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Thibaut Duprey[1] and Benjamin Klaus[2]

[1] Financial Stability Department
Bank of Canada
Ottawa, Ontario, Canada K1A 0G9
tduprey@bankofcanada.ca

[2] Macro-Prudential Policy and Financial Stability Directorate
European Central Bank
benjamin.klaus@ecb.europa.eu

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Abstract

This paper predicts phases of the financial cycle by using a continuous financial stress measure in a Markov switching framework. The debt service ratio and property market variables signal a transition to a high financial stress regime, while economic sentiment indicators provide signals for a transition to a tranquil state. Whereas the in-sample analysis suggests that these indicators can provide an early warning signal up to several quarters prior to the respective regime change, the out-of-sample findings indicate that most of this performance is owing to the data gathered during the global financial crisis. Comparing the prediction performance with a standard binary early warning model reveals that the Markov switching model is outperforming the vast majority of model specifications for a horizon up to three quarters prior to the onset of financial stress.

Bank topics: Business fluctuations and cycles; Central bank research; Econometric and statistical methods; Financial markets; Financial stability; Financial system regulation and policies; Monetary and financial indicators
JEL codes: C54, G01, G15

Résumé

Cette étude vise à prévoir les phases des cycles financiers grâce à une mesure de l'intensité des tensions financières intégrée dans un modèle de Markov avec changement de régime. Le ratio du service de la dette et les variables liées au marché de l'immobilier annoncent une transition vers un régime caractérisé par de fortes tensions financières. À l'inverse, les indicateurs mesurant la confiance des agents économiques annoncent la fin de la période de stress élevé. L'analyse des résultats sur échantillon montre que ces indicateurs peuvent offrir un signal précoce plusieurs trimestres avant que ne se produise le changement de régime considéré. Les résultats hors échantillon montrent, en revanche, que la performance des indicateurs repose pour l'essentiel sur les données constituées pendant la crise financière mondiale. La comparaison de la qualité des prédictions du modèle avec celles d'un modèle d'alerte précoce binaire standard révèle que le modèle de Markov à changement de régime surclasse la grande majorité des spécifications dans le cas d'un horizon pouvant atteindre trois trimestres avant le début des tensions financières.

Sujets : Cycles et fluctuations économiques; Recherches menées par les banques centrales; Méthodes économétriques et statistiques; Marchés financiers; Stabilité financière; Réglementation et politiques relatives au système financier; Indicateurs monétaires et financiers
Codes JEL : C54, G01, G15

Non-Technical Summary

The global financial crisis had severe implications for the real economy. For the US alone, Luttrell et al. (2013) estimate output losses in the range of 6 to 14 trillion USD. It is hence not surprising that policy makers are keen to develop models that can issue warning signals ideally sufficiently early to implement policies that increase the resilience of financial institutions and ultimately mitigate at least some of the risks and costs associated with financial crises. Two types of methods can broadly be distinguished: (i) Markov switching (MS) models have been used extensively to identify business cycle turning points and (ii) discrete choice models have been used to understand the drivers of currency, banking and financial crises.

This paper combines two strands of literature by applying an MS model to identify the drivers of financial market stress for a sample of 15 EU countries. The paper investigates to what extent a set of candidate leading indicators affects the probability of entering and exiting a high-financial-stress regime, and analyzes how early a leading indicator can issue a signal and whether the indicator would have provided a valid signal prior to the global financial crisis. In addition, the paper evaluates the informational gains in terms of signal timing and quality for the prediction of high-financial-stress episodes, compared with the signals issued by a binary logit model.

The in-sample results indicate that the debt service ratio, the property price-to-rent ratio and the annual property price growth significantly affect the probability of entering a high-financial-stress regime, whereas the credit-to-gross-domestic-product (GDP) gap and the economic confidence indicator drive the likelihood of exiting a high-financial-stress episode. Of those indicators, the debt service ratio predicts the switch to the high-financial-stress regime up to six quarters ahead, while the property price-to-rent ratio is able to issue such a signal up to 12 quarters ahead. Regarding the return to low financial market stress, the credit-to-GDP gap can issue a signal up to nine quarters ahead, while the economic sentiment indicator can provide such a signal up to two months ahead.

The results from an out-of-sample exercise reveal that the estimated coefficients for most of the identified leading indicators become significant only over the course of the global financial crisis. This finding suggests that most of the predictive in-sample performance of those indicators is owing to the data obtained during the global financial crisis, which is consistent with the results of Gadea-Rivas and Perez-Quiros (2015).

Finally, the MS model is outperforming a binary early warning model in the vast majority of model specifications for a horizon up to three quarters prior to the onset of financial stress. The results also suggest that the early warning indicators in the transition function of the MS model statistically improve the prediction power relative to an MS model that excludes all explanatory variables from the transition function.

1 Introduction

Markov switching (MS) models have been used extensively in the business cycle literature to identify turning points and to ultimately date recessions. Because of the lack of appropriate continuous measures, discrete choice models, in particular binary logit or probit models, have been applied in the literature on currency, banking and financial crises with the aim of understanding the drivers of those particular crises events. Policy makers are keen to use these two methods to extract warning signals ideally sufficiently early to increase the resilience of financial institutions and therefore mitigate some of the risks and costs associated with financial crises.

This paper combines both strands of literature by applying an MS model to identify the drivers of financial market stress for a sample of 15 EU countries. We investigate to what extent a set of candidate leading indicators affects the probability of entering and exiting a high-financial-stress regime. But then, a good predictor should both provide a signal sufficiently early, and have good out-of-sample properties. We analyze how early a leading indicator can issue a signal and whether the indicator would have provided a signal prior to the global financial crisis. In addition, the paper evaluates the informational gains in terms of signal timing and quality for the prediction of high-financial-stress episodes, compared with the signals issued by a simple binary logit model.

This paper assesses the usefulness of a continuous measure of financial stress, namely the Country-Level Index of Financial Stress (CLIFS) metric defined by Duprey et al. (2017), as a tool for the prediction of different regimes in the financial cycle.[1] Only recently have MS models been put forward in the literature on measuring financial market stress, linking it to different macroeconomic regimes. For example, Hollo et al. (2012) test the ability of a fixed transition probability MS model to fit the peaks of the euro area financial stress index, while Duprey et al. (2017) use a similar MS model to identify periods of financial market turmoil for each EU country. In the context of an MS-vector autoregressive (VAR) model, Hartmann et al. (2013) or Hubrich and Tetlow, 2015 show that high financial stress is particularly detrimental to the real economy and reduces the effectiveness of conventional monetary policy. The present paper complements this work by looking at the ability of the MS framework to identify leading indicators of financial market stress.

Two main aspects motivate the use of MS models for analyzing episodes of low and high financial stress. First, one does not need to define a binary indicator to identify periods as “tranquil” or “turbulent,” which is usually subject to expert judgment and may lead to a possible misclassification of financial stress episodes. Second, the MS model allows for a non-symmetric analysis of financial cycle turning points by modeling

[1] While there is no consensus on the definition of the financial cycle, Borio (2014) characterizes it as “self-reinforcing interactions between perceptions of value and risk, attitudes toward risk and financing constraints, which translate into booms followed by busts”.

separately the entry and the exit from periods of financial stress. Thus, the MS model can provide information about the time-varying probability of entering versus exiting an endogenously determined regime of financial stress.

When using the information available from the entire sample at the quarterly frequency, we find that indicators explaining the probability of *entering* a regime of high financial stress are mainly credit and residential property market variables. Those are the credit-to-GDP gap, the debt service-to-income ratio (DSR), the annual property price growth and the property price gap, as well as the property price-to-rent and the price-to-income ratio. At the monthly frequency, the annual growth rate of loans to households for house purchases, the economic confidence indicator, mortgage rates and banks' leverage ratios contribute significantly to the probability of entering a high-financial-stress regime. Only a few indicators help to predict the *exit* from a high-financial-stress regime. Those are the credit-to-GDP gap when using quarterly data and the economic sentiment indicator when using monthly data.

