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Shifting horizons:

assessing macro trends before, during, and following systemic banking crises

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Abstract

This paper assesses the trends of some main macroeconomic and macro-financial variables across different time horizons related to systemic banking crises. Specifically, by gradually shifting the observation horizon of the same statistical model across time, it observes how these variables are associated with banking crises in the past, present and future. The associations vary considerably when shifting horizons. Domestic house price growth increases the probability of observing a crisis in the future, but its effect disappears when moving closer to a crisis. The inverse holds true for the effect of the global credit gap, while global credit growth consistently and significantly increases the probability of a future banking crisis. Also, banking crises seem to be spatially correlated in the very short run. In all, the results can help policy makers by shedding light on the temporal horizon of the variables they monitor in addition to evaluating their predictive power.

JEL Classification: C23, C51, E43, E51, G01

Keywords: banking crisis, credit, time horizons, binary time series cross section data

Non-technical summary

Inspired by what is arguably the largest financial crisis in living memory, researchers and policy makers have over the past few years tried to understand and even predict this phenomenon they have been witnessing. As part of this broader endeavour, the empirical finance literature has seen the development of so-called early warning models which aim to predict systemic banking crises. An important aspect of this approach concerns the evaluation of such models, a process by which researchers try to optimise model performance given some (assumed) policymakers' preferences vis-à-vis missing a crisis and wrongfully calling a crisis. Fundamental to the success of this process is the estimation of an appropriate and robust model. This, however, has played a minor role in many recent studies, even though there is no generally accepted baseline empirical model of banking crises available in the literature.

This paper focuses on finding a robust model for predicting banking crises. It does so by assessing the trends of a set of macroeconomic and macro-financial variables across different periods of time (or time horizons) surrounding banking crises. Driving this exercise is a notion that policy makers have an interest in being able to signal a banking crisis well in advance of its occurrence. Indeed, most existing empirical models trying to predict banking crises incorporate a lead time of a number of quarters (or years). Having said this, most of these studies select a single time horizon, often without considering the effects of this choice. As this paper shows, however, the selection of a particular horizon can have considerable implications for the performance and behaviour of a model and its policy implications. By analysing and comparing the trends of different macroeconomic and macro-financial variables across different time horizons, one obtains a broader picture of how these variables relate to systemic banking crises. This improves the robustness of many single horizon early warning models which have been developed in the crisis literature. In this way, this paper sheds a new light on the early warning properties of some of the main explanatory variables as identified by the literature.

As part of the exercise, this paper accounts for both temporal and spatial correlation of banking crises, a novelty in the banking crisis literature. Most of the early warning literature treats banking crises as independent events. However, there is reason to believe that such crises correlate across space and time, an observation that is generally accepted in the political science literature in the context of political crises and civil wars.

Two main findings come out of the analysis. The first is that banking crises appear to have short-term spill-over effects between countries, whereas they tend to reoccur in the same country after longer periods of relative stability. Second, the results indicate major differences between the trends of main macroeconomic and macro-financial variables before, during, and after systemic banking crises. For some of these variables, the effects only vary in terms of size, but other variables actually change sign over time, thus demonstrating different cyclical patterns over time. For example, domestic house price growth has a positive sign when a banking crisis is a relatively long time ahead, but its coefficient becomes negative as one moves closer to a crisis (at least in some of the specifications). Global macroeconomic and macro-financial variables tend to be strongly associated with banking crises, whereas their effects on the probability of a future banking crisis deviate from those coming from domestic variables. Global credit and equity price growth are positively related to future banking crises irrespective of the selected horizon, whereas the global credit gap's positive association grows stronger as banking crises draw closer. The opposite applies to global house prices, which tend to peak before domestic house prices in the run up to a banking crisis.

The observed variation in the strength in and sign of the association between macro variables and the probability of future banking crises indicates that it is possible that two early warning studies using the same explanatory variables could produce very different results (and could thereby lead to different policy recommendations) when selecting different time horizons for their early warning models. Moreover, the results suggest that researchers could benefit from taking the different (cyclical) patterns of macro-financial variables between countries and over time into account so as to build more robust early warning models. This will not only improve the predictive power of these models, but could also lead to more consistent, better coordinated and thereby more effective macro-prudential policy measures.

Introduction

Against the background of the longest and most severe financial crisis in decades, researchers and policy makers around the world have put considerable effort into understanding and predicting systemic banking crises. In doing so, the empirical literature concerned with predicting banking crises has been focusing on developing early warning models which seek to predict future crises either by means of a (single-variable) signalling approach (see e.g. Kaminsky et al. 1998; Kaminsky and Reinhart 1999; Borio and Drehmann 2009; Alessi and Detken 2011) or in a multilateral framework (e.g. Lo Duca and Peltonen 2013; Behn et al. 2013). The latter, more complex approaches tend to entail two separate steps, namely the estimation of statistical models followed by the evaluation of these models' predicted probabilities. In recent applied research, most efforts have been geared towards the second step of this process, where much progress has been made with regard to, for example, establishing threshold values of predicted probabilities, improving noise-to-signal ratios, incorporating policy makers' preferences and assessing the usefulness of models' signals.[2] At the same time, however, the different ways in which one can specify an appropriate and robust statistical model have received less attention in many recent studies. This is surprising, as no common modelling strategy has been agreed upon in the literature.

One topic in the early warning literature that has been researched less is the choice of time horizons in relation to banking crises.[3] As banking crises are rare events with potentially serious (costly) consequences, policy makers have an interest in knowing some time in advance that a crisis might be coming. Due to this, most empirical models which try to predict banking crises take a lead time of several quarters (or years) into consideration, thereby essentially predicting a period of time before the onset of a banking crisis. Still, many studies apply a specific time horizon without motivating how long this lead time should be[4] or testing the performance of their models against alternative time horizons.[5] The selection of a particular horizon can, however, have considerable implications for the performance of the

[2] Berg et al. (2005) discuss different early warning models in a comparative fashion, even though their assessment does not focus on the performance of the explanatory variables in the different models.
[3] Rose and Spiegel (2009) highlight the issue of timing a crisis as an important aspect of early warning models.
[4] There are, of course, exceptions to this. See, for example, Behn et al. (2013) for a discussion on this issue in the context of the countercyclical capital buffer.
[5] Several papers include an alternative time horizon in their robustness sections (e.g. Alessi and Detken 2011, Behn et al. 2013), but the results of such exercises are rarely discussed in detail (other than confirming the results of the main empirical models). Moreover, Babecky et al. (2012; 2013) gauge different time horizons to identify the most appropriate time lag for each explanatory variable in their early warning models. These papers, however, do not assess the performance of a model (i.e. multiple variables) across different time horizons.

overall model and the effects of the explanatory variables and, as a consequence, the evaluation of the predicted probabilities and the lessons drawn by policy makers.[6]

This paper seeks to address exactly this issue by analysing the effects of a common set of macroeconomic and macro-financial variables on the probability of a systemic banking crisis across different forecasting horizons. By shifting these horizons, this study assesses the development of macro trends before, during, and directly following banking crises, with the goal of broadening our understanding of the economic and financial context in which banking crises occur.

In doing so, this paper seeks to contribute to the literature in the following ways. First, by analysing and comparing the trends of different macroeconomic and macro-financial variables across various time horizons, it draws a more complete picture of how these variables affect systemic banking crises in a multivariate framework. By doing so, this approach improves the robustness of many early warning models which have been developed in the crisis literature and which often focus on one time horizon. As such, the paper sheds a new light on the early warning properties of some of the main explanatory variables as identified by the literature in showing their trends vis-à-vis banking crises in the past, present and future. In this light, however, it is important to note that this paper does not provide an early warning model itself. It does not focus on signal extraction or model evaluation based on the predicted probabilities, nor does it include any assumptions on policy makers' preferences with regard to missing crises or falsely calling crises. Rather, this paper focuses on what one could call the first step of the analytical process, namely the estimation of a comprehensive and robust statistical model of banking crises. By putting the emphasis on this step, this paper seeks to improve our understanding of the 'correlates of banking crises', which could also help other research efforts which entail model evaluation.

A second contribution of this paper is that it accounts for both temporal and spatial correlation of banking crises, which is a novelty in this literature. Most of the early warning and banking crisis literature treats the probability to observe a banking crisis as independent from the occurrence of crises in a country's past or in other countries. This is a strong assumption and one that is not very credible given the anecdotal evidence of, for example, financial stress spill-overs during the previous (current) global financial crisis. Moreover, the fact that banking crises have been a returning phenomenon in many countries despite imposing post-crisis regulations suggests that banks (and policy makers) lose their vigilance

[6] For example, Schularick and Taylor (2011) show that the effects of credit supply on the probability of observing a banking crises changes considerably depending on the choice of the lag structure.

to crises after some time (see also the “this time is different” argument by Reinhart and Rogoff 2008a). In the political science literature studying violent political crises (civil war), for example, the debate on spatial and temporal dependence has led to a common understanding that any binary cross-section time-series model of these types of crises requires taking account of time (Beck et al 1998; Carter and Signorino 2010) and space (Gleditsch 2007). Drawing on some of these insights, this paper includes an account of both types of potential interdependence.

The empirical analysis identifies major differences between the trends of macroeconomic and macro-financial variables before, during, and following systemic banking crises. Domestic variables, in particular the domestic credit-to-GDP gap (or the difference between the domestic credit-to-GDP ratio and its long-term backward-looking trend) and domestic house price growth, are positively related with the probability of a future banking crisis, but their impact wanes as a country moves closer to a crisis. This suggests that these variables’ predictive capacities are stronger at an earlier pre-crisis stage (this holds in particular for house price growth, of which the effect on the probability of observing a crisis even switches sign as one moves closer to a crisis in some of the specifications), a result which echoes that of several previous studies identifying domestic credit-to-GDP gap and house prices as important (very) early warning variables. Domestic credit and equity growth cannot be positively associated (at least robustly) with future banking crises if one accounts for the credit gap. Global macroeconomic and macro-financial variables tend to be strongly associated with banking crises, but with different effects than domestic variables. Global credit and equity price growth increase the probability of banking crises across any future horizon, whereas the global credit gap’s positive association is stronger when banking crises are nearer, a result which seems to speak against some other papers that the global credit gap provides the best (or at least most consistent) early warning signal in a single variable framework.[7] Conversely, global house prices tend to fall in the run up to a banking crisis, in a development that precedes that of domestic house prices by 1.5 years on average.

