25]Credit to households and to non-financial enterprises are divided by GDP before de-trending and constructing gap measures.

Inspecting Table 3, it is evident that both household credit and credit to non-financial enterprises have a positive and highly significant effect on the likelihood of a crisis. This finding is in contrast to Büyükkarabacak and Valev (2010), who only find a robust effect of household credit on crisis probabilities considering a sample of 37 developed and non-developed countries over the period 1990–2006. We shall later see that differences in time periods considered explains the discrepancies in results.

Although our results suggest an important effect of both types of credit, they also suggest that – if anything – household credit is marginally more important than credit to non-financial enterprises. This may indicate that excessiveness in household credit, on the margin, poses a greater threat to the soundness of the financial system than excessiveness in lending to the non-financial sector.[26]

Though the samples are not identical for the results reported here and in the previous section, it is clear that both the pseudo R^2 and the AUROC are higher across all model specifications when we decompose the total credit measure into its two main components.[27]

Global developments

"*A tree's risk of catching fire is usually small, except when the forest is ablaze*" (Jorda, 2011). With this quote in mind, this section explores whether global developments in house prices and credit have an impact on domestic financial vulnerabilities.

In the literature on early warning systems, this spill-over effect has been accounted for by including global variables. These are typically constructed on the basis of GDP weights, or as a simple arithmetic average of these measures in some "important economies" (see e.g. Alessi and Detken (2011), Behn et al. (2013) and LoDuca and Peltonen (2013)). A drawback with this approach is that not all countries are equally interconnected, and that these interlinkages may change over time. For this reason, we have constructed a set of country-specific "global" variables. In particular, we have followed the GVAR literature (see e.g. Pesaran et al. (2004), Dees et al. (2007a) and Dees et al. (2007b)) and used time-varying trade weights. This entails that the exposure of a given country to other countries at a particular point in time depends on trade exposures (details are described in Appendix C). Results when we include global measures of both credit and house prices are shown in Table 4.[28]

It is clear that we do not find a significant effect of the global credit-to-GDP gap. The global house price-to-income gap, however, is highly significant across specifications, suggesting the importance of global housing market imbalances for estimated crisis probabilities. This result is in line with the perception that real estate bubbles in international housing markets were an important trigger of the global financial crisis (see e.g. Allen and Carletti (2013)), and suggest that global house price imbalances should be important in the overall assessment of financial stability. The bursting of an international housing

[26]Note that the reported coefficients in Table 3 are not marginal effects (confer Section 2.1). The marginal effects of household credit is, however, significantly higher than the corresponding effect of credit to non-financial enterprises in the full model also when we look at the marginal effects.

[27]If we reestimate the models of the previous sections using the same sample as in this section, this finding still holds true.

[28]Because of the high correlation between domestic credit and house prices and their global counterparts, we have orthogonalized the global variables.

bubble and the macroeconomic effects that follow may easily transmit both through trade and an interconnected financial system.

Table 4: Results from models that account for global developments in credit and house prices

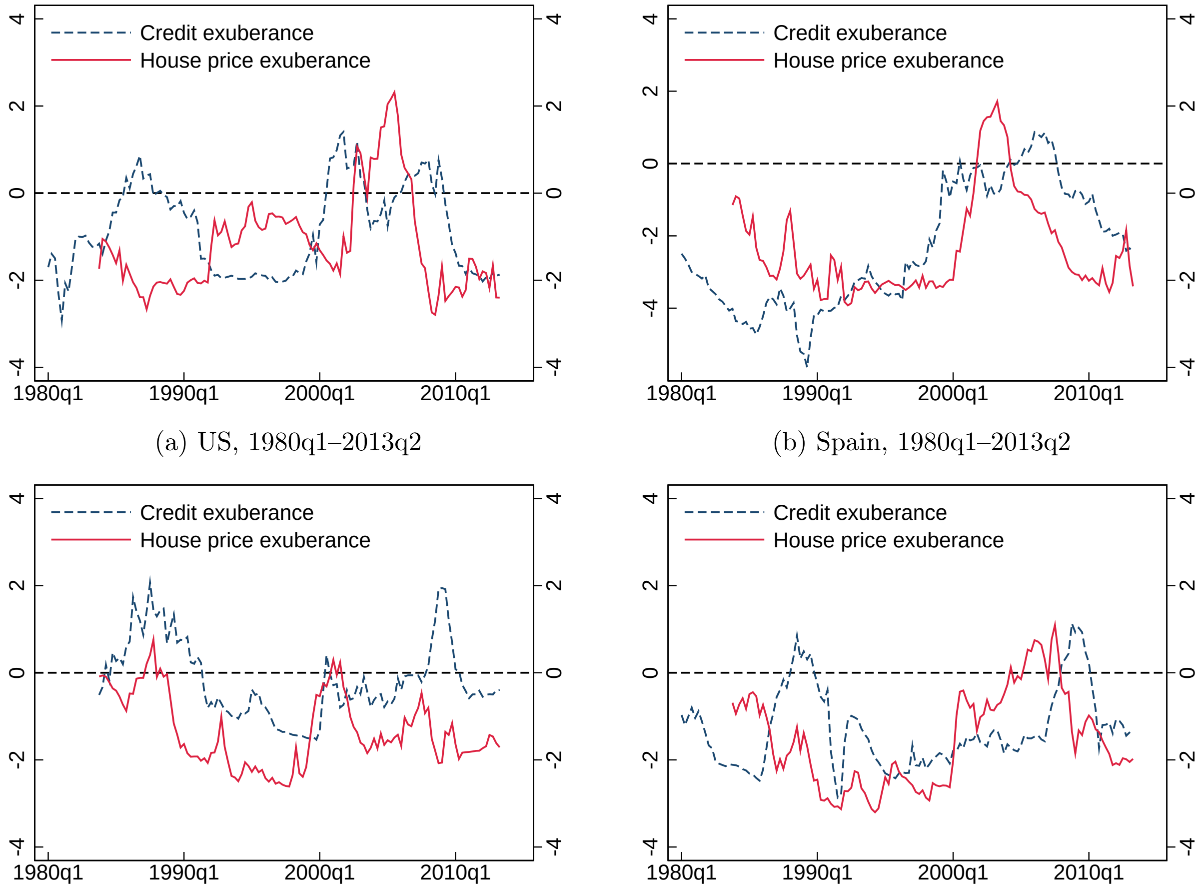
	(1)	(2)	(2')	(3)
Private credit growth (yoy)	15.48***	13.99***	14.63***	18.54***
	(3.343)	(2.535)	(3.273)	(3.159)
Household credit-to-GDP gap	22.13***	18.84***	29.87***	26.05***
	(3.728)	(3.679)	(4.863)	(5.433)
NFE credit-to-GDP gap	25.41***	30.10***	23.48***	24.18***
	(4.135)	(4.078)	(4.357)	(3.739)
House price-to income gap	7.249**	9.036***	5.352***	5.413***
	(3.218)	(3.234)	(1.798)	(1.979)
Non-core funding gap				33.92***
				(7.380)
Equity ratio				-57.60***
				(11.36)
Global credit-to-GDP gap	5.422	3.860	-4.471	-15.77
	(5.452)	(5.206)	(9.954)	(9.796)
Global house prices-to-income gap	16.50***	19.66***	18.08***	32.42***
	(4.370)	(4.657)	(6.397)	(7.383)
Output gap		44.08***	52.82***	37.15**
		(7.948)	(14.77)	(15.80)
Pseudo R-Squared	0.360	0.401	0.412	0.443
AUROC	0.885	0.900	0.871	0.911
$U_r(\theta = 0.9/0.95)$	0.51/0.37	0.53/0.42	0.51/0.39	0.57/0.43
$TPR(\theta = 0.9/0.95)$	0.86/0.92	0.81/0.95	0.75/0.96	0.88/0.89
$FPR(\theta = 0.9/0.95)$	0.34/0.45	0.28/0.47	0.23/0.51	0.30/0.32
Country fixed effects	Yes	Yes	Yes	Yes
Countries	16	16	14	14
Crisis	24	24	19	19
Observations	1691	1691	948	948

Notes: The table shows the results where we include trade-weighted global variables for house prices and credit. All models are estimated using a logit model of the type represented by (2), and the data set cover a panel of 16 OECD countries over the period 1975q1–2013q2. Column (1) reports results from a model including the four-quarter growth in total private credit, the household credit-to-GDP gap, the credit-to-GDP-gap for non-financial enterprises, the house price-to-income gap, the global credit-to-GDP gap and the global house price-to-income gap. In Column (2), the output gap is added, while Column (3) reports results from a model where also the non-core funding gap and the equity ratio of banks enter. Column (2') reproduces the results from Column (2) using only data for countries where banking data are available. The global variables are constructed using time-varying trade weights, see Appendix C for details. Clustered standard errors are reported in parenthesis below the point estimates, and the asterisks' denote significance level; * = 10%, ** = 5% and *** = 1%.

Bubbles and crises

We will now explore whether periods of extreme imbalances (a state of exuberance) in housing and credit markets affect the probability of a crisis. For this purpose, we have constructed country-specific exuberance measures for house prices and credit using novel developments in the time series literature, see Phillips et al. (2011), Phillips et al. (2012) and Phillips et al. (2013). In short, the exuberance measures are based on econometric tests for a transition to a regime with explosive behavior, which is interpreted as a state of exuberance. Further details on the construction of these measures are described in Appendix D.