Can these indicators provide a warning signal sufficiently early? Based on an in-sample analysis, we find that the DSR predicts the switch to the high-financial-stress regime up to six quarters ahead, while the property price-to-rent ratio is able to issue such a signal up to 12 quarters ahead. The dynamics of residential property prices appear particularly valuable regarding their early warning properties. While positive property price growth is associated with financial stress occurring over a medium-term horizon (i.e., between seven and 12 quarters), negative growth rates, in particular in combination with a still-positive property price gap, indicate that financial stress is likely to occur within a rather short time (i.e., within the next three quarters). The economic sentiment indicator issues a warning signal for the occurrence of high financial stress up to two months ahead. Regarding the return to tranquil financial market conditions, the credit-to-GDP gap issues a signal up to nine quarters ahead, while the economic sentiment indicator provides such a signal up to two months ahead.

How useful would those indicators have been prior to the global financial crisis? The previous results are obtained when all information available to date is used for estimating the models and predicting the regime changes. We also perform an out-of-sample exercise to investigate the extent to which the identified leading indicators would have provided an early warning signal ex-ante, i.e., prior to the global financial crisis. The recursively estimated coefficient of the DSR becomes statistically significant only from 2008Q3 onwards, while those for the property price-to-rent ratio and the annual property price growth become significant only in 2007Q2 and 2008Q2, respectively. The ultimate conclusion from this finding is that most of the predictive in-sample performance of those indicators is owing to the data obtained during the global financial crisis. The credit-to-GDP gap would not have been a significant contributor to the probability of entering a high-financial-stress regime throughout the entire out-of-sample period, which is in line with the findings of Gadea-Rivas and Perez-Quiros (2015). However, the peaks in the fitted probabilities of high financial stress at the start of each financial stress event are consistent over time and seem robust to the addition of new data.

Finally, what is the value added compared with standard early-warning models? We compare the signalling ability for elevated financial market stress of the MS model with the traditional early warning model relying on a binary dependent variable. In terms of the in-sample prediction performance as measured by the area under the receiver operating characteristic curve (AUROC), the MS model with a regime-dependent mean significantly outperforms the logit model up to two quarters prior to the high-financial-stress episode. This is not surprising, as the MS model makes use of the intensity of observed financial stress together with the information from the leading indicators. Between three and 12 quarters prior to the onset of financial market stress, the predictive abilities of both models are statistically indistinguishable. Indeed, for lower levels of financial stress, the MS uses mostly the information from the leading indicators, just like the logit model, although the latter mixes the dynamics of entry into/exit from financial stress. Several robustness tests are carried out. In particular, we compare the in-sample prediction performance of the MS model and the logit model for different MS model specifications and different definitions of high-financial-stress periods. Out of the resulting 120 different specifications, the MS model is outperforming the logit model in 70% of the cases for a horizon up to three quarters prior to the financial stress, while the logit model outperforms the MS model in only 20% of the cases for a six-quarter horizon. Regarding the out-of-sample exercise, with recursively estimated coefficients, the MS model with a regime-dependent mean has a significantly higher AUROC than the logit model up to only one quarter prior to the occurrence of the high-financial-stress episode, while at all other horizons the predictive capabilities of both models are not statistically different. At almost all horizons, the early warning indicators in the transition function of the MS model statistically improve the prediction power relative to the MS model that excludes those explanatory variables.

The paper most closely related to this one is Abiad (2007), which evaluates the signalling ability of MS models for the case of the Asian crises and compares it with the results from standard binary early warning models. Our contribution to the literature is to compare the predictive power of both approaches on the basis of particular statistical measures. While Abiad (2007) analyzes currency crises, the focus of this paper is on periods of low and high financial market stress. Our paper is also related to Gadea-Rivas and Perez-Quiros (2015), which analyzes the role of credit in predicting the Great Recession. The authors find that credit did not significantly improve forecasts of business cycle turning points, as the strong relation between credit and GDP growth was driven by the Great Recession itself and hence the information could not have been exploited ex-ante. Our results confirm their findings as we show that the effect of the credit-to-GDP gap on the probability of switching to a high-financial-stress regime was not statistically significant prior to the global financial crisis. Whereas Gadea-Rivas and Perez-Quiros (2015) investigate the impact of credit on business cycle turning points, we study the informational content of a set of candidate leading indicators for predicting both the entry into and the exit from episodes of elevated financial market stress.

The remainder of the paper is structured as follows. Section 2 discusses the limitations of traditional early warning models and presents the model specification as well as the estimation strategy of the MS model. Section 3 provides the MS model results for the probabilities of entering and exiting periods of high financial market stress. Section 4 discusses the ability of the identified predictors to send signals sufficiently early to be relevant for policy makers, while section 5 tests if those indicators would have been useful prior to the great financial crisis. Section 6 compares the results from the MS model with those from a binary logit model. Section 7 concludes.

2 A Markov switching framework for the analysis of financial stress phases

2.1 Limitations of traditional early warning models

Traditional early warning models applied in the literature on currency, banking and financial crises can be classified into three categories: (i) the signalling approach, in which the candidate leading indicator is used as an input without further transformation (Kaminsky et al. (1998)), (ii) the discrete choice approach, which transforms the variable into crises probabilities using a logit or probit model (Bussière and Fratzscher (2006)), and (iii) so-called "decision trees," which are based on numerical algorithms that allocate a set of variables with larger discriminatory power in a decision tree format (Frankel and Wei (2004)). While the signalling approach is used mainly in a univariate setting, i.e., analyzing one indicator at a time, the discrete choice approach and decision trees allow different variables to be included in the same model.

The advantage of the discrete choice model lies in its simplicity and its flexibility. First, it can be estimated with standard methods and it requires the identification of only a limited set of parameters. Second, the use of a binary dependent variable provides some degree of freedom about the definition of crises versus tranquil regimes. For example, predicting "vulnerable" periods before the actual occurrence of a crisis may be more suited when designing early warning models for policy use. There is typically a trade-off between the strength of a signal and its value for policy makers. Early signals tend to be noisier (i.e., they are associated with a higher rate of false alarms), but would at the same time allow for an earlier implementation of policy tools.[2] Third, additional statistical methods

[2]For example, when activating the countercyclical capital buffer (CCyB), which aims to increase the resilience of banks and potentially leaning against the build-up phase of the credit cycle, a jurisdiction

help to select the most relevant explanatory variables from a larger set of candidate regressors. Holopainen and Sarlin (2015) use the least absolute shrinkage and selection operator, while Babecky et al. (2014) apply Bayesian model averaging.

However, the simplicity and flexibility of the discrete choice approach come with a number of limitations. First, models with a binary dependent variable require an exogenous definition of crises indicators. The search for leading indicators of crises crucially depends on the timing of the crises considered. The identification of crises episodes usually relies on expert judgment.[3] The possible misclassification of crises episodes introduces an additional source of model uncertainty.

Second, current models require a sufficient number of stress or crises events in order to generate robust results. While the apparent solution to mitigate the "rare events problem" is to pool similar countries, those models use mainly cross-sectional information while discarding most of the time dimension on the intensity of the crisis event within each country. However, differences in the intensity of crises may have very different effects on the real economy. For instance, the literature on financial crises (Reinhart and Rogoff, 2009; Reinhart and Rogoff, 2014) finds that recessionary events are longer when they are associated with simultaneous financial market stress. In addition, Romer and Romer (2015) suggest that output decline following financial crises varies across countries member of the Organisation for Economic Co-operation and Development (OECD) and depends on the length of the financial market stress itself. For EU countries, Duprey et al. (2017) find that the depth and length of a crisis depend on the intensity of financial market stress.

Last, the models with a binary dependent variable can detect either a tranquil or a crisis episode, but they are not able to model the dynamics of both regimes at the same time. Crises probabilities are not conditional on the initial state of the economy. One can assess the probability of being in a crisis regime, but it is not possible to disentangle the probability of moving into a crisis regime from the probability of exiting this regime. The use of a binary dependent variable gives rise to the so-called "post-crisis bias": the model is not able to distinguish the set of tranquil periods into those periods where the economy is back to a sustainable growth path and those periods where the economy is still adjusting after the crisis (Bussière and Fratzscher, 2006). One possibility is to remove post-crisis episodes from the analysis, at the cost of fewer observations.

will pre-announce its decision to raise the CCyB level by up to 12 months in order to give banks time to adjust their capital planning (Basel Committee on Banking Supervision, 2010).