The effects of the explanatory variables are more in line with one another during banking crises, as these episodes are characterised by decreasing credit and house price growth, even though the domestic and global credit gap tends to widen during crises. The latter trend may be caused by the fact that these variables are ratios where a decline could be driven by the numerator and/or the denominator. The (domestic) credit gap becomes negative only

[7] For example, Alessi and Detken (2011) find that the global credit gap provides the best early warning signal for costly asset price booms across a selection of variables of which many are included in this study. However, their approach compares single variables, so one should be careful not to make too strong inferences from a comparison of these results.

immediately after a crisis ends, a period which is defined by continuous credit and asset price corrections but also by increasing nominal GDP growth.

This paper is structured as follows. The section below describes the data used in this study and a discussion of the applied methodology. This section is followed by a discussion of the results of the various empirical models and some concluding remarks.

Data and methodology

This section introduces the data used for this study, starting with the identification of banking sector crises in the European Union and proceeding by introducing the explanatory variables used in the empirical analysis. Finally, it presents some descriptive statistics on the development of key variables around banking sector crises in the sample countries.

Identifying banking crises

Following the methodology developed by Frankel and Rose (1996) and Demirgüç-Kunt and Detragiache (1998), a series of multivariate models are developed addressing different episodes prior to, during, and following a banking crisis. As discussed earlier in this paper, the purpose of analysing these different models is to get a better understanding of how different and potentially important explanatory variables relate to these episodes.

In order to identify banking crises, a dataset originally compiled by Babecky et al. (2012) as part of a data collection exercise organised by the European System of Central Banks (ESCB) Heads of Research Group (HoR) is used here. This HoR database covers banking, currency and debt crises in 27 EU countries between 1970Q1 and 2010Q4. The crisis occurrence index takes value 1 when a crisis occurred (and value 0 when no crisis occurred). The index aggregates information about banking crisis occurrence from “several influential papers”, including (in alphabetical order): Caprio and Klingebiel (2003); Detragiache and Spilimbergo (2001); Kaminsky (2006); Kaminsky and Reinhart (1999); Laeven and Valencia (2008; 2010; 2012); Reinhart and Rogoff (2008b); and Yeyati and Panizza (2001). The crisis occurrence indices from these papers have subsequently been cross-checked by the Heads of the European System of Central Banks’ (ESCB) research departments. In this paper, an updated version of the HoR database is used.[8] The database has been extended to 2012Q4 and

[8] The ESCB crisis database was updated in 2013 by an expert group working under the Instruments Working Group (IWG) of the European Systemic Risk Board (ESRB). The expert group consisted of representatives from central banks which are part of the ESCB and was created in the context of providing recommendations for setting up the countercyclical capital buffer as proposed by the Basel Committee on Banking Supervision and the European Commission under the Capital Requirement Directive (CRD) IV.

contains a number of changes in the existing country quarters. The crisis dates according to the updated database are provided in Table 1.

The dependent variable is dichotomous, being equal to 1 in the defined time horizons and 0 in all other country quarters, including crisis quarters. As suggested by Bussière and Fratzscher (2006), one may prefer to exclude these quarter for early warning exercises. This paper, however, does not seek to develop an early warning model in the sense that it evaluates the predictive probabilities of an explanatory variable or model against a threshold based on policy preferences. Instead, the purpose of the present paper is to analyse and compare the effects of the same set of explanatory variables across different episodes over time. Excluding crisis or post-crisis episodes would defeat this purpose. The following periods are defined: five pre-crisis periods, namely 14 to 6 quarters before the onset of a banking crisis, 12 to 4 quarters, 10 to 2, the final eight pre-crisis quarters and the final four pre-crisis quarters; two crisis periods, namely the first four quarters and the first eight; finally, one post-crisis period containing the first eight quarters following the end of a banking crisis is included in the models. However, before discussing the results of these shifting horizon models, a set of standard models predicting (the onset of) banking crises are specified and discussed as a starting point.

Macroeconomic and macro-financial variables

The panel dataset used in the analysis contains quarterly macro-financial and banking sector data spanning across 1979Q2-2012Q3 and 27 EU member states.[9] The data are sourced through Haver Analytics and originally comes from the Bank for International Settlements (BIS), the ECB, Eurostat, the International Monetary Fund (IMF), and the Organisation for Economic Cooperation and Development (OECD). In addition to domestic macro variables, a number of global variables is included in the dataset, as several studies have indicated the salience of global developments in country-level early warning models (e.g. Rose and Spiegel 2009; Alessi and Detken 2011; Lo Duca and Peltonen 2013; Behn et al. 2013). Table 2 summarises the list of variables included in the time horizon analysis, while Table 3 shows the bivariate correlations between all variables included in the models.

Following Borio and Drehmann (2009) and Drehmann et al. (2011), the empirical models include variables measuring the supply of credit to the private sector, using the "long series on total credit and domestic bank credit to the private non-financial sector" compiled by the BIS.

[9] Due to, inter alia, data availability issues and the fact that not all EU countries witnessed a banking crisis in the mentioned time period, the effective sample in the analysis is limited to 19 EU countries. See Table 1 for an overview of the included and excluded countries and/or crises.

These data include “credit [that] is provided by domestic banks, all other sectors of the economy and non-residents. The private non-financial sector includes non-financial corporations (both private-owned and public owned), households and non-profit institutions serving households [...] in terms of financial instruments, credit covers loans and debt securities” (see Dembiermont et al. 2013 for a description of the database). As far as this paper is concerned, the BIS credit series offers the broadest definition of credit provision to the private sector, while having been adjusted for data gaps and structural breaks. Four different measurements of credit are included in the models, accounting for credit growth and leverage, both at the domestic and at the global level. Credit growth is entered as a percentage (annual growth), while leverage is measured by the deviation of the credit-to-GDP ratio (using nominal GDP data) from its long-term backward-looking trend (using a backward-looking Hodrick-Prescott filter with a smoothing parameter[10] (λ of 400,000).[11] Global credit variables have been computed using a GDP-weighted average of the variable in question for several countries (see also Alessi and Detken 2011), including Canada, Japan, the United States and all European countries in this study.

In order to test the importance of credit variables in a comparative fashion as well as to analyse the potential importance of other factors, a number of additional variables are included in this study. Data availability for these variables tends to be more limited than for credit variables. Variables are selected based on the existing literature and on data availability and follow the selection procedure undertaken in Behn et al. (2013). In order to account for the macroeconomic environment and monetary stance, the analysis includes annual nominal GDP growth (domestic and global), annual inflation and 3 month money market interest rates. Furthermore, following Reinhart and Rogoff (2008b), data on domestic and global equity and house price (annual) growth are included, using the same methodology to calculate the global variables as in the case of the credit variables. The individual series come from the following original sources: data on total credit to the private non-financial sector are obtained from the BIS and – for those countries where BIS data is not available – from Eurostat. Information on nominal GDP growth and inflation rates comes from the IMF’s International Financial

[10] This smoothing parameter is suggested by Borio et al. (2010), who find that trends calculated with a λ of 400,000 perform well in picking up the long-term development of private credit. Specifically, a λ of 400,000 is consistent with the assumption that credit cycles tend to be four times longer than business cycles while following a rule developed by Ravn and Uhlig (2002) which holds that an optimal λ of 1,600 for quarterly data should be adjusted by taking the fourth power of the observation frequency ratio. As such, taking into account that credit cycles tend to be four times longer than business cycles, λ should be equal to 4 to the power of 4 which approximates 400,000.

[11] There have been critiques on the reliability of credit-to-GDP gaps as predictive variables in early warning models (see e.g. Edge and Meisenzahl 2011). Still, in this paper these variables are complemented by other variables in a multivariate framework, which allows for testing their explanatory power and robustness.

Statistics (IFS). Data on equity prices and interest rates are obtained from the OECD, while data on house prices is provided by the BIS.

Last but not least, the models include a number of variables which model (at least some of the) temporal and spatial dependence. As discussed by Beck, Katz and Tucker (1998) and Carter and Signorino (2010) in the context of the international relations and political economy literature, binary cross-section time-series data (which are used in this study) tend to be serially correlated. Not accounting for such correlation may produce biased (often exaggerated) coefficients for some of the explanatory variables. Moreover, rather than treating temporal dependence as a nuisance (which is still better than not treating it at all), it may be interesting to actually model it. Indeed, this has been frequently done, for example, in the international relations literature, where the length of peace spells and the subsequent probability of civil war onset have been predicted using models that include variables that account for time. Yet, in the banking crisis literature these developments have been largely absent,[12] even though there is little reason why, from a statistical point of view, the structure of banking crises would be different from that of other types of crisis such as civil war, as both in essence constitute tail events. Indeed, it seems unlikely that the probability of observing a banking crisis following a spell of financial calm is independent from the length of this period or from past crisis occurrences. Rather, having witnessed a crisis in the recent past may induce a higher level of vigilance on the side of policy makers or banks, reducing the likelihood that crises might happen soon after one another. However, as argued by Reinhart and Rogoff (2008a), past crises do not necessarily help prevent future ones as the assessment of risks in the banking sector changes over time (“this time is different”). Either way, there is ample motivation to account for time in this kind of empirical research. As such, and following Carter and Signorino (2010), three time variables are included in the regression models: one counting the number of quarters since the end of the previous banking crisis in a particular country (t), plus t^2 and t^3 in order account for nonlinear temporal dependence.

In addition to temporal dependence, one can easily argue that banking crises are unlikely to be uncorrelated across space. In fact, it is well known that the last (or current) financial crisis started in the United States and consequently spread to European countries. As such, it seems inappropriate to exclude an account of such spatial dependence in a model.[13] The issue of spatial correlation in banking sector stress has received much more attention in applied empirical research than temporal dependence, and this paper by no means aims to provide a

[12] Demirgüç-Kunt and Detragiache (1998) is a notable exception.

[13] Of course, there is a growing literature focusing on banking crisis contagion, see for example Dungey et al. (2010).

new insight in the on-going academic debate. Yet in order to avoid exaggerating the effects of the other explanatory variables, a dummy variable is included in all models, being equal to 1 when a banking crisis started in another EU country during the past year and 0 otherwise.[14]

Given the empirical set-up of this paper (binary choice panel data), the potential for non-stationarity of one or more of the independent variables is an issue that warrants further investigation (Park and Phillips 2000). This is done by applying two different unit root tests, namely one developed by Im, Pesharan and Shin (2003) which can be performed on the entire panel of countries as well as the one suggested by Dickey and Fuller (1979) which can be performed on individual time series. The panel unit root test suggests that the hypothesis that all cross sections (i.e. countries) contain a unit root can be rejected for all variables except the (domestic and global) credit-to-GDP gap. The Dickey-Fuller test suggests that in addition to the credit gap, some of the variables depicting nominal growth figures (nominal GDP growth, credit growth, interest rates) demonstrate non-stationarity in some of the countries included in the sample.