Figure 3 plots the implied measures for the US, Spain, Norway and Sweden, where a value greater than zero indicates that there are signs of exuberance.[29]



(a) US, 1980q1–2013q2

(b) Spain, 1980q1–2013q2

(c) Norway, 1980q1–2013q2

(d) Sweden, 1980q1–2013q2

Figure 3: *House price (red) and credit (blue) exuberance indicators for some selected countries. The figures show the test statistic less the critical value based on a 5% significance level for house prices to income and private credit to GDP. A positive difference indicates exuberant behavior. See Appendix D for details.*

[29]The implied measures for the other countries in our data set are plotted in Figure A.1 in Appendix A.

Looking first at the house price exuberance measure for Norway, we see that there are some signs of exuberance in the late 1980s – just before the collapse of the Norwegian housing market and the ensuing banking crisis that lasted until 1993. There are also some signs of exuberant behavior at the beginning of the 2000s, but not thereafter. This is in sharp contrast to the US, where the exuberance indicator for house prices clearly suggests that the US housing market entered a state of exuberance in the early 2000s. This finding parallels Anundsen (2014), who constructs an econometrically based bubble indicator for the US housing market. The exuberance indicators for house prices also suggest that there were signs of bubble-like behavior in Sweden and Spain in the 2000s.

Turning to the credit measures, we see that there were signs of exuberance in Norway both in the mid 1980s and more recently. For the US and Sweden, a similar pattern emerges, while in Spain the only period with signs of credit market exuberance is the period preceding the Great Recession.

While these measures are interesting in their own right, as they may provide an alternative to the HP-filter based measures of excessiveness in house prices and credit[30], the interpretation of the coefficient of these measures in an early warning model is less clear – though it is clear that a higher value increases the evidence in favor of explosive (bubble-like) behavior. Due to the interpretability of the results, we do not include these measures directly. Instead, we define an indicator variable

$$I(Exuberance_{i,t}) = \begin{cases} 1 \text{ if } Exuberance(X_{i,t}) \geq 0 \\ 0 \text{ if } Exuberance(X_{i,t}) < 0 \end{cases} \quad (7)$$

where $Exuberance(X_{i,t})$ denotes the exuberance measure for $X_{i,t} \in \{\text{House prices, Credit}\}$. Thus, $I(Exuberance_{i,t})$ takes the value one when the series $X_{i,t}$ exercises explosive behavior and a value of zero otherwise.[31] When augmenting our econometric models with these exuberance measures, we get the results displayed in Table 5.[32]

The results are intriguing. First of all, it is clear that both exuberance measures have a positive and highly significant impact on the probability of crises, and the coefficients remain quite stable across specifications. Furthermore, looking at the pseudo R^2 and the AUROC, it is clear that adding these variables to the model improves the fit. The other coefficients in the models are relatively invariant to this extension.

[30]The correlation between the credit-to-GDP gap and the credit exuberance measure is 0.54. The correlation between the house price-to-income gap and the house price exuberance measure is 0.16.

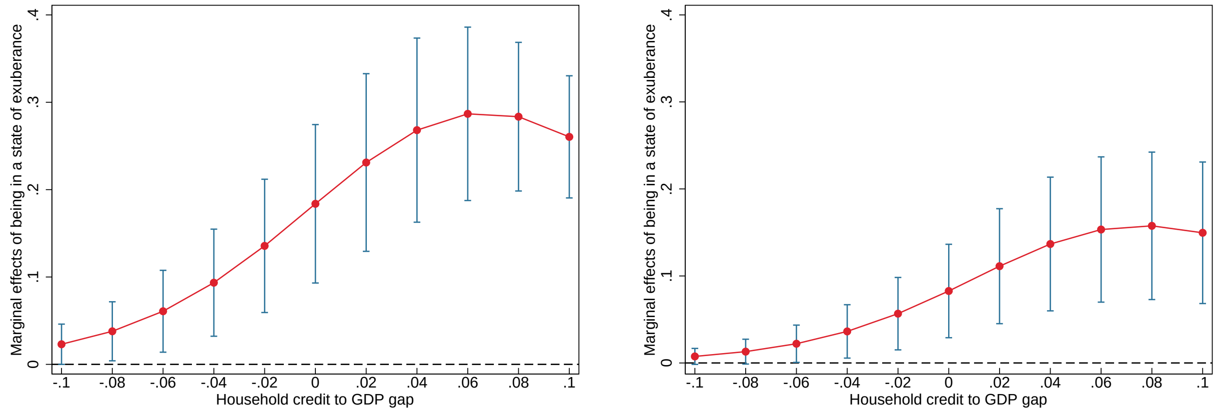
[31]The exuberance measures displayed in Figure A.1 also detect explosive behavior in certain countries where the house price to disposable income ratio has *declined* rapidly (e.g. Japan, Germany and Korea in the late 1990s, early 2000s.) Thus, when constructing the exuberance indicator $I(Exuberance)$, we have also conditioned on an increasing house price to income ratio (and credit to GDP ratio).

[32]Since the global credit-to-GDP gap turned out insignificant in all specifications, we decided to drop that variable from the model. Results are not materially affected by this modeling decision.

Table 5: Results from models including indicators for exuberance in credit and house prices

	(1)	(2)	(2')	(3)
Private credit growth (yoy)	26.19***	20.53***	11.69***	16.08***
	(4.427)	(3.588)	(3.541)	(3.524)
Household credit-to-GDP gap	9.016**	8.960**	22.48***	19.30***
	(4.187)	(3.811)	(4.140)	(4.534)
NFE credit-to-GDP gap	11.52***	16.26***	17.87***	18.73***
	(4.002)	(3.804)	(4.465)	(4.110)
House price-to-income gap	6.738**	7.654**	3.186*	1.471
	(2.920)	(3.038)	(1.884)	(2.029)
Non-core funding gap				33.79***
				(9.931)
Equity ratio				-59.82***
				(13.55)
Global house prices-to-income gap	28.49***	28.80***	20.95***	30.34***
	(6.080)	(5.972)	(6.647)	(9.140)
House price exuberance (yes/no)	0.975***	1.034***	1.367***	1.884***
	(0.330)	(0.300)	(0.395)	(0.403)
Credit exuberance (yes/no)	1.481***	1.620***	1.841***	1.489***
	(0.299)	(0.301)	(0.328)	(0.351)
Output gap		41.65***	64.57***	48.26***
		(10.19)	(14.61)	(14.34)
Pseudo R-Squared	0.407	0.431	0.434	0.461
AUROC	0.904	0.912	0.891	0.920
$U_r(\theta = 0.9/0.95)$	0.56/0.46	0.60/0.45	0.58/0.46	0.62/0.47
$TPR(\theta = 0.9/0.95)$	0.81/0.97	0.84/0.95	0.85/0.96	0.84/0.89
$FPR(\theta = 0.9/0.95)$	0.23/0.47	0.23/0.43	0.26/0.45	0.21/0.29
Country fixed effects	Yes	Yes	Yes	Yes
Countries	15	15	14	14
Crisis	23	23	19	19
Observations	1220	1220	873	873

Notes: The table shows the results where we include measures of housing and credit market exuberance. All models are estimated using a logit model of the type represented by equation (2), and the data set cover a panel of 16 OECD countries over the period 1975q1–2013q2. Column (1) reports results from a model including the four-quarter growth in total private credit, the household credit-to-GDP gap, the credit-to-GDP-gap for non-financial enterprises, the house price-to-income gap, the global credit-to-GDP gap, the global house price-to-income gap, as well as measures for housing and credit market exuberance. In Column (2), the output gap is added, while Column (3) reports results from a model where also the non-core funding gap and the equity ratio of banks enter. Column (2') reproduces the results from Column (2) using only data for countries where banking data are available. The global variables are constructed using time-varying trade weights, see Appendix C for details. For details on the construction of the exuberance measures, see Appendix D. Clustered standard errors are reported in parenthesis below the point estimates, and the asterisks' denote significance level; * = 10%, ** = 5% and *** = 1%.



(a) House price exuberance

(b) Credit exuberance

Figure 4: *Marginal effects on crisis probability (red) of exuberance in house prices and credit for different values of the household credit-to-GDP gap. The blue bars represent a 95% confidence interval.*

In Figure 4, we have plotted the marginal effect on the probability of crisis of being in a state of exuberance for different levels of the household credit-to-GDP gap.[33] The figure shows that the effect is particularly strong when the household credit-to-GDP gap is already high, suggesting that a combination of exuberance and high household leverage increases the vulnerability of the financial system substantially.[34] On average (across the different specifications reported in Table 5), if there is a state of exuberance in the housing market, the probability of a crisis increases by 20-30 percentage points. The corresponding figures for the credit-to-GDP exuberance measure is 8-10 percentage points. Thus, monitoring whether the housing market is in a state of exuberance seems particularly important in the overall assessment of systemic risk.

4.2 Robustness: Alternative transformations of key variables

The unit root tests did not unambiguously support the underlying modeling assumption of stationarity. In particular, the gap measures – intended to capture long cycles in credit and asset prices – are very persistent (see also Drehmann and Juselius (2014)), which may lead to misleading inference. To investigate the robustness of our results to alternative transformations, we re-estimated the final specification reported in each of the previous sub-sections (the specification reported in Column (3) in Table 2–5) using both four-quarter changes in the ratios and four-quarter growth rates in the underlying series as alternatives to the gap measures (both these measures show less persistence than the corresponding gap-based measures). The results are presented in Table B.2 and Table B.3 in Appendix B.