[3] The most commonly used databases of banking, sovereign debt and currency crises are Laeven and Valencia (2013), and Babecky et al. (2014) with a focus on EU countries.

2.2 The proposed Markov switching model

One way to address the shortcomings of the discrete choice models is to use a Markov switching model with time-varying transition probabilities (MS), which involves, however, a more complex estimation method. This model relies on the seminal work by Hamilton (1989) that distinguishes between different states of the economy by relying on a continuous dependent variable that captures the intensity of crises. The model does not require any assumptions on the timing of the crises episodes; rather, it infers the probability of being in a specific state as well as the probability of switching from one state to the other. The transition between the different regimes can be modelled as a hidden Markov chain. The transition matrix allows for a differentiated analysis of the dynamics of entering and exiting a crisis regime. As such, the MS model allows for a non-symmetric analysis of financial cycle turning points. Filardo (1994) and Diebold et al. (1994) provide an extension of the framework in which the transition probabilities of the Markov process are time-varying. This allows making transition probabilities conditional on a set of leading indicators that are considered to be good predictors of the cyclical fluctuations. But it also means that the endogenous identification of the high and low regimes will impact the identification of leading indicators for the probability of switching from one regime to another.

This class of models has been extensively used in the business cycle literature as a tool to identify and possibly predict turning points in the business cycle.[4] The underlying assumption is that the data, usually GDP growth rates, are generated by a mixture of two distributions—one for the phases of expansions and the other for the phases of recessions. The ability of this class of model to endogenously distinguish and predict different regimes makes it also particularly useful for the analysis of other types of crises events, especially currency crisis, by modeling the dynamics of the exchange rate.[5] However, the use of MS models is still limited for banking or financial crises because of the lack of a commonly agreed-upon metric to capture the intensity of banking or financial crises.[6]

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[4]This class of model is usually found to better match the dynamics of the business cycle. These techniques allow for the construction of coincident measures of the business cycle providing a chronology of turning points (see, for example, Kim and Nelson (1998); Chauvet (1998); Bardaji et al. (2009)). Chauvet and Piger (2008) show that the MS method improves over the National Bureau of Economic Research methodology in the speed at which business cycle troughs are identified. Alessandri and Mumtaz (2014) show that a regime-switching VAR could have sent a credible early warning signal ahead of the Great Recession.

[5]Different MS models were used, mostly to analyze currency crises, while very few focus on banking crises: Engel and Hakkio (1996) or Martinez-Peria (2002) for the European Monetary System currency crisis; Cerra and Saxena (2002), Arias and Erlandsson (2004) or Brunetti et al. (2007) for the South-East Asian currency crisis; (Simorangkir, 2012) for bank runs during the Asian banking crisis in 1997-98.

[6]Hollo et al. (2012) look at switches in a measure of European systemic financial stress, while Duprey et al. (2017) use those regime switches to identify periods of financial market turmoil for each EU country. With a MS-VAR model, Hartmann et al. (2013) show that the response of output to financial stress is much larger in case of a negative shock when allowing for regime switches. Hubrich and Tetlow, 2015 further show that monetary policy is less effective in regimes of high financial stress. But those papers

Model specification. The MS model is given by equation (1) and models financial stress as captured by the CLIFS[7] for each of 15 EU countries c.[8] This continuous measure of financial stress is allowed to have different dynamics depending on whether the economy is in a low- or in a high-financial-stress state $S_{c,t} = \{0, 1\}$. Duprey et al. (2017) show that high levels of financial stress are associated with a more pronounced economic downturn. Figure 1 shows that a CLIFS above the 90th percentile of each country's distribution is associated with a drop in the industrial production. Each state $S_{c,t}$ is endogenously determined and associated with a probability of being observed. The model allows for a regime-specific mean and possibly a regime-specific variance or autoregressive parameter (respectively μ^s, σ^s and β^s). The model pools the 15 EU countries $c \in \{1, ..., 15\}$ and allows for country dummies γ_c to affect the level of financial stress.

$$CLIFS_{c,t} = \begin{cases} \mu^0 + \sum_c (\gamma_c^0 \mathbb{1}_c) + \beta^0 CLIFS_{c,t-1} + \sigma^0 \epsilon_t \text{ in regime } S_{c,t} = 0 \\ \mu^1 + \sum_c (\gamma_c^1 \mathbb{1}_c) + \beta^1 CLIFS_{c,t-1} + \sigma^1 \epsilon_t \text{ in regime } S_{c,t} = 1 \end{cases}, \tag{1}$$

where $\epsilon_t \rightarrow \mathcal{N}(0, 1)$. Our main focus, however, is on the introduction of covariates $\mathbf{X}_{c,t-1}$ in the transition equation (2) instead of the level equation (1), as the purpose of the paper is to identify the leading indicators of entering and exiting financial stress. The transition across the regimes of financial stress follows a Markov chain that specifies the probabilities of switching both from a low- to a high-financial-stress regime, denoted by p_t, and from a high- to a low-financial-stress regime, denoted by q_t.[9] The switching probabilities are specified in a logistic form, and are computed conditional on a set of observable leading indicators $\mathbf{X}_{c,t-1}$.

$$P(S_{c,t} | S_{c,t-1}, \mathbf{X}_{c,t-1}) = \begin{bmatrix} 1 - p_t & p_t = \frac{\mathtt{exp}(\theta_{p,0} + \theta_{p,1} \mathbf{X}_{c,t-1})}{1 + \mathtt{exp}(\theta_{p,0} + \theta_{p,1} \mathbf{X}_{c,t-1})} \\ q_t = \frac{\mathtt{exp}(\theta_{q,0} + \theta_{q,1} \mathbf{X}_{c,t-1})}{1 + \mathtt{exp}(\theta_{q,0} + \theta_{q,1} \mathbf{X}_{c,t-1})} & 1 - q_t \end{bmatrix}. \tag{2}$$

do not look at the determinants of the switching behaviour.

[7]For more details on the CLIFS and its construction, see Duprey et al. (2017). The CLIFS indices are publicly available on the Statistical Data Warehouse of the European Central Bank (ECB) in the macroprudential database http://sdw.ecb.europa.eu/browse.do?node=9689344. The authors define financial stress as simultaneous financial market turmoil across a wide range of assets (equity markets, government bonds and foreign exchange), reflected by (i) the uncertainty in market prices, (ii) sharp corrections in market prices, and (iii) the degree of commonality across asset classes.

[8]The sample of selected EU countries includes Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the United Kingdom. The time series length may differ for each country depending on data availability, but in principle it starts in 1970Q1 and ends in 2015Q4. The effective sample size is provided at the bottom of each result table.

[9]The assumption of two regimes is the most appealing from an economic point of view by looking at "tranquil" versus "turbulent" times. The introduction of a third regime could allow for capturing of mild versus extreme stress events. However, those events would be less frequent, and finding leading indicators of this extra regime would be very costly in terms of degrees of freedom and harder to interpret. Such estimation fails in most instances and, when successful, the results were not very appealing for our purpose of early warning, and are thus not reported.

If the set of observable leading indicators $\mathbf{X}_{c,t}$ is empty, then the Markov chain of equation (2) excludes all information from possible leading indicators. The estimated transition probabilities from the Markov chain are constant over time: this collapses to the benchmark model of Hamilton (1989).

Estimation strategy. The benchmark estimation includes only a switch in the mean of the CLIFS, as the primary focus of this type of financial stress indicator is to reflect the level of financial stress within an economy. In fact, the construction of the CLIFS already embeds various measures of volatilities in different market segments, so it is unclear that a change in the volatility of the CLIFS would necessarily provide further information. Another reason is that the Markov chain captures a common switch in all the regime-specific parameters. Allowing for a change in the autoregressive term or the variance would restrict the model to the identification of those episodes where a simultaneous switch occurs in all the parameters. These alternative specifications are left as robustness checks.