The existence of a potential unit root in some of the variables raises concerns for the interpretation of the results (in particular the error term) and could be reason to resort to, for example, first differencing of the respective variables. However, two arguments speak against such a transformation. First, most of the variables in question represent growth rates and are thereby already transformations of original (level) variables. Taking the first difference of growth rates might well render variables that are stationary, but these variables are at the same time less meaningful in terms of their substantive economic interpretation. Second, the empirical strategy in the present study tackles some of the potential biases related to non-stationarity by accounting for temporal dependence by including fixed effects.[15] Third, the trend that lies behind the test results indicating non-stationarity appears to be related to the fact that the relevant variables represent nominal growth rates and are thus affected by inflation levels which declined across several European countries over the sample period, in particular after the start of the monetary union in 1999. As inflation levels are included in the various models, the potential bias induced by downward trending nominal growth variables should be limited. Finally, by using quarterly instead of annual growth rates one could also tackle the issue (these series are hardly non-stationary according to the two tests discussed

[14] One could also account for the spatial correlation of other types of financial crises (e.g. debt crises) in addition to pure banking crises. In fact, the ESCB heads of research database contains data on such crises. However, and as indicated by Babecky et al. (2013), banking crises are more likely to affect the probability of debt crises than vice versa. Also, including these crises in the various models did not produce any significant result. Hence, in this study only the spatial effect of banking crises is reported and discussed.

[15] Fixed effects reduce model bias related to unit heterogeneity by within-transforming the data.

above), but this introduces the issue of seasonality which also requires additional transformations of the data. As such, all variables as mentioned enter the regressions without further transformation.

Descriptive statistics

In preparation of the discussion of the main statistical results below, the following charts shed an interesting light on some of the main explanatory variables' properties.[16] Figure 1 presents the average development over time before and after the onset of a systemic banking crisis of six domestic macro variables in which this paper is interested. For the purpose of predicting crises, one would hope to see a variable which (on average) peaks (or bottoms out, or at least changes direction) a number of quarters before the onset of a banking crisis, which would render it a useful signal. Yet, in the current exercise of tracking the effects of the explanatory variables across different time spans, gauging these figures could give us some idea of how these variables 'behave' during these episodes in a stand-alone fashion.

In this context, one can observe that credit growth (as depicted in % year-on-year growth) does appear to hit a peak about two years before the onset of a crisis, even though its fall only becomes clear during the last pre-crisis year. A similar development can be observed in nominal GDP growth and equity (stock) price growth figures. These variables peak before a crisis (on average), but any sign that a crisis is coming only becomes evident shortly before the crisis happens. This makes it difficult, at least by eyeballing these charts, to identify a coming crisis based on these variables. However, house price growth tends to peak about 3 years before a crisis happens on average, starting a clear descent (although prices are still rising) that lasts into the crisis where growth stalls. Conversely, short-term interest rate growth continues on average until about two years pre-crisis, after which growth slows down and becomes negative early into the crisis. Taking these charts together, based on this evidence one would conclude that house prices appear to be a useful descriptive tool to motivate a decision on the counter-cyclical capital buffer (CCB), as it clearly passes the early warning requirement of six quarters (i.e. one year of implementation plus one or two quarters of publication lag).

Conversely, among the six variables depicted here, the credit-to-GDP gap, using a recursive (backward-looking and thus real-time) Hodrick-Prescott filter to calculate the long-term trend of credit-to-GDP, shows one of the least clear patterns in terms of signalling an impending crisis. On average, the credit gap increases slowly prior to a crisis and only starts

[16] See Borio and Drehmann (2009).

falling about one year into the crisis. Yet, this does not need to be a very surprising development, as GDP may fall quicker than credit at the onset of a banking crisis. So at least from a descriptive standpoint, it is clear that it makes sense to gauge the developments of different macro-financial variables to predict or signal coming crises. Whether this result holds in a more rigorous comparative (multivariate) framework will be discussed in the remainder of this paper.

Methodology

This section introduces the methodology used for the empirical analysis. In order to assess (and compare) the effects of macroeconomic and macro-financial variables in a multivariate framework, panel logistic regression models[17] of the following form are specified:

$$Prob(Y_{it} = 1) = \frac{e^{\alpha_i + X'_{it}\beta}}{1 + e^{\alpha_i + X'_{it}\beta}}$$

where $Prob(Y_{it} = 1)$ denotes the probability that country i in period t finds itself in a particular episode, which, depending on the selected model, could be a pre-crisis, crisis or post-crisis period. As described in the data section, in addition to predicting (the onset of) actual crisis episodes, several horizons are analysed in this paper, varying from 14-6 quarters pre-crisis to the first 8 quarters post-crisis. On the right hand side, the vector X_{it} includes various macroeconomic and macro-financial variables on the domestic and global level as well as variables accounting for temporal and spatial dependence. The models include a set of dummy variables α_i indicating countries in order to account for unobserved heterogeneity.[18] All specified models include robust standard errors.

The analysis has been conducted as much as possible in a real-time fashion, implying that only the information which was available to policy makers at a particular point in time has been used. This means that all the de-trended variables (credit-to-GDP gap) have been generated using backward trends, thereby only using information available up to a particular

[17] A similar methodology is used by Demirgüç-Kunt and Detragiache (1998), Davis and Karim (2008) and Barrell et al. (2010) using annual country-level data and by Lo Duca and Peltonen (2013) and Behn et al. (2013) using quarterly country-level data.

[18] As discussed in Behn et al. (2013), Davis and Karim (2008) and Demirgüç-Kunt and Detragiache (1998), there is an argument for omitting these dummy variables from the estimations as they push out all countries without a banking crisis from the models, hence introducing selection bias. However, not including these variables introduces omitted variable bias caused by unit effects to the models. Given that it is unlikely that banking crises are caused by identical factors across all countries (Candelon 2008), unit dummy variables are included in the model. A Hausman test provides further statistical support for this decision. Having said this, pooled logit models have also been analysed as part of this project, generating similar (though stronger) results.

point. This explains (partly) why the mean credit gap is positive instead of zero, which is what one would expect if the trend would be calculated ex post. Furthermore, all explanatory variables have been lagged by one quarter, not least to account for a publication lag and endogeneity bias through simultaneity. Of course, this simple procedure does not crowd out all endogeneity-related bias, but this is arguably a smaller problem when considering that the dependent variable identifies an episode (or time horizon).

Empirical results

As discussed earlier, the aim of this empirical exercise is to assess and compare the trends of some main macroeconomic and macro-financial variables across different time horizons before, during, and directly following a banking crisis by estimating a number of multivariate logistic regression models. Assessing these trends is interesting and important to take into account for at least two reasons. The first, more conservative (or modest) reason is that these models provide a robustness check on single-horizon models which are common in the early warning literature, adding 'depth' to their findings. In fact, the models show how dependent the impact of a particular explanatory variable can be on the selection of a specific time period. A second, arguably more contentious motivation to shift horizons is that policy makers might be interested in the trends of these variables over time as they help obtaining a more comprehensive picture of the 'average' macroeconomic and macro-financial environment surrounding banking crises. This information is interesting in itself, but can also help to reassess early warning modelling strategies, for example by focusing on those variables which tend to change sharply on average at a particular time before a banking crisis starts.

For this study, two alternative model specifications are used, one containing exclusively domestic variables and one covering domestic and global variables. The reason to specify these two types of models is that they provide the reader with the opportunity to assess the effects of domestic variables with and without the inclusion of global factors, which gives an insight into how global factors may influence the salience of domestic trends. Assessing these differences may also help policy makers in choosing which macro variable to observe more closely on a domestic versus a global level of aggregation. Second, given evidence in the literature that global variables tend to have strong signalling and predictive properties,[19] it is interesting to see to what extent global variables add to the overall fit of the specifications.

[19] See e.g. Alessi and Detken (2011), Lo Duca and Peltonen (2013) and Behn et al. (2013).

The two model types are discussed in turn. As a further, probably more intuitive, illustration of the changing effects of the different explanatory variables across the various time horizons, reference heat maps using a colour scheme to depict the main effects are presented in Appendix I.

Before moving to the discussion of the different time horizons, however, a series of baseline logit models is first presented in order to provide a starting point for the empirical analysis and to discuss the salience of accounting for temporal and spatial dependence.

Predicting banking crises

Table 4 presents ten different specifications of a regression model predicting banking crises. In the spirit of the overall exercise, namely to compare the effects of domestic and global variables, the odd numbered models only include domestic variables whereas the even ones include both domestic and global factors. Models A1 to A6 predict crisis onset, while models A7 to A10 focus on the full sample of crisis quarters. One reason for analysing crisis onset (the quarter in which a crisis starts) instead of the entire crisis is to get an idea of the behaviour of the explanatory variables around the point of transition from a non-crisis quarter to a crisis quarter. However, a downside of this approach is that as events, onsets are of course much rarer than crisis quarters (as there is only one of these events per crisis), reducing the degrees of freedom needed for statistical inference, thereby making it harder to identify effects that are meaningful and/or statistically significant. Also, the small number of observations in which the dependent variable equals 1 necessitates pooling the analysis (i.e. not using fixed effects) which may produce biased results. Still, given that the aim of the exercise is to present some first patterns, this potential problem does not pose a major concern at this stage. Models A7 to A10 include all crisis quarters in the estimation and thereby have much higher degrees of freedom. Still, for the sake of comparability, A7 and A8 apply the same pooled estimation strategy as the onset models, whereas A9 and A10, in line with the models estimated in the subsequent sections, include fixed effects in order to account for unit heterogeneity.

Three main observations can be made when gauging these models. To start with, the main results of the onset and the full crisis episode models are economically intuitive and appear to be broadly homogeneous across the different specifications. Most heterogeneity in terms of coefficient signs between the onset and full crisis specifications occurs in the set of domestic variables, which can be explained by the fact that many of these (e.g. domestic equity price growth) are themselves influenced by the on-going crisis in the latter models.[20] Model fit is considerably higher in the full crisis episode models than in the onset models, as becomes evident when comparing models with same explanatory variables (i.e. A3-A7 and A4-A8). This difference is not surprising given that it is arguably more difficult to fit a model on the relatively rare event that is an onset of a banking crisis than on a full crisis episode.