It is evident that the key results are qualitatively unchanged. In particular, the results

[33]These marginal effects are based on specification (3) in Table 5.

[34]Conditioning on the credit-to-GDP gap to non-financial enterprises produces similar results

regarding the importance of the domestic credit-to-GDP, the non-core funding ratio in the banking sector, global house prices and the measures of exuberance in credit and housing markets for crisis probability are maintained. The importance of the equity ratio is less robust, being insignificant in the first two models.

4.3 Major crises: Which factors were important?

To have a closer look at the relative importance of some of the most important explanatory variables, we decompose the change in predicted probability in the run-up to crisis episodes.[35] The approximate contribution from a variable j in country i at date t, $x_{j,i,t}$, to the change in predicted probability from one period to another is given by

$$\frac{\partial \Delta p_{i,t}}{\partial x_{j,i,t}} = \beta_j \frac{\partial \Phi(\beta_j x_{j,i,t-1} + \mathbf{x}'_{-j,i,t}\boldsymbol{\beta})}{\partial x_{j,i,t}} (x_{j,i,t} - x_{j,i,t-1}) \tag{8}$$

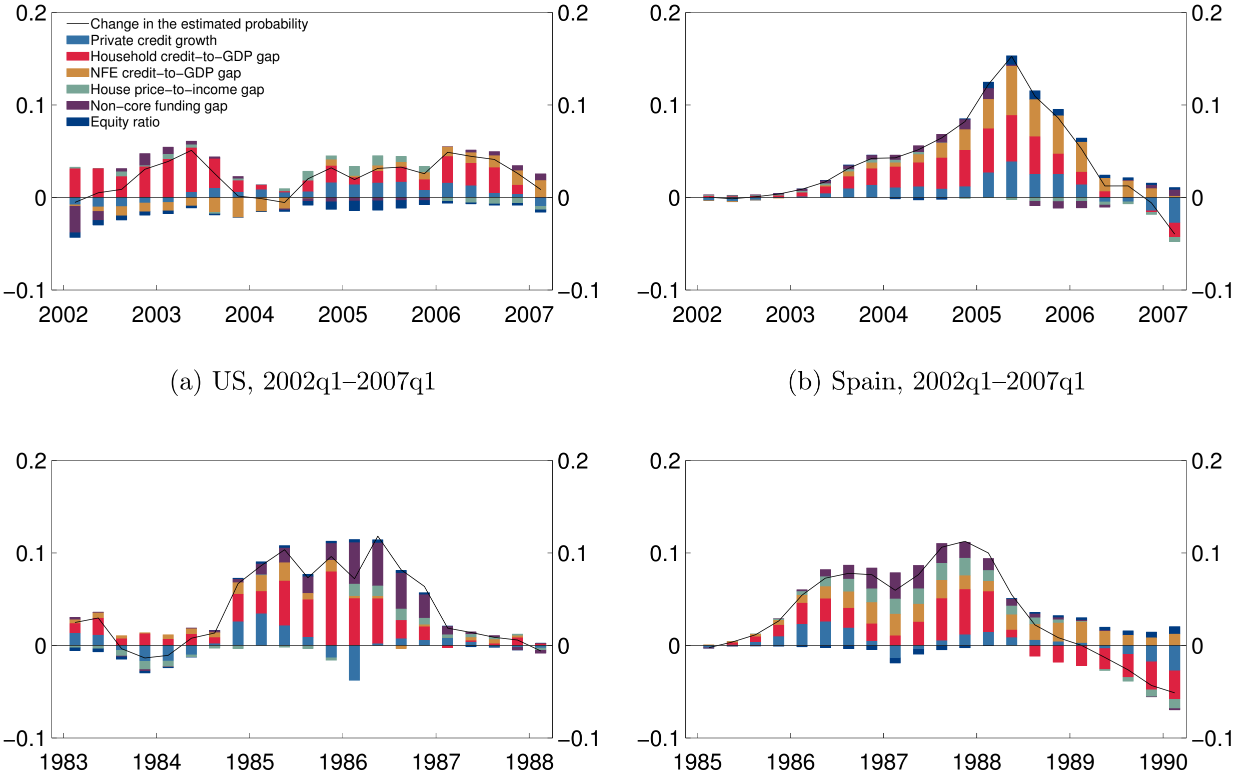
Using (8), we make such a decomposition for the following four crisis episodes: the US financial crisis of 2007-09, the Spanish crisis of 2008, the Norwegian banking crisis in the late 1980s and the Swedish banking crisis in the early 1990s. The decompositions are conducted using specification (3) in Table 3, and results are illustrated in Figure 5.

It is evident that excessiveness in household credit was one of the main contributors to the build-up of vulnerabilities in all of these crisis episodes. Credit to non-financial enterprises was also important in the run-up to the Spanish crisis in 2008 and the Swedish banking crisis in the early 1990s.

An interesting cross-country difference relates to non-core funding in the banking sector, which seems to have been very important for the Scandinavian crises of the late 1980s/early 1990s, while it did not have a notable impact on either the recent crisis in the US or Spain. One possible reason for this may be the dominant role banks play in the Scandinavian market. For example, while a large share of credit is financed through the bond market in the US (see e.g. Adrian et al. (2012)), almost 80 percent of domestic credit in Norway is financed through the banking sector (see Norges Bank (2013)).

Figure A.2 in Appendix A plots the non-core funding ratio for the countries in our sample. It is evident that the share of non-core funding in Norwegian and Swedish banks is at a high level compared to US and Spanish banks, and that the shares display a more pronounced increase ahead of financial crises. However, this does not necessarily mean that countries with high levels of non-core debt relative to assets are more vulnerable to financial market instability *per se*. It may simply imply that the non-core funding ratio in the banking sector is a stronger indicator of the stage of the financial cycle in these countries.

[35]Note that we decompose the *change* in predicted probability, not the level. The reason for this is that decomposing the level (i.e. to determine the importance of e.g. credit in the overall probability of a crisis) is difficult due to the non-linear nature of the model.



(a) US, 2002q1–2007q1

(b) Spain, 2002q1–2007q1

(c) Norway, 1983q3–1988q1

(d) Sweden, 1985q1–1990q1

Figure 5: *Decomposing the quarterly change in predicted crisis probability for some selected crisis episodes.*

5 How useful are the models in an operational setting?

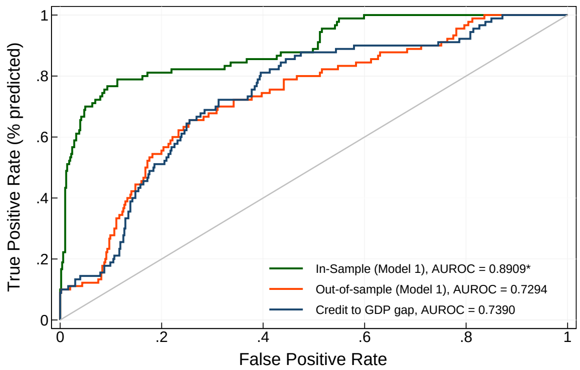
5.1 Out-of-sample performance

A natural way of testing the usefulness of an early warning model in an operative policy setting is to evaluate its out-of-sample performance, i.e. if the model under consideration is able to identify financial market vulnerabilities in "real time".

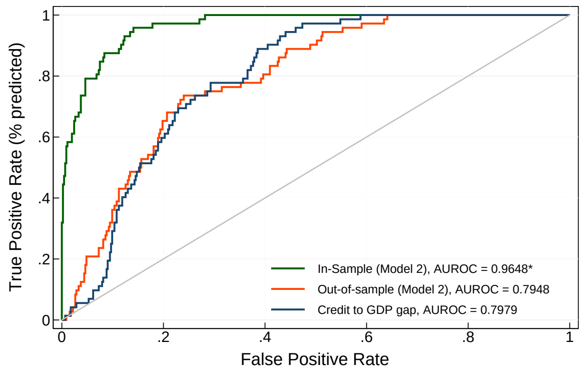
The out-of-sample properties of our models are investigated using two different approaches. The first approach is a quasi real-time forecasting exercise, where only data up to 1999 is used to estimate the parameters of our models and forecasts are constructed for the period 2000–2012. In the second approach, we consider a rolling sample. More precisely, we predict the probability of a crisis for every country when the country under consideration is excluded from the estimation. While the second approach is uninformative regarding the real-time performance of the models, it will nevertheless shed light on the importance of a country's own history of financial crises in predicting the probability of a crisis in that country. This is because country-specific dummies reflect the number of crises each country has experienced, see also the discussion in Drehmann and Juselius

(2014).

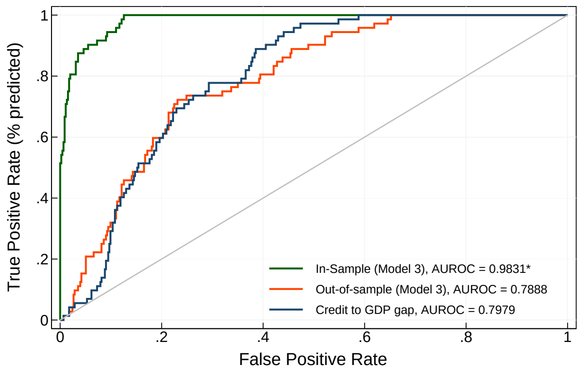
We evaluate the out-of-sample properties for four of the models presented in Section 4. The first model (hereafter *Model 1*) includes growth in private credit, the credit-to-GDP gap, the house price-to-income gap and the output gap. *Model 2* uses decomposed credit instead of total credit. *Model 3* builds on *Model 2*, and includes in addition measures of global credit and housing market imbalances, while *Model 4* also includes the indicators for exuberance in house prices and credit. All models are evaluated relative to the credit-to-GDP gap as a stand-alone indicator, due to its importance and attention in the policy sphere (e.g. Basel Committee on Banking Supervision (2010a) and European Systemic Risk Board (2014)). The out-of-sample performance of the different models is evaluated using ROC and AUROC (confer Section 2).