The paper relies on a cross-country estimation in line with Gadea-Rivas and Perez-Quiros (2015) by pooling all 15 EU countries[10] that are considered to be relatively similar in terms of their economic development.[11] Hence, it is implicitly assumed that financial stress dynamics are comparable across the 15 EU countries. This appears reasonable as the CLIFS in those EU countries exhibit a high degree of co-movement (Figure 2). The reason for choosing a cross-country estimation strategy is that pooling the countries increases the number of financial cycles (i.e., sequence of low- and high-financial-stress episodes), resulting in a substantial reduction in the uncertainty of the parameter estimates. As the out-of-sample predictive power and hence the likelihood to detect future stress episodes increases when the early warning framework incorporates various types of crises, the cross-sectional dimension is exploited as much as possible. To this end, as in Gadea-Rivas and Perez-Quiros (2015), we construct a "fictitious" country by stacking together the individual CLIFS and the leading indicators of each country. The main variable for the identification of stress periods is the level of the CLIFS. Hence, it is useful, as a robustness check, to test the sensitivity of the results to the introduction of country-

[10] Since the MS framework uses the information from the entire distribution of the financial stress index instead of a small set of crises events, as in the case of traditional early warning models based on a binary dependent variable, one could also estimate the MS model for each country. The results are available upon request from the authors.

[11] To the best of our knowledge, Gadea-Rivas and Perez-Quiros (2015) is the only paper that estimates an MS model based on a cross-country sample while imposing the same transition matrix for all countries. The authors focus on the role of credit in predicting the Great Recession. Alternatively, the size of the Markov chain could be expanded to account for recession probabilities that would be different across countries. But this is very difficult to estimate as the number of parameters would increase with the square of the number of regimes across all countries. Hamilton and Owyang (2012) use a panel MS model to study the business cycles at the country and state levels in the US, but the Markov chain is clustered by groups of states. Billio et al. (2016) use a multivariate panel MS-VAR model to study the connection of recessionary events between the US and Eurozone countries.

specific levels of financial stress by using dummies, or by making the level of the CLIFS comparable across countries by adjusting its construction method.[12] The parameters of the MS model are estimated with maximum likelihood methods.

Computing probabilities. The Markov chain allows for the computation of the probability of being in a regime of high financial stress today, the probability of being in a regime of high financial stress tomorrow, or the probability of switching from one regime to the other and vice versa. The different probabilities are recovered as follows.

The predicted conditional probabilities of high financial stress $\hat{p}_t$ and $\hat{q}_t$ obtained from the transition matrix are given by:

$$\begin{aligned} \hat{p}_{c,t} = P\left(S_{c,t} = 1 \,|S_{c,t-1} = 0;\ \mathbf{X}_{c,t-1}\right) &= \frac{\texttt{exp}(\hat{\theta}_{p,0}+\hat{\theta}_{p,1}\mathbf{X}_{c,t-1})}{1+\texttt{exp}(\hat{\theta}_{p,0}+\hat{\theta}_{p,1}\mathbf{X}_{c,t-1})}, \\ \hat{q}_{c,t} = P\left(S_{c,t} = 0 \,|S_{c,t-1} = 1;\ \mathbf{X}_{c,t-1}\right) &= \frac{\texttt{exp}(\hat{\theta}_{q,0}+\hat{\theta}_{q,1}\mathbf{X}_{c,t-1})}{1+\texttt{exp}(\hat{\theta}_{q,0}+\hat{\theta}_{q,1}\mathbf{X}_{c,t-1})}. \end{aligned}$$

Using Bayes rule and the transition probabilities, the out-of-sample one-step-ahead probabilities[13] are given by:

$$\begin{aligned} P\left(S_{c,t} = 1 \,|\, \mathbf{X}_{c,t-1}\right) &= \hat{p}_{c,t} P\left(S_{c,t-1} = 0 \,|\, \mathbf{X}_{c,t-1}\right) \\ &+ \left(1 - \hat{q}_{c,t}\right) P\left(S_{c,t-1} = 1 \,|\, \mathbf{X}_{c,t-1}\right). \end{aligned} \tag{3}$$

Then, using the one-step-ahead probability of high financial stress, the one-step-ahead marginal and joint density distributions of the CLIFS are recovered. The density function of the CLIFS is given by f and the error term is assumed to follow a Gaussian distribution

[12] The CLIFS constructed by Duprey et al. (2017) to measure financial stress in each EU country is specific to each country. The level of stress in each country is normalized against the previous levels of stress obtained in each country to allow for country-specific characteristics. Alternatively, one can normalize the level of stress in each country against the previous levels of stress obtained in all EU countries, making the measure comparable across countries.

[13] Later in the paper, we also use h-steps-ahead forecasts for the probabilities of stress. These h-steps-ahead forecasts are computed with a direct approach. By varying the lag h used for the observables, equation (3) would now relate S_t and X_{t-h}, so that with the current observables X_t, one can project the probability of being in a stress regime h periods ahead S_{t+h}. Another way to compute forecasts multiple periods ahead is to use iterated forecasts with a satellite model to predict the set of observables X_t to X_{t+h-1}, and then compute the regime probabilities one step ahead for S_{t+1} to S_{t+h}. We prefer to use the direct method as it is more robust to model mis-specification (Massimiliano et al., 2006), which is more of an issue in our context with many alternative candidate leading indicators, so that we do not want to add on model and estimation uncertainty.

so that ϕ is the standard normal density function, hence:

$$\begin{aligned}
f\left(CLIFS_{c,t} \,|\, S_{c,t}=1; CLIFS_{c,t-1}; \mathbf{X}_{c,t-1}\right) &= \frac{1}{\sigma^1}\phi\left(\frac{CLIFS_{c,t}-\mu^1-\beta^1 CLIFS_{c,t-1}}{\sigma^1}\right), \\
f\left(CLIFS_{c,t}, S_{c,t}=1 \,|\, CLIFS_{c,t-1}; \mathbf{X}_{c,t-1}\right) &= f\left(CLIFS_{c,t} \,|\, S_{c,t}=1; CLIFS_{c,t-1}; \mathbf{X}_{c,t-1}\right) \\
&\cdot\; P\left(S_{c,t}=1 \,|\, \mathbf{X}_{c,t-1}\right), \\
f\left(CLIFS_{c,t} \,|\, CLIFS_{c,t-1}; \mathbf{X}_{c,t-1}\right) &= f\left(CLIFS_{c,t}, S_{c,t}=1 \,|\, CLIFS_{c,t-1}; \mathbf{X}_{c,t-1}\right) \\
&+\; f\left(CLIFS_{c,t}, S_{c,t}=0 \,|\, CLIFS_{c,t-1}; \mathbf{X}_{c,t-1}\right).
\end{aligned}$$

Finally, the probability of being in a high-financial-stress regime at each point in time is recovered by using the distribution of the CLIFS to update the one-step-ahead probability of high financial stress of equation (3):

$$P\left(S_{c,t}=1 \,|\, \mathbf{X}_{c,t}\right) = \frac{f\left(CLIFS_{c,t}, S_{c,t}=1 \,|\, CLIFS_{c,t-1}; \mathbf{X}_{c,t-1}\right)}{f\left(CLIFS_{c,t} \,|\, CLIFS_{c,t-1}; \mathbf{X}_{c,t-1}\right)}. \tag{4}$$

Candidate leading indicators. The set of candidate predictors $\mathbf{X}_{c,t}$ is listed in Tables 1 and 2. They can be classified into five broad categories: (i) credit-related variables, (ii) housing-related variables, (iii) macroeconomic variables, (iv) financial market variables, and (v) banking-related variables. When estimated at the quarterly frequency, the CLIFS, which is available at the monthly frequency, is taken to be the quarterly average. The estimations are carried out using primarily data at the quarterly frequency, but robustness tests are done using data at the monthly frequency available only since 1998 for the 12 euro area countries.

3 Identifying predictors of financial stress

This section discusses the set of candidate indicators for predicting the entry into and the exit from periods of high financial stress, as identified by the MS model estimated in-sample using all available information to date. Section 3.1 looks at a broad range of candidate predictors one by one, while section 3.2 combines the most promising indicators in the same model.