Second, global macro variables appear to play a salient role in the models, as indicated by their contribution to model fit and the area under the receiver operating characteristics curve (AUROC), which depicts how well a model/variable performs in correctly calling a crisis or a non-crisis event. In particular, the global credit-to-GDP gap and global house price growth demonstrate strong and consistent effects across all models in which they are included. These results are line with the findings of Alessi and Detken (2011) and Behn et al. (2013) and speak in favour of including variables measuring relevant foreign or global macro developments in banking crisis models.

Third, the inclusion of variables accounting for temporal and spatial dependence considerably increases model fit. Comparing the results of models A1, A3 and A5 it is evident that the pseudo R^2 sharply increases, whereas the AUROC shows a steady increase. In other words, it appears that taking these factors into consideration helps predicting future banking crises. Moreover, the coefficient signs are as expected: a positive effect of the spatial lag (suggesting a positive spill-over effect) and a positive but decreasing effect of the temporal dependence variable (suggesting that the likelihood of a crisis increases as more time has passed since a previous crisis, but the effect diminishes over time). However, the importance of temporal and in particular spatial dependence seems to be not significant in the models which include global macro variables (see models A4 and A6), which is probably due to the fact that these effects are largely captured by these global variables, although model A6 incidentally shows that temporal dependence affects crisis probabilities even when accounting for global variables.

Having established a baseline model based on domestic and global macro variables and while acknowledging the salience of temporal and spatial dependence of such variables as well as of banking crisis probabilities, the subsequent analysis aims to show the performance of this model over different time periods before, during and following banking crises. The paper therefore proceeds by specifying two sets of models, one containing domestic variables

[20] This observation might naturally give rise to concerns regarding endogeneity in these models. While acknowledging that such concerns are warranted, this paper will not go into more detail on this matter, not least because the main aim here is not to identify causality between the explanatory and the dependent variables, but rather to identify trends in the explanatory variables across different time horizons, as is shown later.

only and one including domestic and global variables across different time horizons as discussed in the previous section. All models account for the spatial effect of banking crises.

Shifting horizons: domestic variable models

Table 5 presents the main results from the models which include domestic variables only. In the context of comparing the different models, the first thing to take note of is the fact that the sample size is identical across the regressions, with the exception of model D8 as not all countries in the sample witnessed a post-crisis episode (yet). In comparison to models A1-A6 in Table 4, the sample size is larger due to the fact that crisis episodes are not excluded from the specification here as crisis bias is not an issue in this exercise.[21] The only other difference between the specifications is the inclusion of time variables (aimed at accounting for temporal dependence) in the pre-crisis episodes. By construction, these variables (which have been discussed in the data section) only count the number of quarters without a crisis. Also including a variable counting crisis quarters would not have any effect as it would be excluded from the specification due to perfect correlation with the dependent variable.

Reading the models from left to right (thereby essentially moving forward in time from 14-6 quarters before the onset of a banking crisis to the first 8 quarters following a banking crisis), a number of interesting observations can be made. Starting with the variables accounting for spatial dependence, one sees that the spatial lag only has an impact in the short run: the coefficient of the spatial lag is positive and significant in the last 4 pre-crisis quarters and during the first 4 and 8 quarters of a crisis. In other words, the effect of a banking crisis onset in a European country only has a positive effect on the probability of a crisis in another country over a short period of time, suggesting that the spatial lag could serve as a 'late' warning variable. The negative coefficients in models D1 to D3 suggest that there are significantly less crisis onsets in one country which take place 14-6, 12-4 or 10-2 quarters before a crisis onset elsewhere in Europe.

With regard to credit variables, considerable variation between the effects of individual variables within each time horizon can be observed, as well as variation across these episodes. The domestic credit-to-GDP gap has a positive (and significant) effect on observing a future banking crisis across all pre-crisis episodes as well as in all crisis episodes. This might explain why this particular variable is considered to be a good early warning (or signalling) variable by various studies, as it is relatively insensitive to the specification of the time horizon in

[21] As discussed by e.g. Bussière and Fratzscher (2006), it may be desirable to delete crisis (and post-crisis) quarters from the analysis when developing early warning models. This procedure is not applicable here, however, as the present exercise is not aimed at developing an early warning model.

models predicting a future crisis. At the same time, this variable's robust positive effects make it hard to estimate a more precise timing of a future crisis. Having said this, it remains an open question if estimating such a moment in time is a feasible exercise in this type of (macro) models, as the factors directly triggering a banking crisis are at least as likely to be related to individual financial institutions, which would call for a micro-level approach. Nevertheless, also in the current approach one can infer some additional information from the coefficients, for example that the marginal effect of the credit gap is smaller around the starting point of a crisis. Further into a crisis, the effects are again larger (a pattern which resembles that of the descriptive charts), which may well be caused by the fact that this variable is based on a ratio which by construction increases if either the nominator (credit) increases and/or the denominator (nominal GDP) decreases. It has been observed before that the credit gap can increase in early stages of a crisis as nominal GDP falls more sharply than credit, as the latter can be affected by government interventions aimed at preventing a credit crunch. The same line of reasoning can explain that the credit gap becomes negative immediately after the crisis, as nominal GDP is picking up faster than credit.

Moving on to other macro-financial variables, positive nominal GDP growth is associated mostly to a later pre-crisis stage, when the business cycle is peaking before slowing down in the final quarters before a crisis. Into a crisis, the coefficient switches sign, reinforcing the notion that financial cycle downturns tend to coincide with business cycle slumps. The final pre-crisis year can be identified by declining growth and rising inflation as credit-fuelled consumption continues despite the turn of the business cycle. The continuation, by and large, of this pattern during the crisis can be explained by the fact that private spending is partly supported and partly compensated by government spending during crisis times. Only after banking crises are over the economy tends to pick up again, while inflation stays low as part of a price adjustment process. Interest rates tend to increase during boom times that are characterised by rising asset prices and expanding credit.

Finally, rising domestic asset prices seem to signal a boom period preceding a looming but still fairly distant crisis. They (and in particular house prices) cease to increase significantly in later pre-crisis episodes. Indeed, housing prices appear to peak earlier and bottom out later vis-à-vis banking crises than most other macro-financial variables. Interestingly, house prices continue to fall throughout a crisis as well as afterwards.

As such, there is ample variation between the trends of these macroeconomic and macro-financial variables over time and through the crisis cycle, which may help in getting a more comprehensive picture of the macro-financial environment surrounding banking crises.

However, even though the domestic models discussed here have an arguably decent model fit in terms of their pseudo-R^2 and AUROC values, there is considerable support in the literature to include global variables into such regression models. These models are discussed below.

Global models

Table 6 presents the main results from the models which include both domestic and global variables.[22] With regard to spatial dependence of banking crises, one observes positive crisis spill-overs (positive here referring to the sign of the statistical effect, not to a normative interpretation of this effect) during the final pre-crisis episode; the effects over the longer run are negative or non-significant. As such, the onset of a crisis somewhere in Europe has a significant effect on any other country's probability of entering a crisis in the short run, but not over a longer time span (during the so-called vulnerability stage). This confirms the notion that banking crises tend to be clustered over time.

In terms of the main macroeconomic and macro-financial explanatory variables, the differences between the domestic and the global models are somewhat more pronounced, when one compares the domestic credit variables between the models as well as when one compares the domestic to the global credit variables in the latter models. To start with the former, domestic credit growth has a negative significant effect when one accounts for global variables. In turn, the slump in the otherwise positive significant effect of the domestic credit gap is more pronounced in the global models, as this variable no longer produces significant results in the episodes surrounding the onset of a banking crisis.

These results could imply that global economic and financial trends capture the effect of domestic 'excessive leverage' (if that is what one would want to call a positive credit gap). And indeed, especially the global credit gap appears to have a large impact (in terms of significance but also in terms of its marginal effect) on the probability of observing a banking crisis in the near term. Over a longer time horizon, the effect of the global credit gap is negative, which suggests 1) that the global credit cycle tends to trail the domestic one by at least several quarters and/or 2) that the effects of excessive global credit have a more immediate effect on the probability of a banking crisis onset than excessive domestic credit growth. This result could be seen as reinforcing the earlier discussion of Table 4 as it seems that macro trends that are common to all countries in the sample (which is what global

[22] There is no global 'version' of the domestic inflation and interest rate variables, as it was decided to exclude these due to their high correlation with some of the other explanatory variables. Multicollinearity is not indicated in these global models or in any model specified in this study: variance inflation factors stay far below 10 for any of the included explanatory variables.

variables represent) exert a large influence on the probability of banking crises in individual countries. The fact that global credit growth also performs strongly in predicting future crises independent of the other credit variables (this is a ceteris paribus effect, after all) could be seen as further evidence supporting this interpretation.

The coefficients of the nominal GDP, inflation and interest rate variables also demonstrate some noteworthy differences with the domestic models. Interestingly, global growth tends to be inversely linked to some of the early pre-crisis stages which seems counterintuitive, but could perhaps suggest an indirect relationship with banking crisis propensities through other macro variables (e.g. credit, house prices); a simple eyeballing of the table reveals that episodes of negative growth seem to precede episodes of higher credit gaps and lower house prices, both of which can be easily linked to problems in the banking sector. Still, more research would be needed into these links before drawing any firm conclusions. Inflation loses its positive association with imminent banking crises in the global models, while interest rates are negatively associated to banking crises across all pre-crisis episodes, albeit in a gradually declining fashion.

Finally, domestic equity prices lose some of their associative power in particular in later pre-crisis banking crisis episodes, as these effects appear to be captured by global asset price changes. As regards house prices, the overall picture remains largely the same, if somewhat more pronounced than in the domestic models. Early pre-crisis boom periods tend to be associated with rising global asset prices, whereas rising house price growth characterises early pre-crisis stages. Falling house price growth tends to increase the probability of observing a banking crisis in the relatively short term, reinforcing the pattern observed in the descriptive charts. The negative ‘late’ pre-crisis effect of house price growth arguably adds some nuance to the results by Barrell et al. (2010) which demonstrate a consistent positive effect. The difference between these results provide an interesting insight as they could well be attributed to the fact that the present study uses quarterly data, allowing for a more detailed focus on the effects across different time horizons. The results do speak to some extent to those of Reinhart and Rogoff (2009) who find that asset prices strongly fall in the aftermath of a financial crisis. Still, it is interesting to see that global house prices appear to peak earlier than their domestic counterparts (while the reverse holds for the global versus the domestic credit gap), turning positive again as the recovery takes off.