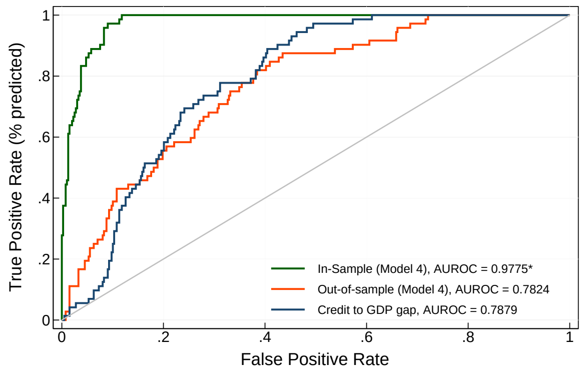
(a) Model 1



(b) Model 2



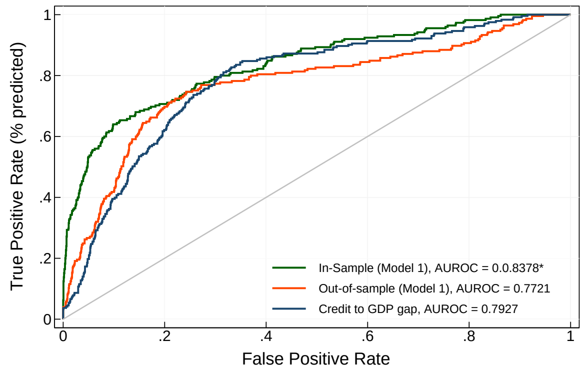
(c) Model 3



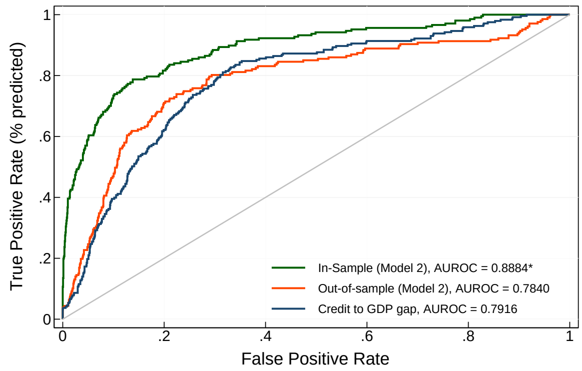
(d) Model 4

Figure 6: *In and out-of-sample AUROC/ROC of some selected models relative to credit-to-GDP gap based on forecasts. Model 1 includes growth in private credit, the credit-to-GDP gap, the house price-to-income gap and the output gap. Model 2 decomposes total credit into household credit and credit to non-financial enterprises. Model 3 is Model 2 augmented with the global variables. Model 4 augments Model 3 with the exuberance measures The models used for the out-of-sample forecast are estimated on data up to 2000. The evaluation period is 2000 - 2012. An asterisk indicates that the AUROC is significantly different from that of the credit to GDP gap using a 5% significance level.*

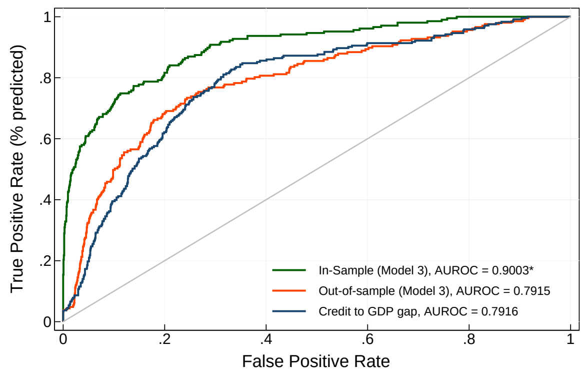
Figure 6 presents the results from the forecasting exercise, where we have plotted the ROC curves for the in-sample and out-of-sample predictions from the four alternative models over the period 2000-2012. The corresponding ROC curve for the credit-to-GDP gap is included in all the figures.[36] It is evident that the in-sample predictions of all the models outperform the credit-to-GDP gap benchmark.[37] The out-of-sample performance of our models is also surprisingly good given the large reduction in our information set. With AUROCs close to 0.8, the out-of-sample predictions do not perform worse than the credit-to-GDP gap.



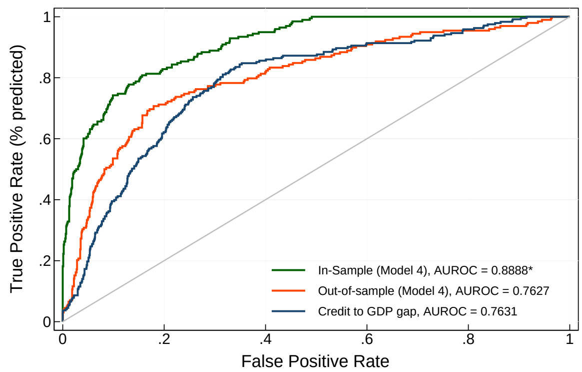
(a) Model 1



(b) Model 2



(c) Model 3



(d) Model 4

Figure 7: *In and out-of-sample AUROC/ROC of some selected models relative to credit-to-GDP gap based on rolling samples. Model 1 includes growth in private credit, the credit-to-GDP gap, the house price-to-income gap and the output gap. Model 2 decomposes total credit into household credit and credit to non-financial enterprises. Model 3 is Model 2 augmented with the global variables. Model 4 augments Model 3 with the exuberance measures. An asterisk indicates that the AUROC is significantly different from that of the credit to GDP gap using a 5% significance level.*

[36]The credit-to-GDP gap and the predictions from the models in Figure 6 are evaluated based on exactly the same sample. As the sample size varies between the different models, so will the AUROC for the credit-to-GDP gap.

[37]For instance, notice the in-sample performance of the model including measures for global imbalances in predicting the recent financial crisis.

The results from the rolling sample exercise are presented in Figure 7. There is indeed considerable information in a country's own history of financial crises, as indicated by the marked drop in the AUROC from the in-sample to the out-of-sample predictions. This is consistent with the findings in Drehmann and Juselius (2014). That said, the models are still highly informative (as indicated AUROCs close to 0.8), but not significantly different from that of the benchmark credit-to-GDP gap.

5.2 Temporal and cross-sectional stability

An important question for policymakers who consider using an early warning model in an operational setting is how stable the effects of e.g. credit and house prices are over time. While the previous section illustrated the usefulness of four of the models considered in this paper in an out-of-sample setting, it is also relevant to analyze in more detail whether the effects of different variables have changed over time. Another important question is cross-sectional sensitivity. The results may be sensitive to the selection of countries, as both the size and the structure of the financial system varies from country to country. The following section analyzes the stability of the estimated parameters, both along the temporal and the cross-sectional dimension.

Temporal stability

In order to shed light on the *temporal stability* of our models, we estimate them on two different subsamples: a *pre-2000* sample, which uses information only up to 2000 and a *post-1994* sample, which includes information from 1994 onwards. As banking sector variables are missing for Australia and the UK, we consider the models excluding these variables to maximize the sample size. That is, we consider the models reported in Column (2) in Table 2–5 when conducting this exercise.[38] The results are presented in Table 6.

Model 1–4 are the same as in the previous section. Independent of the sample period, the marginal effect of the domestic household credit-to-GDP gap is positive and significant in all specifications. The effect of the credit-to-GDP gap for non-financial enterprises is less robust on the post-1994 sample. This suggest that the difference in results in this paper and in Büyükkarabacak and Valev (2010), who consider a post-1990 sample, may at least partly be ascribed to the different sample periods considered. The marginal effect of the house price-to-income gap is also less stable across samples and specifications. Interestingly, the indicator for exuberance in house prices is positive and significant in both cases, suggesting that extreme imbalances in the housing market are an important predictor of financial crises.

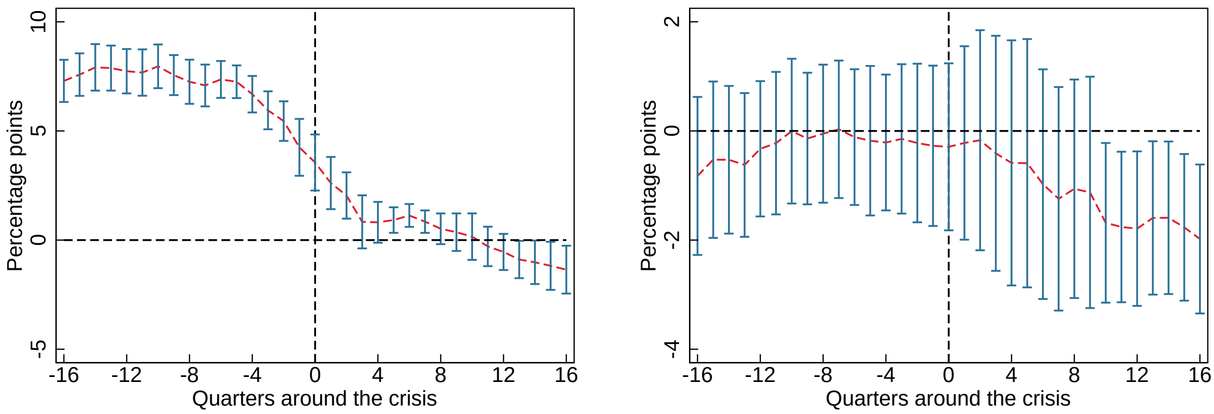
[38] The results are, however, qualitatively similar when we include these variables and omit Australia and the UK. The stability of the non-core funding gap and the equity ratio in the banking sector over time is, however, mixed. While the non-core funding gap has the correct sign and is significant in most of the specifications, the same is not true for the equity ratio, which is positive in the post-1994 sample.