3.1 Analyzing each candidate indicator individually

In a first step, relevant indicators are identified by looking at the impact on the transition probability of each candidate leading indicator individually. Table 3 displays results for four different specifications of the MS model with a regime switch in the level of financial stress. Specification (1) considers the simplest form of the MS model. Specification (2) uses an adjusted CLIFS to make sure that the individual contributors to the level of financial stress within each country are also comparable across countries. Specification (3) includes country dummies in the level equation to allow for different definitions of high versus low financial stress for each country. Finally, specification (4) introduces an autoregressive term.

The candidate leading indicators that explain the probability of entering a regime of high financial stress belong mostly to two categories: credit and housing. On the one hand, the credit-to-GDP gap computed with a smoothing parameter of 400,000 as suggested by the Basel Committee on Banking Supervision (2010), based on both total credit (GAP400_CT2GDP) and bank credit (GAP400_CB2GDP), has a significant impact on the probability of entering financial stress across the different specifications. A similar result is obtained for the debt service ratio, both for total debt (DSR) and for household debt (DSRHH). On the other hand, the annual growth rate of (real) residential property prices (D4_RREPR) and, to a smaller extent, the (real) residential property price gap computed with a smoothing parameter of 26,000 (GAP26_RREPR) also have a significant impact. Put differently, lower property prices increase the probability of entering a period of high financial stress in the next period. A higher ratio of residential property prices over disposable income (RREPR2INC) or over the rental cost of housing (RREPR2RENT) is also a good predictor of a looming high financial stress.

In addition, some macroeconomic variables seem to perform relatively well in-sample too; for instance, the inflation rate (D4_CPIP) or the real effective exchange rate (D4_EERR). Similarly, market variables such as the annual growth rate of the equity price index (D4_EQPI) have good leading indicator properties. One should note that the CLIFS already incorporates information on the real exchange rates and equity prices, which might explain these results. Hence, they are not used in subsequent analyses.

When looking at the probability of exiting a regime of high financial stress, only the annual growth rate of stock prices (D4_EQPI) and the variation of the economic sentiment indicator (D_ESI) appear as good candidate leading indicators of exiting financial stress.

3.2 Analyzing multiple candidate indicators simultaneously

In a second step, the main leading indicators are combined in a single MS model. Table 4 shows the same four specifications that involve a regime-specific mean of financial stress. The mean financial stresses in both regimes are always statistically different from each other. Also, the likelihood-ratio (LR) test confirms that adding explanatory variables in the probability equation always improves the fit of the model despite the higher number of parameters to estimate. The null of fixed transition probabilities—i.e., no explanatory variables in the probability equation of the MS model—is always rejected in favour of the model with time-varying transition probabilities.

All specifications confirm that the DSR, the residential property price-to-rent ratio (RREPR2RENT) and the annual residential property price growth (D4_RREPR) are leading indicators for a switch to a high-financial-stress regime in the subsequent period. However, credit gap variables (GAP400_CT2GDP) are not significant at the standard levels anymore.[14]

Turning to the probability of exiting a regime of high financial stress, a more negative credit-to-GDP gap (GAP400_CT2GDP) signals a higher probability of exiting a period of high financial stress.

3.3 Robustness

Table 5 displays robustness specifications that allow for a regime-specific variance, with or without an (possibly regime-specific) autoregressive term. Only the DSR remains significant at standard levels. Note that the standard deviation tends to be significantly higher in regimes of high financial stress, as well as the persistence of financial stress.

A broadly similar pattern can be observed when the estimations rely on monthly data. This allows for a higher number of observations to be included in the model, while the country coverage is reduced to euro area countries with data starting in 1998. Looking at each indicator individually, Table 6 suggests that mostly a declining growth in loans to households for house purchases (D12_GLHP), lower equity price growth (D12_EQPI), and a decreasing confidence in the economy (D_ESI) contribute to a higher probability of facing financial stress in the next period.

These results are also confirmed in Tables 7 and 8, which combine multiple indicators. In addition, a higher mortgage rate (MORTR) and a lower leverage ratio (i.e., unweighted capital ratio) of banks (LEV) also tend to contribute to a higher probability of entering into a regime of high financial stress. The economic sentiment indicator (D_ESI) regularly appears as a significant contributor of the probability to exit a regime of financial stress.

4 Assessing the timing of early warning signals

Now that the main leading indicators have been identified in the previous section, the next step is to investigate how early they can predict the occurrence of a regime of high financial stress by varying their lag order. Indeed, the standard trade-off is between the strength of an early warning signal and its timing. Warnings are useful for policy makers

[14] Additional robustness tests are performed with alternative combinations of leading indicators. Those results are not reported for sake of space but available upon request. Replacing the credit-to-GDP gap by the bank credit-to-GDP gap does not change the results. Similarly, replacing the residential property price-to-rent ratio by the residential property price-to-income ratio leaves the results unchanged. Last, the narrower DSR for households only is not significant, but the coverage is significantly reduced compared with the broader DSR.

only if they provide a signal of a sufficiently good quality early enough before the start of the episode of financial stress.

Probability of entering financial stress. Figure 3 shows the point estimates and the corresponding confidence bands for each leading indicator with respect to the probability of entering financial stress, when the leading indicators in the Markov chain of equation (2) are lagged from one to 12 quarters. The credit-to-GDP gap is very close to being a significant contributor to the probability of entering financial stress up to five quarters prior to the occurrence of financial stress, while the DSR can predict high financial stress up to six quarters ahead. The residential property price-to-rent ratio appears to have the best early warning properties signalling financial stress more than 12 quarters ahead. A very interesting result is provided by property price growth rates. While a lower annual growth rate of residential property prices is associated with a significantly higher probability of high financial stress up to two quarters ahead, when looking at more than seven quarters ahead, the coefficient sign changes and a higher growth rate is associated with a rising probability of high financial stress. This is consistent with Drehmann and Tsatsaronis (2014) who show that higher property prices are good predictors of stress occurring over a medium-term horizon, while lower property prices (in combination with positive property price gaps) indicate that financial stress is likely to occur within a relatively short time. Finally, the economic sentiment indicator is a significant contributor to the probability of entering financial stress up to two quarters ahead (Figure 5).

Probability of exiting financial stress. Figure 4 shows the contributions of a set of indicators to the probability of exiting financial stress between one and 12 quarters prior to its occurrence. A reduction in the credit-to-GDP gap is associated with a higher probability of exiting financial stress, up to nine periods ahead, and the magnitude becomes somewhat larger after a couple of quarters. This is not surprising, as a higher credit-to-GDP gap tends to increase the probability of entering a regime of stress, so that the credit-to-GDP gap decreases during the period of stress either with lower credit or just because the trend catches up progressively. As far as the economic sentiment indicator is concerned, more confidence in the economy increases the probability of exiting a period of financial stress in the subsequent two quarters (Figure 5).

5 Assessing the usefulness of signals in predicting the global financial crisis

The results presented above suggest that credit and property market variables are the best leading indicators for explaining a rising probability of financial stress in the subsequent quarters. We now investigate the stability of those results over time, especially regarding the global financial crisis. In particular, we are interested to know if credit and property market variables were already good one-period-ahead predictors of high financial stress before the global financial crisis. To that extent, we perform an out-of-sample exercise that uses only information available until each point in time.

Figure 6 shows the evolution over time of the point estimates and the corresponding confidence bands for each leading indicator with respect to the probability of entering financial stress as modelled in equation (2). To this end, the MS model is estimated recursively starting in 2006Q4 by adding one quarter of information at a time. This out-of-sample exercise allows for assessment in real-time of the informational content of the leading indicators for the prediction of financial stress one-period-ahead. The results reveal that the parameter for the DSR becomes positive toward the end of 2006, but starts to be statistically significant only from 2008Q3 onwards. Thus, prior to the global financial crisis, this particular indicator would not have been considered as a useful indicator of a rising probability of entering a regime of financial stress. The ultimate conclusion from this finding is that most of the predictive in-sample performance of this particular indicator is owing to the data obtained since 2007. The results are similar for the residential property price-to-rent ratio and for the growth rate of property prices, both of which become significant only in 2007Q2 and 2008Q2, respectively. Throughout the entire out-of-sample period, the credit-to-GDP gap would not have been a significant contributor to the probability of entering a regime of financial stress. The credit-to-GDP gap became significant for the probability of exiting financial stress from 2010Q2 onwards, precisely at the time when the first countries started to recover from the global financial crisis (Figure 7).