In sum, it is fair to say that adding global macroeconomic and macro-financial variables to the analysis adds considerable perspective to the overall picture of macro trends and banking crises across different time horizons. Having said this, for most variables, doing so does not affect the observed relations between domestic variables and banking crises to the extent that leaving global variables out generates opposite coefficients. Indeed, those explanatory variables that have the largest marginal impact on the probability of observing a future crisis (i.e. the credit gaps) show a consistent result across episodes irrespective of the exact specification of these models. Still, the improvements of the global models over the domestic ones in terms of explained variance and predictive power are considerable, in particular when assessing episodes that lie closer to the onset of a banking crisis. This, together with the observation that the fit of the domestic variable gradually falls when moving closer to a crisis onset while global variable model fit does not, further reinforces the notion that global factors could play an important role in particular in the more immediate background of a banking crisis, perhaps in conjunction with weaknesses that have been building up beforehand domestically. Addressing this potentially interesting interplay stretches beyond the aim of the present paper, but it shows that a policy maker's decision on which model to select for the sake of early warning is a matter of the importance that one attributes to the parsimony versus the predictive power of a model.

<u>Robustness</u>

Even though this study can be seen as a robustness exercise in itself in terms of its analysis of the same selection of explanatory variables across different time horizons, an alternative specification (of the same model) merits a short discussion. As discussed earlier, Tables 5 and 6 apply fixed effects models. A well-known disadvantage of these models (as also discussed earlier in this paper) is the fact that they by construction exclude those countries in which there is no variation in the dependent variable, meaning that in this paper no countries are included which did not experience a banking crisis. For this reason, but also for the sake of completeness, a robustness check is conducted by specifying the domestic and the global models using a pooled logit estimation which includes both crisis and non-crisis countries (see Table 1 for a full list of banking crises). A look at the tables (see Appendix IIa and IIb) shows broadly the same results as the baseline models, in particular as regards the main explanatory variables (e.g. credit gap, house price growth, spatial dependence). Still, some noteworthy differences appear. For example, domestic credit growth exerts a positive significant effect in some of the episodes of the pooled domestic models, whereas the domestic credit gap loses some of its significance. Global credit growth exerts a positive and significant effect on banking crises across all future time horizons. Also, domestic nominal GDP growth appears to have weaker effects in these models. Comparing the global models, the most striking differences refer to domestic equity price growth, but the differences appear to be smaller than between the two domestic specifications.

Having said this, the overall model fit of the pooled models (especially the domestic models) is poorer than that of the baseline models, which could be interpreted as that yet other factors might play a role in determining whether a country avoids banking crises altogether (keeping them out of the fixed effects model). Such an enquiry, although interesting and potentially important, lies beyond the scope of this paper. Still, being aware of these differences between pooled and fixed effects models can be helpful in determining which variables to observe more closely, for example in the context of setting up an early warning system.

Concluding remarks

This paper compares and assesses the trends of various macroeconomic and macro-financial variables across different time horizons before, during, and directly following systemic banking crises. Analysing a large quarterly panel database containing data on 27 EU countries across three decades while taking account of both temporal and spatial correlation of banking crises (a novelty in this literature), the paper presents two main findings. First, banking crises have short-term spill-over effects between countries and tend to reoccur after longer periods of relative stability, warranting that temporal and spatial dependence should be incorporated in banking crisis models. Second, this study finds that the effects of particular economic or financial variables on the probability of observing a banking crisis at some time in the future depend crucially on the time horizon which one analyses. For some variables the effects only vary in terms of size, but other variables actually change sign over time, thus demonstrating different cyclical patterns over time. It can thus happen that two studies which use the same variables produce very different results (and thereby different policy recommendations) if they do not share an understanding of how early an early warning model should warn.

The results illustrate how important it is that researchers or policy makers carefully think about the behaviour of different (cyclical) macro-financial variables over time when specifying an early warning model. Drawing attention to the importance of finding a robust model will likely not only improve the quality of the specified model, but should also have positive knock-on effects for the predictive stage of early warning models.

In terms of future research, there are at least two issues which warrant further exploration. First, the effects attributed to the variables accounting for spatial and temporal dependence in this paper suggest that more work could be done in finding out how banking crises spill over between countries.[23] For starters, one could disentangle the global or spatial macro effects by weighing all spatial variables by, for example, the bilateral exposure of the domestic banking sector in each country in the sample. The effects of a crisis onset in for example Finland should have a larger impact on countries of which banks have large exposures to the Finnish banking sector. Other weighting schemes also could be used, based on factors such as trade openness or financial openness. Also in a broader sense, the interplay between domestic and global developments in macro-financial variables deserves a more careful analysis, in particular as these variables have demonstrated to possess different cyclical properties. Finally, a potentially interesting avenue of further research could be an application to models using micro data (the individual bank level) such as explored by recent work by Betz et al. (2012). Banking crises are after all first and foremost a micro phenomenon with macro implications. It is to be expected that much is to be gained in terms of researchers' and policy makers' understanding of these crises when micro and macro elements are combined in a single modelling strategy.

[23] Interesting work in this area, although with a different focus, has been undertaken by Dungey et al. (2010).

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Table 1. List of banking crises

	start	end	start	end	start	end
Austria	2008q4	ongoing				
Belgium	2008q3	ongoing				
Bulgaria	*1995q2*	*1997q4*				
Cyprus	*2012q2*	*ongoing*				
Czech Republic	*1998q1*	*2002q2*				
Denmark	1987q1	1993q4	2008q3	ongoing		
Estonia	*1992q4*	*1995q2*	*1998q2*	*1998q4*		
Finland	1991q3	1995q4				
France	1993q3	1995q4	2008q1	ongoing		
Germany	2008q1	2008q4				
Greece	2008q1	ongoing				
Hungary	*1992q1*	*1993q4*	*2008q3*	*ongoing*		
Ireland	2008q3	ongoing				
Italy	1994q1	1995q4				
Latvia	*1995q1*	*1995q4*	2008q4	2010q3		
Lithuania	*1995q1*	*1996q4*	2008q4	2010q4		
Luxembourg	2008q2	2008q4				
Malta	no crisis according to definition					
Netherlands	*1976q2*	*1978q2*	2008q3	ongoing		
Poland	*1991q1*	*1995q4*				
Portugal	2008q4	ongoing				
Romania	*1997q2*	*1999q1*				
Slovakia	*1994q1*	*1999q4*				
Slovenia	*1992q1*	*1994q4*	2008q1	ongoing		
Spain	*1978q1*	*1985q3*	2009q2	ongoing		
Sweden	1990q3	1993q4	2008q3	2010q4		
United Kingdom	*1973q4*	*1975q4*	1990q3	1994q2	2007q3	ongoing

Note: banking crises in *italics* are not included in the final sample due to data limitations on the side of the explanatory variables.

Table 2. Descriptive statistics

Variable	N	Mean	Std. Dev.	Min	Max
Domestic credit growth	1310	0.060	0.057	-0.110	0.423
Domestic credit-to-GDP gap	1310	0.060	0.123	-0.291	0.707
Domestic nominal GDP growth	1310	0.036	0.031	-0.051	0.223
Domestic inflation	1310	0.020	0.017	-0.035	0.135
Domestic interest rate	1310	1.569	0.580	0.095	2.941
Domestic equity price growth	1310	0.040	0.240	-0.927	0.641
Domestic house price growth	1310	0.040	0.079	-0.256	0.421
Global credit growth	1310	0.037	0.022	-0.008	0.099
Global credit-to-GDP gap	1310	0.000	0.031	-0.050	0.066
Global nominal GDP growth	1310	0.033	0.044	-0.091	0.175
Global equity price growth	1310	0.029	0.140	-0.410	0.291
Global house price growth	1310	0.009	0.047	-0.108	0.166

Note: these statistics reflect the sample size of the main models.

Table 3. Correlations

	COEU	TIME	TIME2	TIME3	DCG	DGAP	DGDP	DINF	DINT	DEQ	DHP	GCG	GGAP	GGDP	GEQ	GHP
Crisis onset in other EU country (COEU)	1.000															
Time since previous crisis (TIME)	-0.136	1.000														
Time squared (TIME2)	-0.115	0.955	1.000													
Time cubed (/1000) (TIME3)	-0.122	0.897	0.985	1.000												
Domestic credit growth (DCG)	-0.130	0.138	0.070	0.048	1.000											
Domestic credit-to-GDP gap (DGAP)	-0.056	-0.015	-0.052	-0.061	0.505	1.000										
Domestic nominal GDP growth (DGDP)	-0.219	0.188	0.097	0.058	0.486	0.197	1.000									
Domestic inflation (DINF)	-0.028	0.047	0.005	-0.015	0.197	0.177	0.407	1.000								
Domestic interest rate (DINT)	-0.232	0.121	0.111	0.109	0.185	0.017	0.363	0.171	1.000							
Domestic equity price growth (DEQ)	-0.109	0.089	0.078	0.073	0.056	-0.036	0.122	-0.009	0.022	1.000						
Domestic house price growth (DHP)	-0.199	0.146	0.097	0.082	0.329	0.089	0.432	0.110	0.139	0.200	1.000					
Global credit growth (GCG)	-0.299	0.327	0.247	0.218	0.344	0.040	0.454	0.192	0.343	0.074	0.218	1.000				
Global credit-to-GDP gap (GGAP)	0.299	-0.092	-0.073	-0.060	-0.016	0.129	-0.189	0.098	-0.170	-0.160	-0.092	-0.126	1.000			
Global nominal GDP growth (GGDP)	-0.041	0.114	0.088	0.079	0.045	0.006	0.142	0.044	0.147	0.032	0.099	0.226	0.055	1.000		
Global equity price growth (GEQ)	-0.138	0.053	0.040	0.035	-0.026	-0.043	0.009	0.027	-0.048	0.452	0.130	0.005	-0.167	0.079	1.000	
Global house price growth (GHP)	-0.566	0.228	0.165	0.149	0.216	0.033	0.298	0.020	0.150	0.169	0.238	0.600	-0.248	0.181	0.120	1.000