Table 6: Marginal effects for different samples.

	Model 1		Model 2		Model 3		Model 4	
	Pre-2000	Post-1994	Pre-2000	Post-1994	Pre-2000	Post-1994	Pre-2000	Post-1994
Credit growth (yoy)	0.403***	1.456***	0.179	1.701*** *	0.221	3.273***	0.424	3.402***
Private credit-to-GDP gap	3.091***	2.252***						
Household credit-to-GDP gap			2.319***	4.589***	2.340***	1.992***	3.540***	1.984***
NFE credit-to-GDP gap			4.342***	0.914**	4.389***	0.413	3.920***	0.536*
House price-to-income gap	0.0701	0.663*	-0.0538	0.129	-0.0637	0.238	-0.334	-0.0324
Global credit-to-GDP gap					-0.221	1.263		
Global house prices-to-inc. gap					-0.225	6.349***	-1.027	6.821***
Credit exuberance							0.215***	-0.0160
House price exuberance							0.219*	0.114***
Output gap	-0.163	9.580***	0.442	7.689***	0.530	6.617***	-0.475	8.002***

Notes: The table shows the marginal effects from the models excluding banking sector variables in Table (2) to Table (5) estimated on two different subsamples. The *pre-2000* sample includes information only up to 2000 (i.e. we exclude the global financial crisis of 2007/08), while the *post-1994* sample includes information from 1994 onwards. Absolute standard errors are reported in parenthesis below the point estimates, and the asterisks denote significance level; * = 10%, ** = 5% and *** = 1%.

Two interesting observations from Table 6 are that the importance of global house prices and real economic activity have strengthened over time, i.e. they seem to have only played a role in the post-1994 period. To shed further light on this, Figure 8 and Figure 9 plot developments in global house prices and real economic activity before and after the onset of crisis episodes, both for the recent global financial crisis (Panel (a)) and for previous crises (Panel (b)), using the same approach as in Section 3.4.

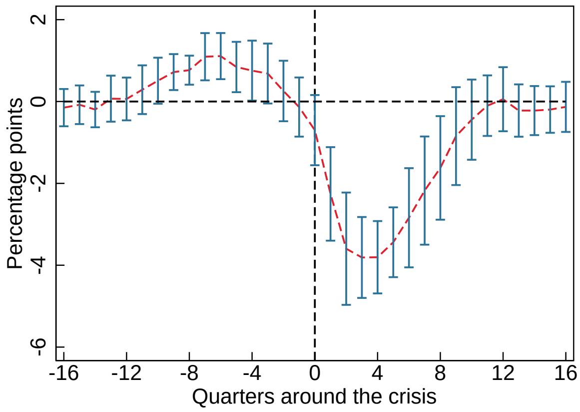


(a) The financial crisis of 2007/2008

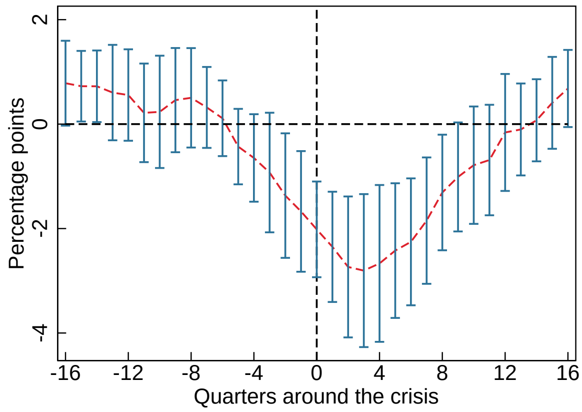
(b) Previous crises episodes

Figure 8: *The behavior of the global house price-to-income gap prior the recent global financial crisis and prior to previous crisis episodes. The dashed red lines are the conditional effects of being $s \in [-16; 16]$ quarters away from a crisis (the parameter $\beta_{j,s}$ in equation (6)), while the blue bars show the corresponding 95% confidence interval. A value different from zero means that the variable takes values that deviate from those in* normal times, *defined as all country quarters outside the event window.*

Looking at Figure 8, it is clear that while global housing market imbalances seem to have been very important during the recent global financial crisis, their role is more doubtful for previous crisis episodes. This does indeed suggest that this time is a bit different, and that in an increasingly integrated and interconnected world economy, the role of global movements in asset prices may be of great importance to the stability of the domestic financial system. Similarly, the role of real economic activity in fueling the boom seems to have been more important in the run-up to the recent crisis (see Figure 9).



(a) The financial crisis of 2007/2008



(b) Previous crises episodes

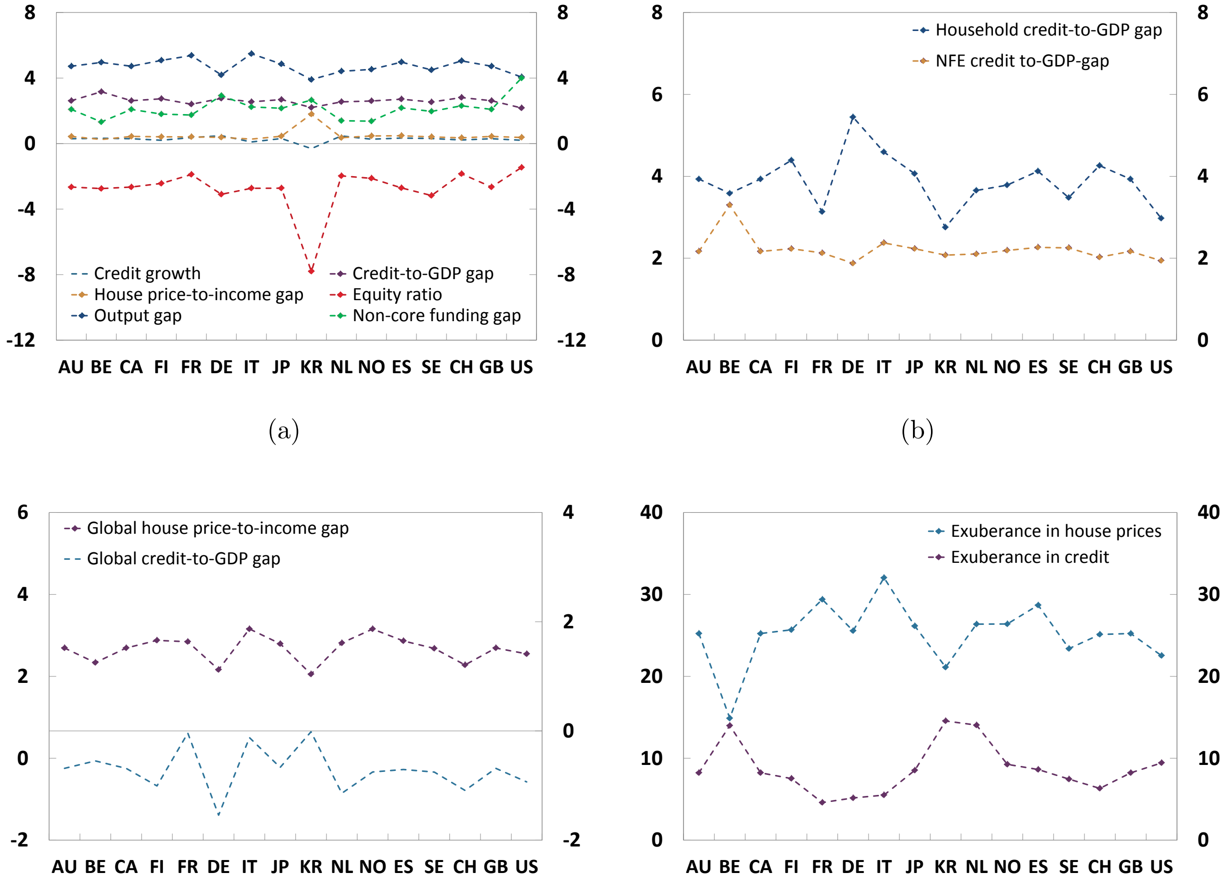
Figure 9: *The behavior of the output gap prior the recent global financial crisis and prior to previous crisis episodes. The dashed red lines are the conditional effects of being* $s \in [-16; 16]$ *quarters away from a crisis (the parameter* $\beta_{j,s}$ *in equation (6)), while the blue bars show the corresponding 95% confidence interval. A value different from zero means that the variable takes values that deviate from those in* normal times, *defined as all country quarters outside the event window.*

Cross-sectional stability

We analyze the cross-sectional sensitivity of our results by re-estimating the models presented in Section 4, excluding each country in turn. The results are shown in Figure 10.

Panel (a) plots the marginal effects from the model reported in Column (3) in Table 2. Overall, the effects are relatively stable, both in terms of signs, numerical size and statistical significance. The banking sector capitalization variable for Korea, however, seems to be an outlier. An interesting observation is that the effect of non-core funding in the banking sector increases when the US is excluded from the sample. This is in line with the discussion in Section 4.3.