However, does it mean that the probability of facing financial stress in the next quarter recovered from the MS model would have failed to correctly identify episodes of high financial stress before 2008? Figure 8 shows the one-step-ahead probability of high financial stress obtained from the MS for each of the 15 EU countries. The solid blue line corresponds to the probability computed in-sample for our benchmark model, including the main leading indicators discussed above. In addition, the red dashed line represents the out-of-sample one-step-ahead probability computed recursively from 2006Q4 onwards by adding one quarter of new information at a time. Both lines show a surprisingly similar pattern despite the high uncertainty involved in the estimation of the Markov chain. We interpret this result as evidence that the main output of the MS model—i.e., the one-step-ahead probability of high financial stress—is relatively consistent over time. Even using only data prior to the occurrence of the global financial crisis, the model would have successfully identified periods of low and high financial stress before the onset of the crisis. However, our results also suggest that some apparent early warning signals issued already in 2006 were obtained from using information that became available only later.

For example, the increase in the in-sample probability of financial stress (solid blue line) for Spain is not visible when considering the out-of-sample probability (dashed red line), which uses only information available at that time. Overall, while the MS model consistently identifies periods of low and high financial stress irrespective of whether the global financial crisis was included in the sample or excluded, the early warning properties of some indicators appear much more limited when considering an out-of-sample exercise.

Figure 8 also reports the one-step-ahead probabilities of high financial stress recovered from an alternative specification that includes a regime change in the variance of the measure of financial stress (green dashed line).[15] Focusing on those regime switches that generate both a different mean and variance, additional episodes are characterized by a high probability of financial stress, in particular for the United Kingdom around 1990, for Finland, France and Greece around 2000, and for Italy in 2013.

In contrast, traditional early warning models would have provided less consistent results prior to the global financial crisis. Those models rely on a time series of exogenously identified binary financial stress episodes as a dependent variable. Removing the financial stress episodes that occurred during between 2008 and 2012 substantially reduces the number of financial stress events against which the model is “trained”, casting doubts on the robustness of the results over time.

6 Assessing the performance of the MS framework relative to traditional early warning models

The MS model mitigates some of the caveats of traditional early warning models. It identifies a reasonable set of leading indicators and detects well-known episodes of financial stress. Another important aspect to investigate is the extent to which the MS framework provides an added value, in particular regarding its predictive abilities, compared with the existing early warning models, which are based on a binary dependent variable.

6.1 Assessing the predictive ability of the MS model against a binary logit model

Predicting a time series of binary financial stress events, as opposed to a continuous measure of stress, results in a loss of information. A continuous measure of financial stress may better capture the gradual build-up of risks by using all information available in the entire distribution of the financial stress measure. However, it is unclear, a priori, whether continuous measures of financial stress improve the quality of the signal, as it

[15] The obtained probability pattern is very similar when computing the out-of-sample one-step-ahead probability recursively from 2006Q4 onwards by adding one quarter of information at a time. This is, however, not shown in the figure, for the sake of visibility.

may also introduce more noise since small changes in the financial stress measure are less relevant for predicting changes in the financial cycle regime.

The MS and the logit model are not nested, although the transition probabilities of the Markov chain also use a logistic transformation. The MS model tries to predict a continuous measure of financial stress by assuming the existence of two distinct financial stress regimes, while the logit model tries to predict a binary financial stress indicator defined exogenously that aims at capturing two financial stress regimes. This puts some constraints on the comparison of the performance of both models.

The continuous measure of financial stress is converted into a binary financial stress indicator. This transformation depends on the threshold above which the high-financial-stress regime is defined. As a benchmark, the binary indicator of financial stress is defined as those periods during which the monthly financial stress indicator is above the 90th percentile of its distribution (p90).[16] This, in itself, is likely to result in a very volatile time series if some stressful events have a level of stress just above/below the cut-off. To that end, the gaps between periods of stress of less than two quarters are filled, and only episodes of financial stress lasting two quarters are considered.

Note that the conversion of the continuous stress measure into a binary indicator is likely to put the logit model in a more favourable position, as the binary time series of financial stress episodes would be smoother and thus potentially easier to predict, while the financial stress index used in the MS model may still contain the short-term variations that are more likely to reflect idiosyncratic market shocks than a sustained period of high or low financial market stress.

The performance of the MS and the logit model is assessed using the AUROC (Fawcett (2006), Schularick and Taylor (2012)). The $AUROC_{m,h}$ for model $m \in \{MS, Logit\}$ and horizon $h \in [0; 12]$ reflects the ability of $P_m\left(S_{c,t-h} = 1 \mid \mathbf{X}_{c,t-1-h}\right)$ to predict stress events $S_{c,t} = 1$ defined as $\{S_{c,t} = 1\} = \{CLIFS_{c,t} > p(90)\}$. An $AUROC_{m,h}$ value above 0.5 means that the prediction is better than a random guess. An $AUROC_{m,h}$ of 1 means that the prediction provides a perfect signal of the future stress event. The AUROC is estimated non-parametrically.

Compared with alternative statistics, the AUROC has two particular advantages. First, there is no need to define a probability threshold on $P_m\left(S_{c,t} = 1 \mid \mathbf{X}_{c,t-1}\right)$ above which the signal is considered to be positive. Second, the AUROC does not make any implicit assumption about the relative preferences of missing events (type-1 error) and issuing false alarms (type-2 error).[17]

[16] As shown in Duprey et al. (2017), this threshold is broadly consistent with the occurrence of real economic stress defined as negative growth of the real industrial production index or real GDP. However, robustness checks are also performed using the 80th percentile, or by directly using the systemic financial stress dates computed by Duprey et al. (2017) based on a combination of a fixed transition probability MS and a selection algorithm.

[17] For instance, it is straightforward to see that the noise-to-signal ratio makes an implicit assumption about the trade-off between having a noisy signal for all events versus signalling only some events with

6.2 Results on the predictive ability of the probabilities of stress

Figure 9 gives a visual representation of the predictive ability of both models for different time horizons, ranging from one quarter up to 12 quarters prior to the occurrence of high financial stress. The graph shows the AUROC of the two models and their bootstrapped confidence bands, computed using information available up until the previous period. When the MS model tracks switches in the mean (Figure 9.a), the one-step-ahead probability of entering a period of high financial stress recovered from the MS model sends a better signal of financial stress occurring over the subsequent three quarters. Beyond one year, both the MS and the logit model have similar early warning properties: the blue line and the red line are not statistically different from each other.

However, the unadjusted AUROC can be less informative for several reasons. First, including too many periods of low financial stress would make the AUROC reflect more the ability to correctly signal calm periods, while the focus of this analysis is rather on the ability to correctly signal financial stress periods. Second, periods of high financial stress may be preceded by a varying number of low-financial-stress periods, especially when computing the AUROC on different time horizons. This could make the confidence bands less comparable across different time horizons as the number of used observations differs. Third, while the focus of this analysis is on the ability to signal the start of high-financial-stress episodes, the AUROC is computed on a sample that also includes the high-financial-stress period itself. Hence, the AUROC also reflects the ability to correctly predict the persistence or continuation of the financial stress episode. Fourth, including the post-crisis period in the computation of the AUROC could lower the ability to predict tranquil periods.

Therefore, a non-parametric AUROC estimation on a restricted sample is also provided in Figure 9.b. It includes only 20 quarters prior to the start of each financial stress episode, removing all but the first quarter of the financial stress episode, and excluding four quarters after each financial stress episode. As expected, the number of observations is reduced and the confidence bands are larger. The predictive ability of the MS model and the logit model is undistinguishable. Only at the start of the stress event is the signal provided by the MS model better. This reflects the nature of the MS model that captures switches in the data and generates a larger increase in the probability of stress once stress is materializing.

Figure 9.c displays very similar results when assessing instead the predictive ability of the one-step-ahead probabilities computed out-of-sample since 2006. In the first iteration, the model parameters are estimated using all the available data until 2006Q4. From 2006Q4 onwards, the model parameters are estimated on a sample that increases one quarter at a time. Therefore, the probabilities do not take into account data that become

a good quality.

available only after the global financial crisis.