Table 4. Models predicting banking crises

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
	pooled models								fixed effects	
	onset	onset	onset	onset	onset	onset	crisis	crisis	crisis	crisis
Domestic credit growth	11.29	-0.38	10.27	-0.63	8.90	0.14	-11.86***	-9.38***	-42.57***	-34.25***
	(6.91)	(9.83)	(6.99)	(9.81)	(8.24)	(10.97)	(3.37)	(3.50)	(5.26)	(6.40)
Domestic credit-to-GDP gap	0.59	0.63	-0.37	0.58	2.32	2.67	-0.05	-2.07*	9.13***	3.29
	(2.21)	(3.53)	(2.21)	(3.50)	(3.20)	(4.41)	(0.96)	(1.15)	(1.91)	(2.24)
Domestic nominal GDP growth	-43.31***	-32.90*	-34.87***	-32.57*	-30.39**	-29.04	-27.54***	-19.67***	-23.88***	-8.00
	(12.99)	(17.83)	(12.20)	(17.86)	(15.18)	(18.62)	(4.78)	(5.07)	(7.20)	(8.34)
Domestic inflation	63.44***	48.19***	55.95***	48.13***	54.02***	55.18***	54.47***	38.45***	88.85***	79.42***
	(13.91)	(18.38)	(14.33)	(18.45)	(19.09)	(19.75)	(7.21)	(8.19)	(10.02)	(10.78)
Domestic interest rate	0.53	-1.16*	0.36	-1.09*	0.16	-1.10	-1.20***	-1.27***	-1.75***	-0.93**
	(0.35)	(0.66)	(0.41)	(0.64)	(0.54)	(0.77)	(0.21)	(0.34)	(0.27)	(0.42)
Domestic equity price growth	-0.10	1.17**	0.43	1.18**	0.84	1.80***	-0.80**	0.38	-2.12***	1.06
	(0.79)	(0.53)	(0.65)	(0.55)	(0.65)	(0.63)	(0.34)	(0.37)	(0.43)	(0.92)
Domestic house price growth	-1.94	-3.92	-2.59	-3.83	-8.02*	-6.75	-6.19***	-7.00***	-9.99***	-13.90***
	(2.78)	(3.40)	(2.77)	(3.38)	(4.24)	(4.16)	(1.58)	(1.66)	(2.66)	(3.04)
Global credit growth		97.79***		93.44***		72.21***		0.39		-38.09**
		(21.01)		(21.11)		(23.75)		(9.83)		(15.85)
Global credit-to-GDP gap		60.29***		53.10***		50.15***		16.28***		35.63***
		(9.75)		(16.31)		(16.52)		(4.33)		(5.80)
Global nominal GDP growth		1.21		-0.67		-5.77		6.47***		2.58
		(5.21)		(5.98)		(6.88)		(2.19)		(2.73)
Global equity price growth		-1.40		-1.26		-2.10		-3.41***		-4.98***
		(2.11)		(2.08)		(2.13)		(0.84)		(1.40)
Global house price growth		-27.66***		-22.71***		-19.74**		-19.28***		-9.95*
		(7.55)		(8.47)		(9.69)		(5.49)		(5.65)
Crisis onset in other EU country			2.06***	0.74	1.66**	0.39	1.66***	0.56**	2.27***	0.74**
			(0.71)	(1.21)	(0.74)	(1.29)	(0.19)	(0.27)	(0.25)	(0.34)
Time since previous crisis					0.84**	0.74*				
					(0.33)	(0.44)				
Time squared					-0.01**	-0.01				
					(0.00)	(0.01)				
Time cubed (/1000)					0.03**	0.03				
					(0.01)	(0.02)				
Intercept	-5.77***	-7.68***	-6.73***	-7.79***	-28.18***	-27.19**	-0.16	0.06	0.66	0.48
	(0.76)	(1.04)	(0.81)	(1.04)	(9.07)	(11.63)	(0.24)	(0.27)	(0.52)	(0.53)
Observations	1,176	1,176	1,176	1,176	1,176	1,176	1,436	1,436	1,310	1,310
Pseudo R-Squared	0.170	0.364	0.233	0.366	0.377	0.447	0.352	0.425	0.535	0.613
AUROC	0.825	0.945	0.888	0.946	0.927	0.957	0.852	0.863	0.888	0.892

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

Table 5. Shifting horizons: domestic variable models

	D1	D2	D3	D4	D5	D6	D7	D8
			Pre-crisis			Crisis		Post-crisis
	14 to 6q	12 to 4q	10 to 2q	last 8q	last 4q	first 4q	first 8q	first 8q
Domestic credit growth	4.09	0.30	1.18	-0.47	4.08	1.70	-9.34**	-3.46
	(3.30)	(3.14)	(3.11)	(2.99)	(3.42)	(5.48)	(4.35)	(4.46)
Domestic credit-to-GDP gap	4.69***	7.11***	7.76***	7.41***	4.97***	3.47*	7.89***	-18.22***
	(1.74)	(1.85)	(1.83)	(1.61)	(1.67)	(1.90)	(1.87)	(3.01)
Domestic nominal GDP growth	3.27	12.68**	17.22***	18.23***	12.30*	-26.73***	-30.69***	8.23
	(6.28)	(6.44)	(6.41)	(5.85)	(6.33)	(8.27)	(6.59)	(10.63)
Domestic inflation	7.32	3.93	-2.95	1.25	13.88*	35.39***	37.15***	-4.59
	(8.42)	(7.87)	(7.23)	(6.76)	(7.97)	(10.21)	(9.17)	(11.86)
Domestic interest rate	-0.76***	-0.00	0.65***	1.00***	0.81***	0.81***	-0.20	-0.52
	(0.22)	(0.24)	(0.24)	(0.23)	(0.31)	(0.24)	(0.23)	(0.32)
Domestic equity price growth	2.02***	1.84***	1.72***	1.02***	0.73	-3.51***	-1.65***	-0.29
	(0.44)	(0.40)	(0.36)	(0.36)	(0.48)	(0.64)	(0.47)	(0.66)
Domestic house price growth	12.76***	9.46***	4.19***	0.38	-2.20	-0.09	-4.78**	-10.21***
	(1.96)	(2.12)	(1.59)	(1.26)	(1.48)	(2.35)	(2.30)	(2.84)
Crisis onset in other EU country	-1.86***	-1.92***	-1.19***	-0.28	1.02***	2.25***	2.83***	0.45
	(0.36)	(0.30)	(0.27)	(0.23)	(0.31)	(0.45)	(0.35)	(0.32)
Intercept	-2.11***	-3.06***	-3.99***	-4.61***	-5.90***	-6.41***	-3.49***	-1.85***
	(0.51)	(0.50)	(0.51)	(0.51)	(0.69)	(0.68)	(0.57)	(0.57)
Observations	1,310	1,310	1,310	1,310	1,310	1,310	1,310	855
Pseudo R-Squared	0.258	0.253	0.217	0.176	0.171	0.363	0.439	0.314
AUROC	0.851	0.819	0.788	0.750	0.785	0.802	0.856	0.801

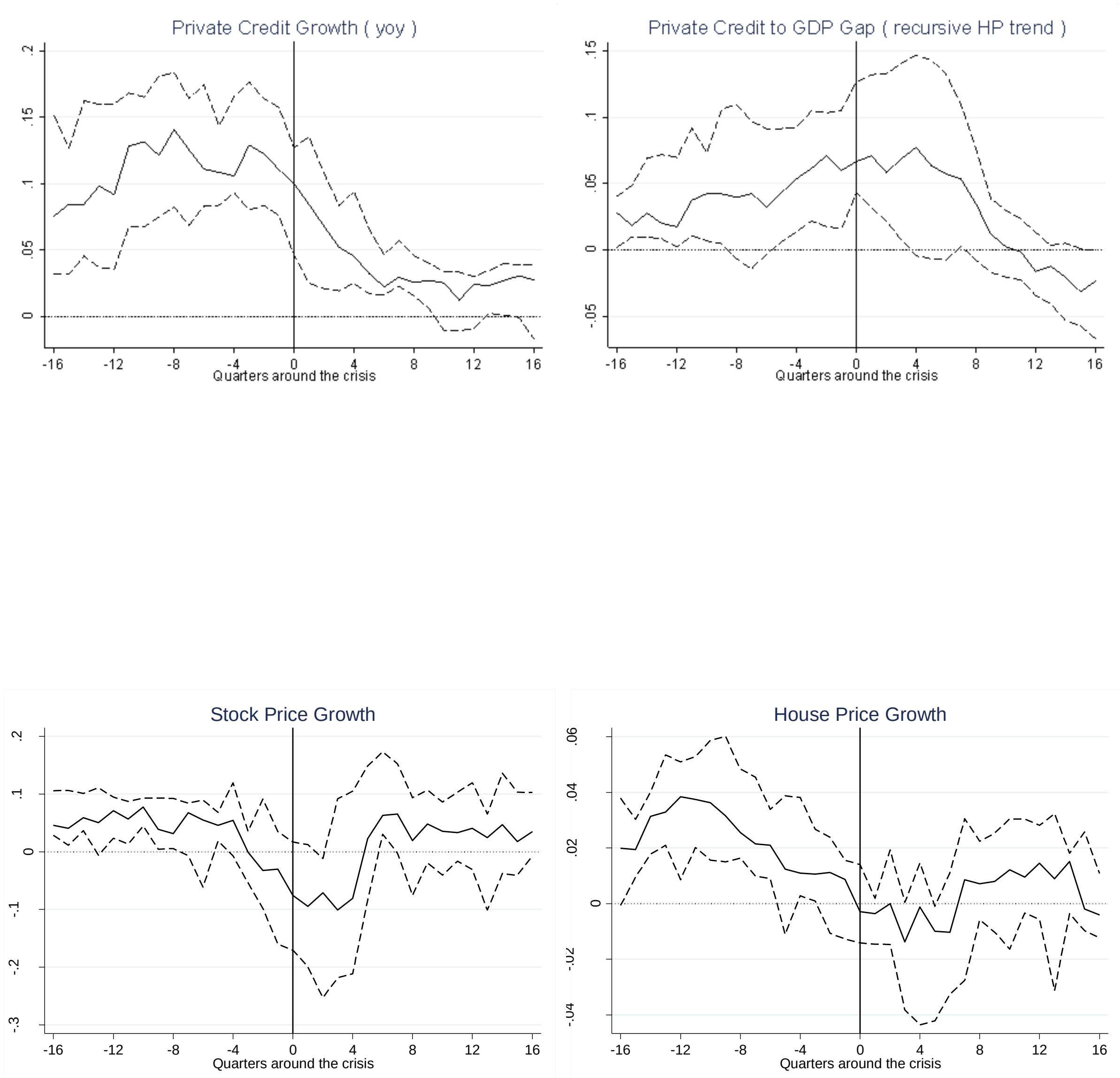
Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