The remaining panels plot the marginal effects when we decompose the credit variable and when global variables and the exuberance measures are added. It is evident that the important role of credit to households and non-financial enterprises is not driven by a single country (see the upper right panel). Interestingly, the role of household credit is more prominent when we exclude Germany from the sample. The reason for this may be related to the steady decline in household indebtedness in Germany in the 2000-2008 period. Finally, the importance of global housing market imbalances (lower left panel) and exuberance in credit and housing markets (lower right panel) is not driven by any particular country.



(a) (b) (c) (d)

Figure 10: *Cross-sectional stability of marginal effects based on specifications reported in Column 3 of Table 2–5. Markers denote that the estimated effect is significantly different from zero at a 5% level.*

6 Conclusion

This paper has analyzed the main determinants of financial market vulnerabilities. We have paid particular attention to the role of booms in global credit and house prices, as well as bubble-like behavior in housing and credit markets.

Our analysis leads to several interesting findings. First, we found that when total private sector credit is partitioned into separate measures for households and non-financial enterprises, both exercise a positive and significant impact on the probability of a crisis. Thus, it seems important to monitor developments in both types of credit – a finding that contests previous findings (Büyükkarabacak and Valev, 2010). A second finding is that global imbalances in house prices increase the fragility of the domestic financial system. Finally, we constructed separate measures of housing market and credit market exuberance using newly developed tests in the time series literature. Including these measures in an early warning model, we find that they both exercise a positive impact on the probability of a crisis. In particular, we find a much stronger effect of exuberant behavior in periods of high leverage.

Our findings highlight the importance of credit and house price developments - both domestically and globally – for the (in)stability of the financial system. This suggests that policy makers should keep a close eye at developments in these markets when monitoring financial stability. An interesting path for future research would be to integrate an early warning model of the form considered in this paper with a full fledged global macroeconomic model. This would allow for simulation studies that can determine the impact on the real economy and the financial system of changes in capital requirements.

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Appendix A: Figures

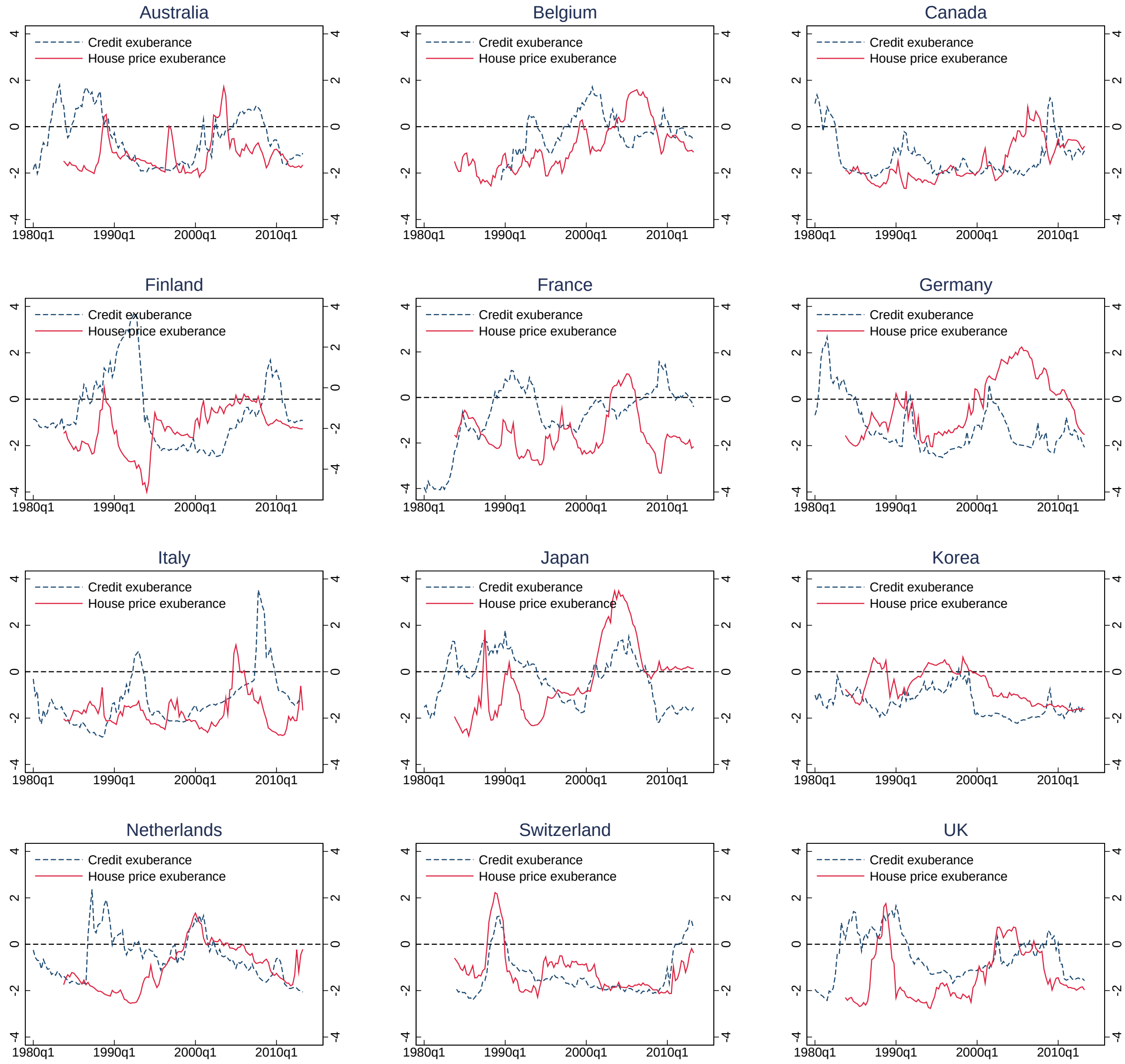

Figure A.1: *Indicator for exuberance in house prices to income and credit to GDP. The figure shows the test statistic less the critical value based on a 5% significance level for house prices to income and private credit to GDP. A positive difference indicates exuberant behavior. See Appendix D for details.*

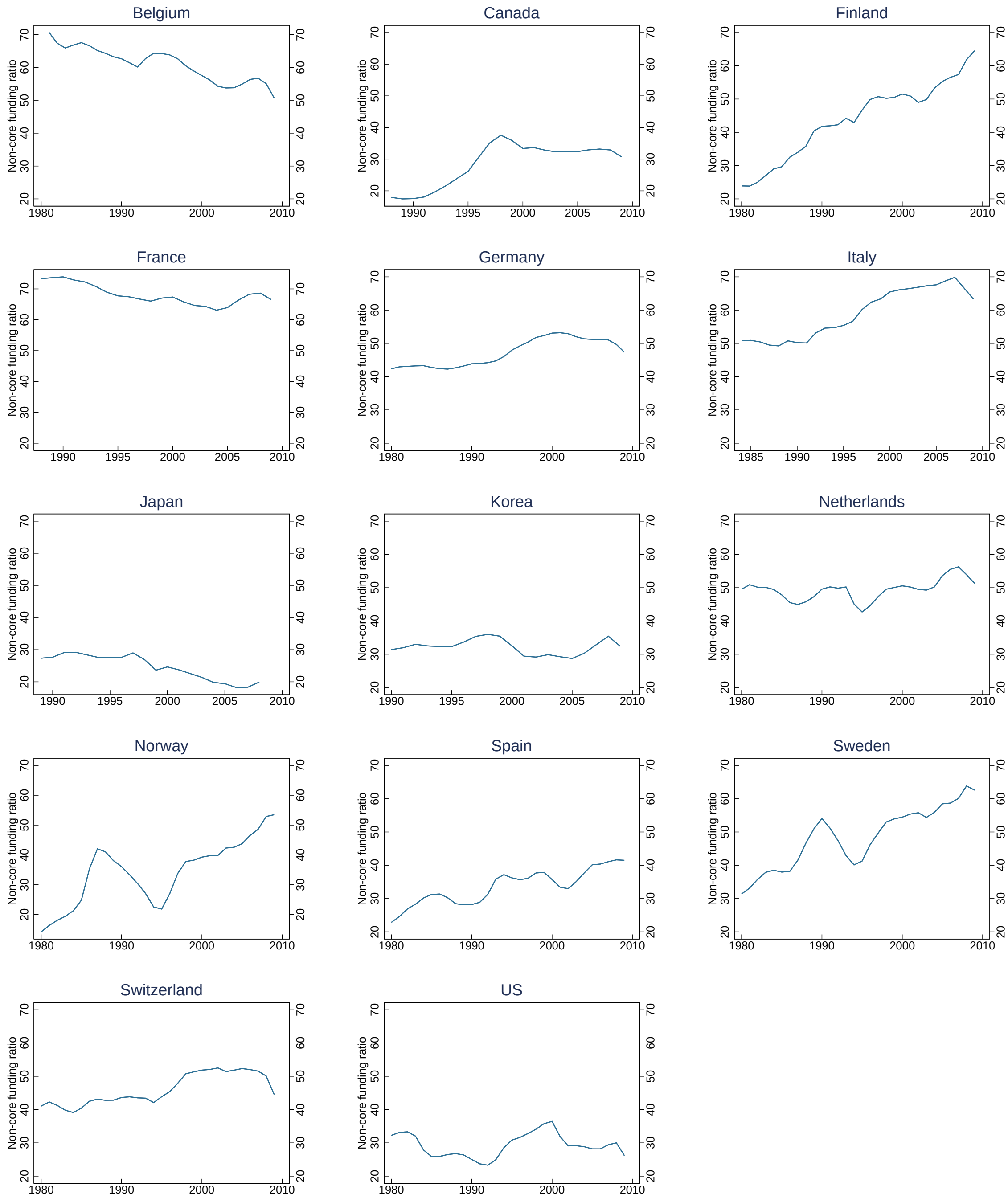

Figure A.2: *Non-core funding relative to total assets. 1980 - 2009. Source: OECD Banking Statistics*