Figure 9.d displays similar results when looking at a MS model that tracks switches in both the mean and variance of the financial stress metric. The ranking of both models, however, is reversed for early signals, i.e., six quarters ahead or more, with an earlier signalling ability of the logit model. The difference between the two models is not too surprising. The logit model predicts only episodes of elevated financial stress. This is closest to an MS model that tracks only changes in the mean of financial stress. Conversely, for the MS model with a switching variance, periods of stress are not only defined by the level of financial stress, but also by its variance, and hence the results are less comparable with those from the logit model. In addition, for predictions several quarters ahead, the MS model tends to issue more false alarms than the logit model. Again, this is not surprising, since the MS model uses the entire distribution of the continuous stress metric to distinguish between periods of low and high financial stress, while the signalling ability is evaluated, in the end, based on the identified binary regimes representing only those episodes corresponding to the 90th percentile of the CLIFS distribution. Thus, by nature, the AUROC, if anything, is rather biased toward the predictions issued by the binary logit model.

Finally, Figure 9 also shows that the introduction of leading indicators of financial stress in the Markov chain add to the prediction ability of the MS model. In each subgraph, the green line with triangles represents the AUROC computed on the probability of high financial stress recovered from a MS model that excludes any information coming from the leading indicators. The Markov chain includes only a constant so that it is not time-varying anymore and the model estimates fixed transition probabilities as in Hamilton (1989). For each subgraph computed in-sample, namely subgraphs a, b and d, the predictive ability of the MS model is always significantly higher when including leading indicators of financial stress, and the MS model with fixed transition probabilities does a rather poor job in sending any useful signal ahead of a stress event. When the probabilities are computed out-of-sample after 2006Q4 (subgraph c), the MS model that excludes leading indicators has somewhat better early warning properties the closer one gets to the stress event, but early warning properties are similar only at the onset of the stress episode. This is not surprising, as probabilities of high financial stress computed for episodes before 2008 are no longer evaluated against the much more stressful 2008 episode. Prior to 2008, breaching a relatively lower threshold of financial stress was enough to qualify as a regime of high financial stress. In this context, a lower level of financial stress is also able to send a signal, and one gains relatively more information by just looking at (smaller) jumps in the financial stress index. However, this result casts doubts on the use of in-sample non-time-varying thresholds in the identification of signals.

6.3 Robustness regarding different model specifications

Since the MS model can be specified in different ways and episodes of high financial stress can be defined in multiple ways, we want to make sure the results are robust to alternative estimation choices. Figure 10 provides the distribution of the gain in terms of AUROC of using the MS probabilities instead of the ones recovered from the logit model, for multiple specifications, forecast horizons and definitions of high financial stress. The AUROC gain is computed as $\Delta AUROC_{h,s} = AUROC_{MS,h,s} - AUROC_{logit,h,s}$ for a specification s over a prediction horizon h. A positive value shown on the y-axis implies that the AUROC is higher for the MS model than for the logit model for the given forecast horizon, i.e., the forecasting power of the MS model for the respective forecast horizon is higher. The x-axis refers to the share of models, out of the total number of estimated models.

The sets of different specifications considered are as follows: (i) a switch in the mean, (ii) a switch in the mean with an autoregressive term, (iii) a switch in the mean and variance, (iv) a switch in the mean and variance with an autoregressive term and (v) a switch in the mean, variance and autoregressive term. Each of these specifications is estimated either with the benchmark computation of the CLIFS, or (i) with the CLIFS adjusted for a cross-country-relative ranking, (ii) with country dummies or (iii) with four lags in the leading indicators. Hence, a total of 40 different models, some of which were presented in more detail above, is estimated at the quarterly frequency (monthly data start only in 1998 and would encompass a limited set of stress events) with the main leading indicators discussed above. The right subgraph of Figure 10 additionally considers different definitions of periods of high financial stress: the AUROC, for each specification s, is computed using not only the 90th percentile, but also the 80th percentile, and the systemic financial stress dates of Duprey et al. (2017). Hence, this chart summarizes the results of 120 different estimations.

The results suggest that when the economy is in a period of high financial stress with a CLIFS above its 90th percentile (left subgraph), the MS model generates an improvement (compared with the logit model) in terms of AUROC in 100% of the cases when the episode of financial stress occurs one period ahead (solid blue line). This prediction gain is reduced to about 80% of the specifications when considering three quarters before the stress event (dashed red line), and the logit model outperforms the MS model in about 50% of the cases when considering a horizon of six quarters (dotted green line). When also considering alternative definitions of periods of high financial stress (right subgraph), similar results are obtained and the MS model is outperforming in about 70% of the specifications up to three quarters ahead (solid blue line and dashed red line), while the logit model outperforms in only 20% of cases for a six-quarter horizon (dotted green line).

7 Conclusion

Whereas MS models are an established tool in the business cycle literature to identify recessionary episodes based on a continuous indicator of real economic activity, the so-called early warning systems rely mainly on univariate signalling approaches or discrete choice models that use an exogenously defined binary dependent variable capturing different types of crises events. This paper bridges the gap between both strands of literature by assessing the usefulness of a continuous measure of financial stress as a tool for the prediction of different regimes in the financial cycle.

The paper uses cross-country estimations at the quarterly and monthly frequency to identify leading indicators for entering and exiting periods of high financial stress and to determine how early those indicators can issue a signal. The in-sample results indicate that the DSR, the property price-to-rent ratio and the annual property price growth significantly affect the probability of entering a high-financial-stress regime, whereas the credit-to-GDP gap and the economic confidence indicator contribute significantly to the likelihood of exiting a high-financial-stress episode. Of those indicators, the DSR predicts the switch to the high-financial-stress regime up to six quarters ahead, while the property price-to-rent ratio is able to issue such a signal up to 12 quarters ahead. Regarding the return to low financial market stress, the credit-to-GDP gap can issue a signal up to nine quarters ahead, while the economic sentiment indicator can provide such a signal up to two months ahead.

In addition to the in-sample analysis, an out-of-sample exercise investigates whether the identified leading indicators would have provided an early warning signal ex-ante, i.e., prior to the global financial crisis. The out-of-sample exercise reveals that the estimated coefficients for most of the identified leading indicators become significant only over the course of the global financial crisis. This finding suggests that most of the predictive in-sample performance of those indicators is owing to the data obtained during the global financial crisis. Ultimately, it implies that, in line with the results of Gadea-Rivas and Perez-Quiros (2015), the information from those indicators could not have been exploited ex-ante to issue early warnings. However, the identification of episodes of financial stress once they occur is robust to adding new data.

Finally, compared with a standard binary early warning model, the MS model is outperforming in the vast majority of model specifications for a horizon up to three quarters prior to the onset of financial stress. This is not surprising, as the MS model makes use of the intensity of observed financial stress together with the information from the leading indicators. The results also suggest that the early warning indicators in the transition function of the MS model statistically improve the prediction power relative to the MS model that excludes all explanatory variables from the transition function.

While this paper is a first attempt to use standard methods from the business cycle literature to identify turning points in the financial cycle, more work is necessary to better characterize and measure the concept of a financial cycle and its interaction with the business cycle and to further investigate models that can provide a probabilistic assessment of upcoming changes in financial cycle regimes.