Table 6. Shifting horizons: domestic and global variable models

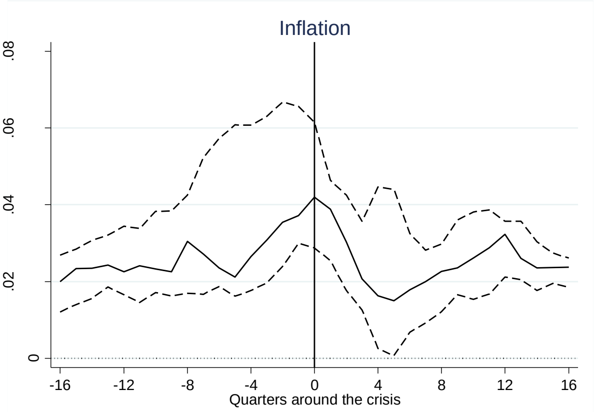
	G1	G2	G3	G4	G5	G6	G7	G8
			Pre-crisis			Crisis		Post-crisis
	14 to 6q	12 to 4q	10 to 2q	last 8q	last 4q	first 4q	first 8q	first 8q
Domestic credit growth	-7.46	-12.69***	-7.90*	-10.80***	-2.65	-2.95	-9.73*	2.45
	(4.62)	(4.28)	(4.13)	(3.68)	(4.29)	(6.72)	(5.37)	(4.82)
Domestic credit-to-GDP gap	8.24***	10.98***	10.67***	10.01***	3.77	2.21	3.98*	-19.77***
	(2.17)	(2.29)	(1.99)	(1.85)	(2.35)	(2.73)	(2.16)	(4.52)
Domestic nominal GDP growth	17.70*	19.87**	20.60**	26.66***	16.34**	-29.22***	-12.69	11.57
	(9.03)	(8.21)	(8.55)	(8.68)	(7.78)	(10.98)	(7.97)	(10.33)
Domestic inflation	19.04	5.08	-12.09	-19.50**	-15.20	32.36***	22.66**	3.71
	(11.96)	(10.65)	(9.53)	(9.21)	(10.72)	(11.51)	(9.26)	(12.80)
Domestic interest rate	-5.77***	-3.88***	-2.58***	-1.95***	-1.39**	0.25	0.40	1.31**
	(1.04)	(0.82)	(0.61)	(0.50)	(0.57)	(0.41)	(0.35)	(0.51)
Domestic equity price growth	-0.88	-2.00**	-1.51*	-1.07	-0.67	0.04	1.49*	-0.46
	(0.79)	(0.79)	(0.79)	(0.87)	(1.00)	(1.03)	(0.83)	(1.05)
Domestic house price growth	13.86***	12.42***	4.96**	-2.04	-6.17***	-0.86	-9.71***	-10.02***
	(2.61)	(3.17)	(2.53)	(2.07)	(2.34)	(2.69)	(2.82)	(2.93)
Global credit growth	116.70***	138.62***	152.40***	164.98***	143.45***	42.96**	-16.97	-91.50***
	(16.57)	(16.45)	(15.78)	(15.75)	(17.81)	(20.58)	(15.77)	(17.93)
Global credit-to-GDP gap	-16.67**	15.42**	41.51***	54.18***	51.16***	37.15***	50.48***	4.37
	(6.80)	(6.18)	(6.86)	(6.19)	(6.82)	(10.75)	(6.29)	(6.66)
Global nominal GDP growth	-0.05	-9.51***	-7.60**	3.80	4.41	-0.57	3.31	-0.32
	(3.52)	(3.68)	(3.82)	(3.41)	(4.00)	(3.57)	(2.85)	(3.79)
Global equity price growth	3.79***	7.27***	9.03***	7.56***	6.81***	-4.78***	-4.52***	0.09
	(1.46)	(1.56)	(1.58)	(1.57)	(1.81)	(1.54)	(1.33)	(1.75)
Global house price growth	18.43**	-12.33**	-30.62***	-36.20***	-24.59***	-7.17	1.32	21.20***
	(7.44)	(6.27)	(5.85)	(4.86)	(4.57)	(6.96)	(4.80)	(7.62)
Crisis onset in other EU country	0.45	-0.50	-1.11*	-0.64	1.44***	1.08	1.46***	-0.09
	(0.33)	(0.49)	(0.60)	(0.50)	(0.47)	(0.85)	(0.45)	(0.36)
Intercept	-1.51**	-3.11***	-5.33***	-7.39***	-9.44***	-6.65***	-3.85***	-2.64***
	(0.60)	(0.61)	(0.63)	(0.74)	(0.98)	(0.78)	(0.54)	(0.64)
Observations	1,310	1,310	1,310	1,310	1,310	1,310	1,310	855
Pseudo R-Squared	0.458	0.454	0.487	0.508	0.438	0.447	0.544	0.368
AUROC	0.934	0.917	0.928	0.938	0.940	0.820	0.853	0.818

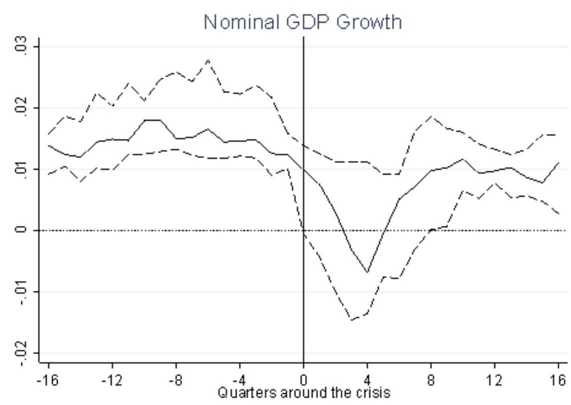
Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

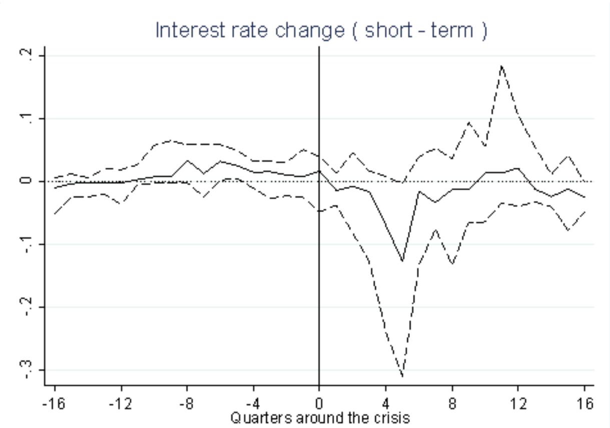
Figure 1. Descriptive charts[24]



[24] The figure depicts the development of selected key variables around banking crises within the sample countries. The start date of a banking crisis is indicated by the vertical line, while the solid line shows the development in the median country and the dashed lines represent the countries at the 25th and the 75th percentile, respectively.

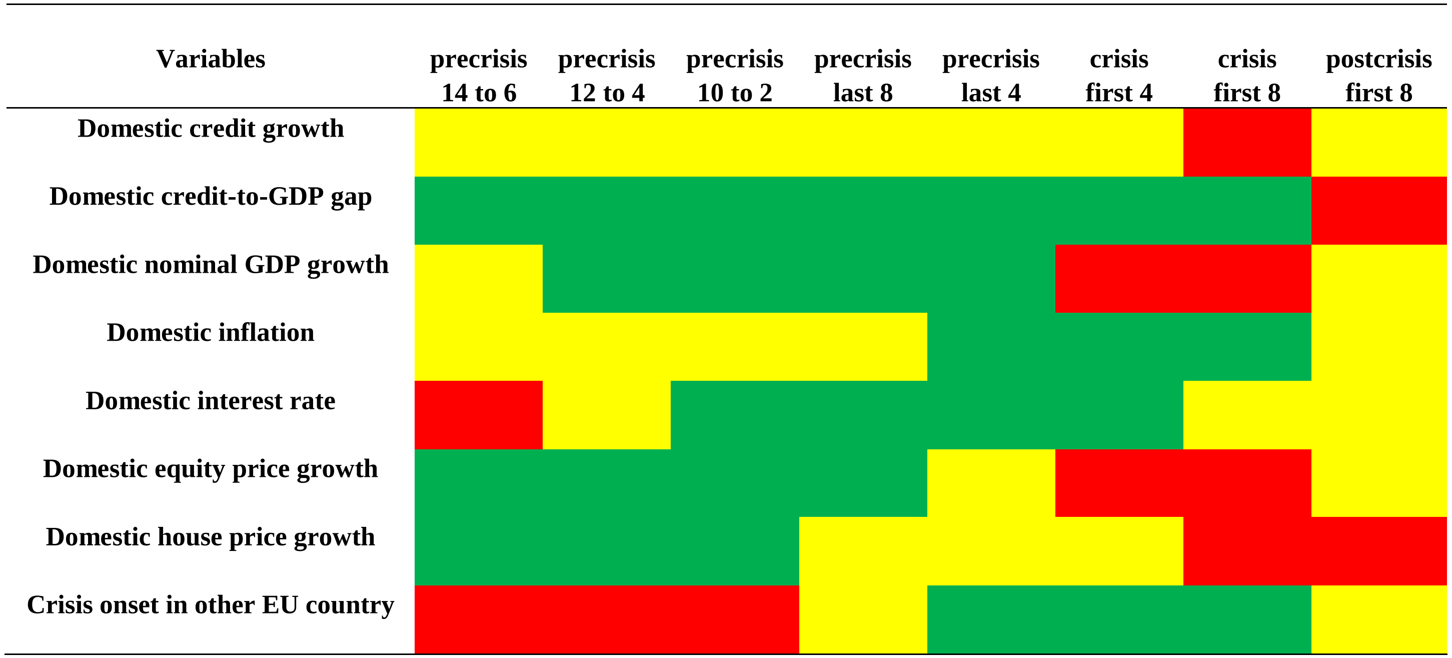

Inflation
0
.02
.04
.06
.08
-16
-12
-8
-4
0
4
8
12
16
Quarters around the crisis


Nominal GDP Growth
-.02
-.01
0
.01
.02
.03
-16
-12
-8
-4
0
4
8
12
16
Quarters around the crisis


Interest rate change (short - term)
-.3
-.2
-.1
0
.1
.2
-16
-12
-8
-4
0
4
8
12
16
Quarters around the crisis