Appendix B: Tables

Table B.1: Results from unit root tests

	ADF-test	Im-Pesaran-Shin test	Fisher-type test
	Stationary (#/total)	Stationary (p-value)	Stationary (p-value)
Private credit growth (yoy)	0.500	Yes (0.0000)	Yes (0.0001)
Private credit to GDP (yearly change)	0.500	Yes (0.0000)	Yes (0.0000)
Private credit to GDP gap	0.250	Yes (0.0005)	Yes (0.0339)
Household credit growth (yoy)	0.467	Yes (0.0001)	Yes (0.0000)
Household credit to GDP (yearly change)	0.067	Yes (0.0449)	No (0.1392)
Household credit to GDP gap	0.200	Yes (0.0595)	No (0.6986)
Firm credit growth (yoy)	0.667	Yes (0.0000)	Yes (0.0000)
Firm credit to GDP (yearly change)	0.467	Yes (0.0000)	Yes (0.0000)
Firm credit to GDP gap	0.400	Yes (0.0006)	Yes (0.0003)
House price growth (yoy)	0.750	Yes (0.0000)	Yes (0.0000)
House prices to income (yearly change)	0.688	Yes (0.0000)	Yes (0.0000)
House prices to income gap	0.375	Yes (0.0003)	Yes (0.0059)
Non-core funding ratio (yearly change)	0.571	Yes (0.0000)	Yes (0.0000)
Non-core funding gap	0.357	Yes (0.0033)	Yes (0.0005)
Equity ratio	0.143	Yes (0.0079)	Yes (0.0004)
Real GDP growth	0.813	Yes (0.0000)	Yes (0.0000)
Output gap	1.000	Yes (0.0000)	Yes (0.0000)

Notes: The table shows results for the Im-Pesaran-Shin (see Im et al. (2003)) and the Fisher-type (see Choi (2001) panel unit-root tests. The table also reports the results from country-specific Augmented Dickey-Fuller tests (see Dickey and Fuller (1979)). For all tests, we started with an initial lag length of 8, and the optimal lag truncation was decided based on a sequence of t-tests. Only an intercept was included in the ADF-regressions, and – as a cut-off for the country-specific unit root tests – we used critical values from the Dickey-Fuller distribution consistent with a 10% significance level.

Table B.2: Results when using 4-quarter changes instead of gaps

	(1)	(2)	(3)	(4)
Change in private credit-to-GDP	0.196***			
	(0.0274)			
Change in household credit-to-GDP		0.246***	0.204***	0.201***
		(0.0475)	(0.0470)	(0.0456)
Change in NFE credit-to-GDP		0.212***	0.260***	0.175***
		(0.0363)	(0.0517)	(0.0392)
Change in house prices-to-income	0.0538	0.0328	-0.00685	-0.0580**
	(0.0353)	(0.0325)	(0.0300)	(0.0253)
Change in non-core funding ratio	20.78***	21.54***	26.94***	30.60***
	(4.844)	(5.096)	(5.623)	(7.042)
Equity ratio	-12.34	-7.050	-22.73*	-35.46**
	(13.85)	(12.91)	(12.15)	(14.76)
Change in global credit-to-GDP			-10.73	
			(10.34)	
Change in global house prices-to-income			25.35***	17.89**
			(6.993)	(8.312)
House price exuberance (yes/no)				2.828***
				(0.462)
Credit exuberance (yes/no)				2.445***
				(0.343)
Output gap	40.63***	47.41***	45.77***	62.77***
	(9.725)	(10.65)	(10.71)	(13.83)
Country fixed effects	Yes	Yes	Yes	Yes
Pseudo R-Squared	0.204	0.231	0.256	0.350
AUROC	0.800	0.820	0.829	0.884
Countries	14	14	14	14
Crisis	20	19	19	19
Observations	1005	904	904	845

Notes: The table shows results when we use substitute gap measures in Table 2–5 with the 4-quarter change in the credit to GDP, house prices to disposable income and the non-core funding ratio. In all cases, we consider the specification reported in Column (3). The reported numbers are the β's in equation 2, and absolute standard errors are reported in parenthesis below the point estimates. The asterisks' denote significance level; * = 10%, ** = 5% and *** = 1%.

Table B.3: Results when using 4-quarter growth rates instead of gaps

	(1)	(2)	(3)	(4)
Real private credit growth	32.45***			
	(5.170)			
Real household credit growth		14.69***	12.78***	6.519**
		(2.894)	(3.624)	(3.110)
Real firm credit growth		21.83***	23.19***	20.60***
		(3.871)	(3.993)	(4.090)
Real house price growth	2.892	1.562	-3.868	-3.764
	(2.343)	(2.090)	(2.439)	(2.957)
Change in non-core funding	25.33***	27.69***	39.17***	38.94***
	(5.028)	(5.443)	(6.337)	(7.215)
Capitalization	-25.26**	-17.97*	-17.27	-33.77**
	(10.77)	(10.15)	(10.89)	(13.50)
Global credit growth			1.095	
			(3.169)	
Global house price growth			34.78***	30.73***
			(6.096)	(6.455)
House price exuberance (yes/no)				2.630***
				(0.457)
Credit exuberance (yes/no)				1.823***
				(0.303)
Output gap	3.790	2.417	-4.510	26.54*
	(9.310)	(9.879)	(11.91)	(14.35)
Country fixed effects	Yes	Yes	Yes	Yes
Pseudo R-Squared	0.231	0.269	0.328	0.399
AUROC	0.821	0.841	0.867	0.904
Countries	14	14	14	14
Crisis	20	19	19	19
Observations	1009	908	908	849

Notes: The table shows results when we use substitute gap measures in Table 2–5 with the 4-quarter growth in real credit and real house prices. In all cases, we consider the specification reported in Column (3). The reported numbers are the β's in equation 2, and absolute standard errors are reported in parenthesis below the point estimates. The asterisks' denote significance level; * = 10%, ** = 5% and *** = 1%.

Appendix C: Constructing global variables

Let $\boldsymbol{x}^*_{i,t}$ be a $k \times 1$ vector of country-specific foreign (global) variables for country $i = 1, \ldots N$, i.e. global variables that might affect the probability of a crisis in country i. This vector is defined as a weighted average of the country-specific variables for the countries to which country i is exposed, $\boldsymbol{x}_{j,t}$, $\forall\ j \neq i$. In other words, $\boldsymbol{x}^*_{i,t}$ is a measure of the global variables, as seen from the viewpoint of country i, or the variables in other countries that might affect the probability of a crisis in country i.

Let $\boldsymbol{w}_i$ be a $1 \times N$ weighting vector determining the degree to which area i is influenced by each of the other areas in the sample, where $w_{ii} = 0$ and $\sum_{j=1}^{N} w_{ij} = 1$, with w_{ij} measuring the importance of area j in influencing area i. For a given variable $x^s_{i,t} \in \boldsymbol{x}_{i,t}$, define the vector $\boldsymbol{x}^s_t$ in the following way: $\boldsymbol{x}^s_t = \left(x^{s\prime}_{1,t}, \ldots, x^{s\prime}_{N,t}\right)'$. This vector simply stacks the values of the variable $x^s_{i,t}$ (for example house prices) for all countries. Given this, the foreign variable $x^{*s}_{i,t}$ may be defined in terms of the stacked vector in the following way:

$$x^{*s}_{i,t} = \boldsymbol{x}^s_t \boldsymbol{w}'_i \qquad \text{(C.1)}$$

i.e. as a weighted average of this variable in all other areas.

We follow Pesaran et al. (2004), Dees et al. (2007a) and Dees et al. (2007b) to define the weighting matrixes. In particular, we use time-varying trade weights based on import and export shares. Thus, the global variables considered in this paper are both country specific and we take account of changes in trade patterns over time.

Appendix D: Constructing the exuberance indicators

In this section, we explain how the exuberance measures have been constructed. We will focus on the measures for house prices, where the theoretical rationale is the clearest, but the econometric approach used to construct the exuberance measures for house prices has also been applied to construct credit exuberance measures.

Theoretical background

If we look at housing as any other asset, then the current value of the asset (the house) should be equal to the expected discounted stream of pay-offs. This framework is similar to a standard present value model (see e.g. Gordon and Shapiro (1956) and Blanchard and Watson (1982)), and Clayton (1996) argue that it may equally be considered for housing.

In the housing context, the alternative return to living in a house is the imputed rent, i.e. what it would have cost to rent a house of similar quality. Asset pricing theory therefore suggests that the price of a house at time t is given by:

$$PH_t = \mathbb{E}_t \left(\frac{PH_{t+1} + R_{t+1}}{1+r} \right) \tag{D.1}$$

where $\mathbb{E}_t$ is an expectations operator, PH_t denotes house prices, R_t is the imputed rental price and r is a risk free rate that is used for discounting. This equation simply states that the price of a house today is equal to the discounted sum of the price of that house tomorrow and the value of living in the house for one period (as measured by the alternative cost, i.e. the imputed rent). Equation (D.1) may easily be solved by forward recursive substitution j times to yield:

$$PH_t = \mathbb{E}_t \left[\sum_{i=1}^{j} \left(\frac{1}{1+r} \right)^i R_{t+i} + \left(\frac{1}{1+r} \right)^j PH_{t+j} \right] \tag{D.2}$$

The transversality condition (TVC) that rules out explosive behavior is given by:

$$\lim_{j \to \infty} \left(\frac{1}{1+r} \right)^j PH_{t+j} < \infty \tag{D.3}$$

Imposing the TVC, the unique solution to the difference equation in (D.2) is given as:

$$PH_t = \mathbb{E}_t \left[\sum_{i=1}^{\infty} \left(\frac{1}{1+r} \right)^i R_{t+i} \right] \tag{D.4}$$

showing that the value of a house today, PH_t is equal to the expected discounted value of all future rents, i.e. the pay-off stream in the infinite future. The expression in (D.4) may be thought of as a fundamental house price according to asset pricing theory.

It is important to notice that imposing the TVC rules out explosivity, and thus ensures a unique solution to the difference equation.

If we relax the TVC, it can be shown that the (non-unique) solution to the difference equation in (D.2) (see Sargent (1987) and LeRoy (2004)) is given by:

$$PH_t = \mathbb{E}_t \left[\sum_{i=1}^{\infty} \left(\frac{1}{1+r} \right)^i R_{t+i} \right] + B_t \tag{D.5}$$

where B_t is an explosive bubble component. Campbell and Shiller (1987) have shown that (D.5) may alternatively be expressed as:

$$PH_t - \frac{1}{r} R_t = \frac{1+r}{r} \mathbb{E}_t \left[\sum_{i=1}^{\infty} \left(\frac{1}{1+r} \right)^i \Delta R_{t+i} \right] + B_t \tag{D.6}$$

If the fundamentals (the rents), R_t, is a RW process with a drift μ, then:

$$\Delta R_t = \mu + \varepsilon_t, \ \varepsilon_t \sim IIN(0, \sigma^2) \tag{D.7}$$

Conditional on this, we see that $\mathbb{E}_t \Delta R_t = \mu$, and hence that (D.6) may be written as:

$$PH_t - \frac{1}{r} R_t = \frac{1+r}{r} \left[\sum_{i=1}^{\infty} \left(\frac{1}{1+r} \right)^i \mu \right] + B_t \tag{D.8}$$

Solving the infinite geometric sequence above, we find:

$$PH_t - \frac{1}{r} R_t = \frac{1+r}{r^2} \mu + B_t \tag{D.9}$$

Thus, in the absence of explosivity, i.e. when the TVC holds ($B_t = 0$), the asset pricing model implies that house prices should also have a unit root, and that house prices and rents are cointegrated.[39] However, conditional on the assumption that $R_t \sim RW$, any explosive behavior in PH_t suggests that $B_t \neq 0$, i.e. that there is an explosive bubble component that affects house prices (TVC is violated).

With reference to (D.8), it is clear that the bubble hypothesis is rejected as long as house prices are integrated of the first order, I(1). However, if house prices has an explosive root, the asset pricing theory would suggest that there is a bubble (violation of TVC). In the next section, we discuss how we operationalize this model using novel econometric methods.

[39] With time-varying risk-free rates, house prices, rents and the risk-free rate should be cointegrated. That said, it seems relatively uncontroversial to assume that the risk-free rate follows an I(0)-process, which implies that it will not help for cointegration.

An econometric operationalization

We have followed Pavlidis et al. (2014) and applied the recursive ADF-based framework suggested by Phillips et al. (2011),Phillips et al. (2012) and Phillips et al. (2013) to explore whether there are signs that house prices in a given country moves from following an I(1) process (TVC satisfied and no bubble) to having an explosive root (violation of TVC and thus bubble). A structural break that moves the process from I(1) to explosivity would suggest that there has been a bubble. Though the theory is not directly applicable to the credit market, we have used the same methods to test for explosive behavior also in credit variables.

Consider the following standard ADF-regression model for country i:

$$\Delta X_{i,t} = \mu_i + \rho X_{i,t-1} + \sum_{j=1}^{p} \Delta X_{i,t-j} + \varepsilon_{i,t} \tag{D.10}$$

When $\rho = 0$, we say that $X_t \sim I(1)$, i.e. that it has one unit root. The standard ADF-test, tests the null of a unit root against the alternative of stationarity ($\rho < 0$). With reference to the asset pricing model, the alternative of stationarity seems less relevant, however. The hypothesis we are interested in testing is whether house prices are I(1) v.s. the alternative that they are explosive, i.e. $\rho > 0$. This approach does however have low power to detect the alternative of explosivity when such episodes are followed by large drops.

The framework suggested by Phillips and co-authors is to consider a recursive version of the ADF test, so that we can explore whether there are periods when a time series exercises I(1) behavior, while there are other periods where it has an explosive root. The general ADF regression that this test is based on takes the following form:

$$\Delta X_{i,t} = \mu_{i,r_1,r_2} + \rho_{i,r_1,r_2} X_{i,t-1} + \sum_{j=1}^{p} \gamma_{i,r_1,r_2} \Delta X_{i,t-j} + \varepsilon_{i,t},\ \varepsilon_{i,t} \sim IIN(0, \sigma^2_{i,r_1,r_2}) \tag{D.11}$$

where $r_1 = \frac{T_1}{T}$ and $r_2 = \frac{T_2}{T}$, with T_1, T_2 and T denoting the sample starting point, end point and the total number of observations. Thus, with reference to the standard ADF regression, we would have $T_1 = 0$ and $T_2 = T$. What we are interested in testing is the hypothesis that $\rho_{i,r_1,r_2} = 0 \Rightarrow X_{i,t} \sim I(1)$ against the alternative that $\rho_{i,r_1,r_2} > 0 \Rightarrow X_{i,t}$is explosive. The relevant test statistic is the ordinary ADF statistic, i.e. $ADF_{r_1}^{r_2} = \frac{\hat{\rho}_{i,r_1,r_2}}{se(\hat{\rho}_{i,r_1,r_2})}$

Phillips et al. (2011) suggested setting $T_1 = 0$, while varying T_2 from $\tilde{T}$ to T, i.e. an expanding forward recursive strategy. To test whether there are any periods with evidence of explosive behavior, they suggested using the sup ADF statistic (SADF), which is given by:

$$SADF(r_1 = 0) = \sup_{r_2 \in [\tilde{r}, 1]} ADF_{r_1=0}^{r_2} \tag{D.12}$$

with $\tilde{r} = \frac{\tilde{T}}{T}$. Like the ordinary ADF statistic, the SADF statistic has a non-standard limiting distribution that is skewed to the left. Moreover, the distribution depends on both r_2 and the nuisance parameters. These critical values may, however, be simulated and the null of non-stationarity is rejected in favor of explosivity when the SADF statistic is greater than the corresponding critical value from the right-tail distribution.

While this test has been shown to perform well in the case of only one bubble, it has been shown to function poorly when there are multiple bubbles (see Homm and Breitung (2012)). Therefore, Phillips et al. (2012) and Phillips et al. (2013) suggest a modified version of the test, where both T_1 and T_2 are allowed to vary, i.e, both the sample starting point and the sample end point varies. The relevant test statistic is called the generalized SADF (GSADF) statistic and is given by:

$$GSADF = \sup_{r_2 \in [\tilde{r}, 1], r_1 \in [0, r_2 - \tilde{r}]} ADF_{r_1}^{r_2} \tag{D.13}$$

As with the standard ADF statistic and the SADF statistic, the GSADF statistic has a non-standard limiting distribution, and the distribution of GSADF under the null of non-stationarity depends on both r_1, r_2 and the inclusion of nuisance parameters.[40] A rejection of the null hypothesis indicates that there are signs of explosive behavior.

In most cases it is relevant to ask for what period(s) – if any – the series $X_{i,t}$ exercises explosive behavior. Consider the case where we keep the sample end point fixed, i.e. $r_2 = \bar{r}_2$, and consider the backward ADF (BADF) statistic (Phillips et al. (2012)):

$$BADF(r_2 = \bar{r}_2) = \sup_{r_1 \in [0, \bar{r}_2 - \tilde{r}]} ADF_{r_1}^{r_2 = \bar{r}_2} \tag{D.14}$$

By (forward) recursively changing $\bar{r}_2$, we then obtain a time series for the BADF statistic. Comparing this to the relevant critical values, $CV_{r_1}^{r_2}$, we can determine for what periods there is evidence of explosive behavior. In our analysis, we have constructed a variable $Exuberance(X_{i,t})$, which is given as:

$$Exuberance(X_{i,t}) = BADF(r_2 = \bar{r}_2) - CV_{r_1}^{r_2} \tag{D.15}$$

which measures the degree of explosive behavior in the variable under consideration at different points in time. When $Exuberance(X_{i,t}) \geq 0$, there is evidence of explosivity in $X_{i,t}$, while there is no evidence of explosivity if $Exuberance(X_{i,t}) < 0$. Thus, we are interested in testing the hypothesis that an increase in $Exuberance(X_{i,t})$ increases the probability of a crisis.

[40] We use the Matlab program accompanying Phillips et al. (2013) to simulate consistent finite sample critical values.