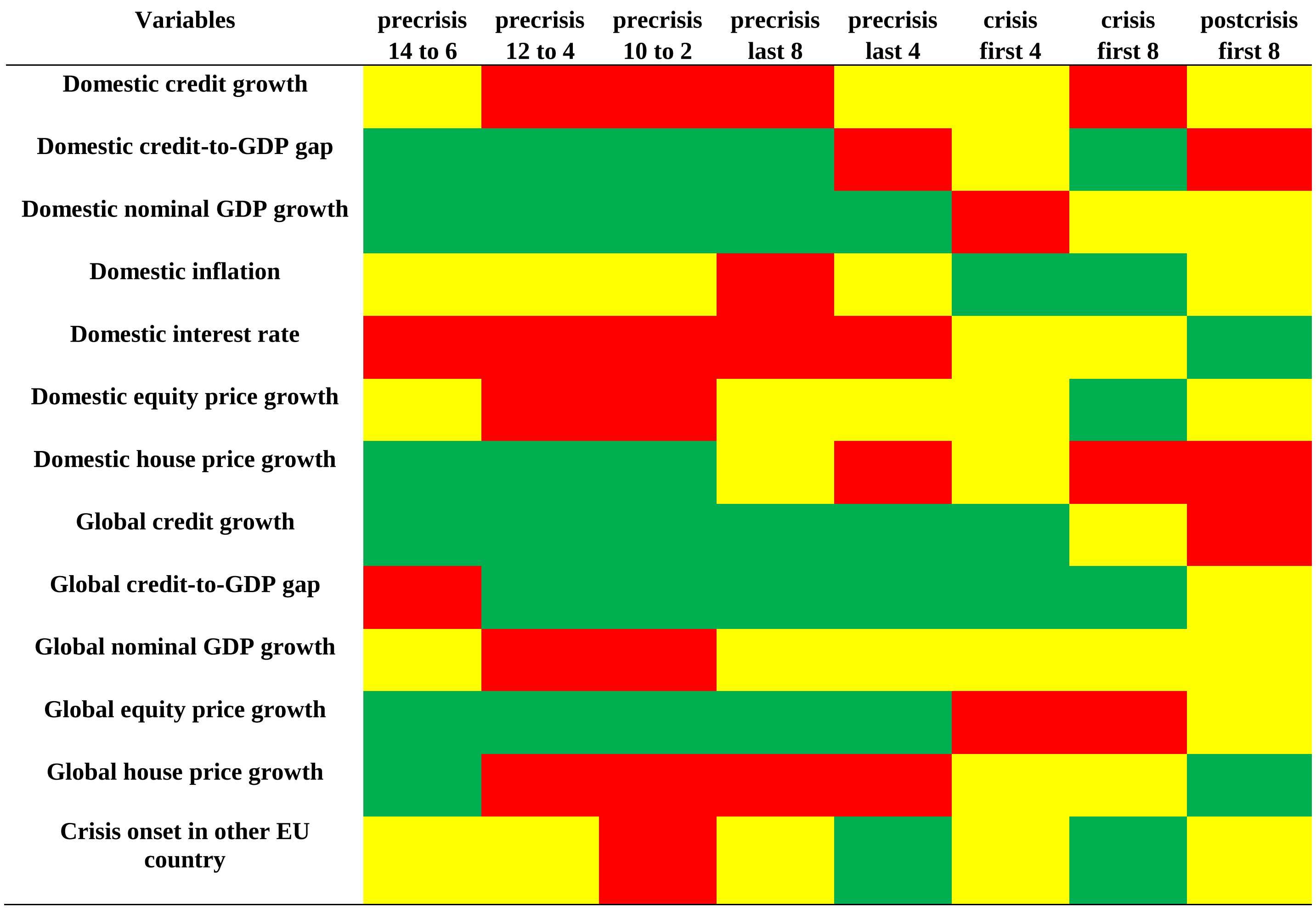
Appendix I: Reference heat maps[25]

A: Domestic variables model



[25] These heat maps serve to get a quick overview of the macroeconomic and macro-financial trends across different episodes before, during, and directly following a systemic banking crisis. A green colour corresponds to a significant positive effect on the probability of being in a particular time period (depicted by the columns) vis-à-vis a banking crisis, while a red colour implies a negative significant effect on the same probability. All effects (coefficients) which are not significant at the $p<0.05$ threshold are depicted by a yellow colour scheme.

B: Global variables model



Appendix IIa: Robustness: Pooled logit models (domestic)

	D1	D2	D3	D4	D5	D6	D7	D8
			Pre-crisis			Crisis		Post-crisis
	14 to 6q	12 to 4q	10 to 2q	last 8q	last 4q	first 4q	first 8q	first 8q
Domestic credit growth	3.99*	2.03	2.83	3.96*	8.25***	7.68**	-1.38	-10.40*
	(2.32)	(2.13)	(2.09)	(2.03)	(2.40)	(3.63)	(3.76)	(5.51)
Domestic credit-to-GDP gap	0.62	1.66*	1.73**	1.48**	0.22	0.22	2.67***	-9.54***
	(0.96)	(0.88)	(0.78)	(0.71)	(0.93)	(1.15)	(0.95)	(2.04)
Domestic nominal GDP growth	-8.00*	-0.15	6.36	6.15	1.30	-24.68***	-23.27***	13.30*
	(4.46)	(4.51)	(4.74)	(3.77)	(4.52)	(5.44)	(4.63)	(7.05)
Domestic inflation	4.95	2.21	-3.26	2.30	8.63	35.63***	32.83***	-13.56**
	(6.94)	(6.45)	(6.03)	(5.87)	(6.97)	(7.44)	(7.14)	(6.55)
Domestic interest rate	-0.15	0.37**	0.73***	0.79***	0.71***	0.29	-0.42**	-0.57**
	(0.19)	(0.19)	(0.19)	(0.18)	(0.25)	(0.20)	(0.19)	(0.29)
Domestic equity price growth	0.23	0.14	0.15	0.01	0.07	-0.69**	-0.44	0.21
	(0.20)	(0.19)	(0.17)	(0.16)	(0.21)	(0.34)	(0.33)	(0.35)
Domestic house price growth	6.96***	6.08***	3.81***	1.68	-0.83	-2.16	-5.70***	-4.40
	(1.29)	(1.34)	(1.22)	(1.14)	(1.36)	(1.65)	(1.66)	(2.79)
Crisis onset in other EU country	-2.02***	-2.04***	-1.24***	-0.32	0.85***	2.35***	2.65***	0.86***
	(0.32)	(0.28)	(0.22)	(0.20)	(0.28)	(0.43)	(0.30)	(0.26)
Intercept	-2.19***	-3.06***	-3.81***	-4.18***	-5.42***	-5.47***	-3.31***	-1.85***
	(0.31)	(0.31)	(0.31)	(0.29)	(0.39)	(0.43)	(0.33)	(0.35)
Observations	1,436	1,436	1,436	1,436	1,436	1,436	1,436	1,436
Pseudo R-Squared	0.164	0.168	0.135	0.0982	0.110	0.260	0.344	0.209
AUROC	0.808	0.790	0.767	0.719	0.763	0.788	0.838	0.743

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

Appendix IIb: Robustness: Pooled logit models (global)

	G1	G2	G3	G4	G5	G6	G7	G8
			Pre-crisis			Crisis		Post-crisis
	14 to 6q	12 to 4q	10 to 2q	last 8q	last 4q	first 4q	first 8q	first 8q
Domestic credit growth	-1.29	-3.63	-2.96	-3.77	1.31	-2.26	-8.60**	-7.68
	(2.47)	(2.51)	(2.87)	(3.00)	(3.69)	(4.12)	(3.64)	(5.84)
Domestic credit-to-GDP gap	1.95*	3.02***	3.34***	3.52***	1.55	1.03	1.65	-8.84***
	(1.07)	(1.05)	(1.10)	(1.17)	(1.60)	(1.53)	(1.19)	(2.17)
Domestic nominal GDP growth	-13.69**	-5.36	3.92	8.25	5.22	-22.90***	-8.74	15.34**
	(5.51)	(6.03)	(6.50)	(5.65)	(6.19)	(7.61)	(5.48)	(6.83)
Domestic inflation	23.31***	9.39	-5.02	-7.27	-7.17	30.75***	18.54**	-14.62*
	(8.76)	(8.29)	(8.13)	(7.45)	(8.98)	(8.53)	(7.59)	(7.98)
Domestic interest rate	-3.71***	-2.69***	-1.97***	-1.70***	-1.36***	-0.40	-0.65**	0.29
	(0.68)	(0.66)	(0.50)	(0.41)	(0.46)	(0.39)	(0.32)	(0.35)
Domestic equity price growth	-1.44***	-1.73***	-1.50***	-1.31***	-1.14***	1.05***	0.78**	0.27
	(0.33)	(0.29)	(0.25)	(0.27)	(0.33)	(0.33)	(0.34)	(0.40)
Domestic house price growth	7.18***	5.88***	2.76*	-0.08	-3.27	-1.17	-6.32***	-3.04
	(1.44)	(1.68)	(1.59)	(1.59)	(2.08)	(1.75)	(1.68)	(2.78)
Global credit growth	84.92***	109.69***	127.76***	138.27***	128.78***	47.01***	16.54	-44.76***
	(13.56)	(13.94)	(13.80)	(13.02)	(15.03)	(15.95)	(12.09)	(11.95)
Global credit-to-GDP gap	-12.39**	15.55***	37.24***	51.34***	51.38***	35.62***	39.38***	-3.94
	(5.28)	(4.76)	(5.19)	(5.35)	(6.68)	(11.69)	(6.91)	(4.26)
Global nominal GDP growth	-2.54	-8.47***	-6.78*	4.16	6.02*	-0.46	3.28	-2.90
	(2.95)	(3.26)	(3.51)	(3.06)	(3.52)	(3.31)	(2.66)	(3.33)
Global equity price growth	4.56***	6.98***	8.66***	7.17***	7.10***	-5.70***	-3.50***	-0.35
	(1.22)	(1.14)	(1.16)	(1.02)	(1.36)	(1.05)	(0.92)	(1.19)
Global house price growth	19.36***	-7.02	-24.07***	-31.63***	-25.03***	-9.78	-8.39*	1.41
	(6.07)	(5.37)	(4.87)	(4.19)	(4.55)	(6.30)	(4.74)	(4.67)
Crisis onset in other EU country	-0.33	-0.88**	-0.99**	-0.72*	1.07**	1.15	1.48***	0.43
	(0.39)	(0.41)	(0.45)	(0.40)	(0.45)	(0.88)	(0.49)	(0.29)
Intercept	-1.85***	-3.23***	-5.01***	-6.38***	-8.52***	-5.69***	-3.36***	-1.81***
	(0.39)	(0.45)	(0.42)	(0.46)	(0.63)	(0.43)	(0.30)	(0.35)
Observations	1,436	1,436	1,436	1,436	1,436	1,436	1,436	1,436
Pseudo R-Squared	0.368	0.362	0.389	0.406	0.370	0.399	0.449	0.241
AUROC	0.909	0.903	0.915	0.923	0.925	0.805	0.843	0.750

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.