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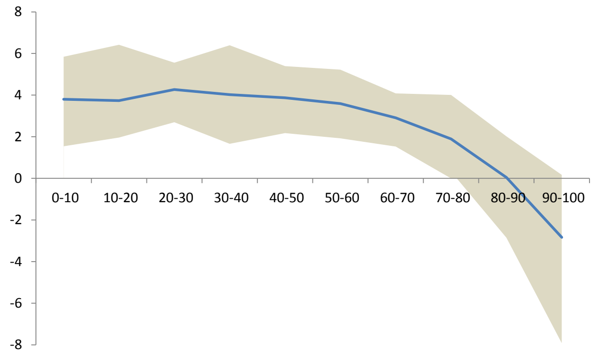
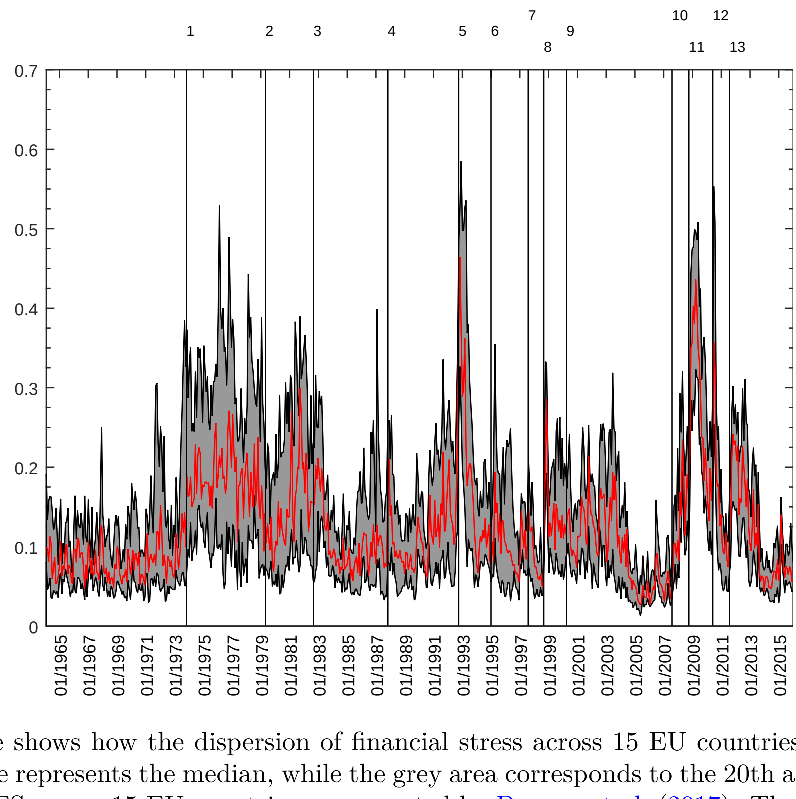
A Appendix

Figure 1: Industrial production growth per quantiles of Country-Level Indices of Financial Stress (CLIFS)



Note: This figure shows the average annual industrial production growth on the y-axis and the quantiles of the country-specific financial stress indices on the x-axis. The blue line corresponds to the country average, while the grey area corresponds to the 20th and 80th percentile. The data are pooled both in the time and cross-sectional dimension over the 27 EU countries. Source: Duprey et al. (2017).

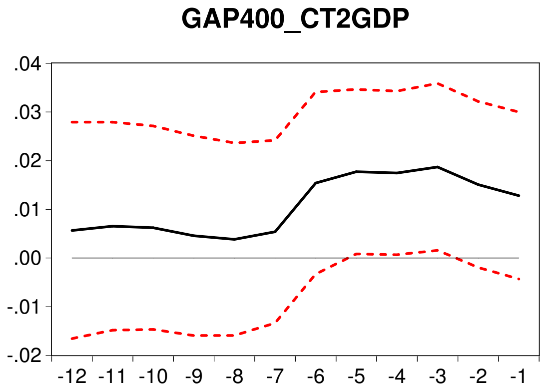
Figure 2: Country-Level Indices of Financial Stress (CLIFS) across 15 EU countries



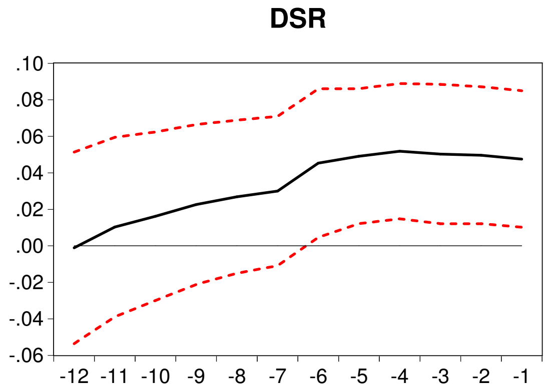
Note: This figure shows how the dispersion of financial stress across 15 EU countries has evolved over time. The red line represents the median, while the grey area corresponds to the 20th and 80th percentile range of the CLIFS across 15 EU countries as computed by Duprey et al. (2017). The events, which are depicted as vertical black lines, are as follows: 1 - first oil shock; 2 - second oil shock; 3 - Mexican debt crisis; 4 - Black Monday; 5 - crisis of the European exchange rate mechanism; 6 - Peso crisis; 7 - Asian crisis; 8 - Russian crisis; 9 - dot-com bubble; 10 - subprime crisis; 11 - Lehman Brothers; 12 - 1st bailout Greece; 13 - 2nd bailout Greece.

Figure 3: Parameters of the probability of entering financial stress for key leading indicators, up to 12 quarterly lags

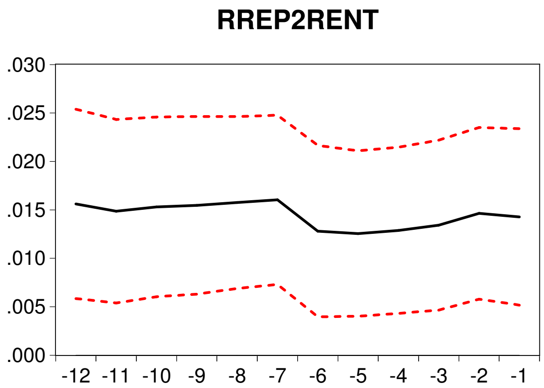
(a) Credit-to-GDP gap ($\lambda = 400000$)



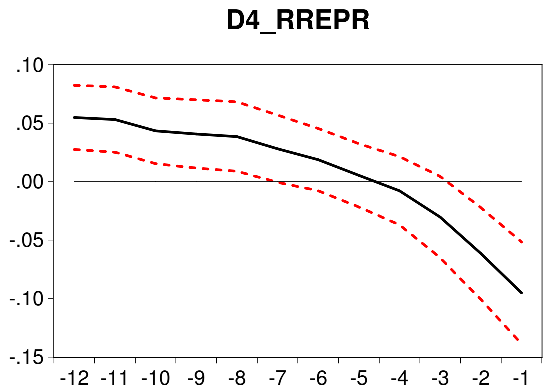
(b) Debt service ratio



(c) Residential property price to rents



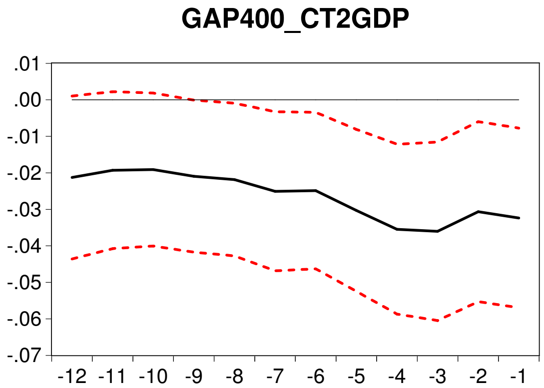
(d) Residential property price growth



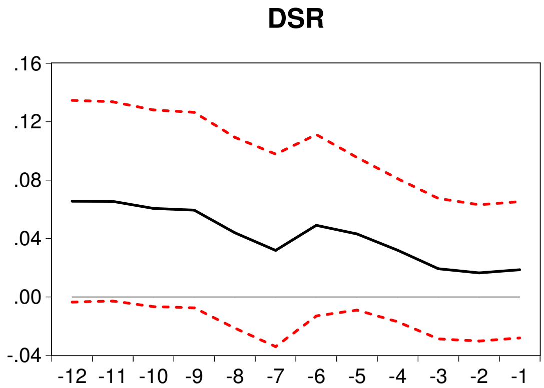
Note: This figure shows the parameter values of the different indicators included in the Markov switching (MS) model as leading indicators of the probability to enter financial stress, with up to 12 lags. The solid black line represents the point estimate from the switching probability of the Markov chain, and the dashed red lines provide the 90th percentile confidence interval (+/- 1.65 standard deviations). The MS model includes a switch in the mean. Inflation is controlled for separately so that all other indicators are expressed in real terms.

Figure 4: Parameters of the probability of exiting financial stress for key leading indicators, up to 12 quarterly lags

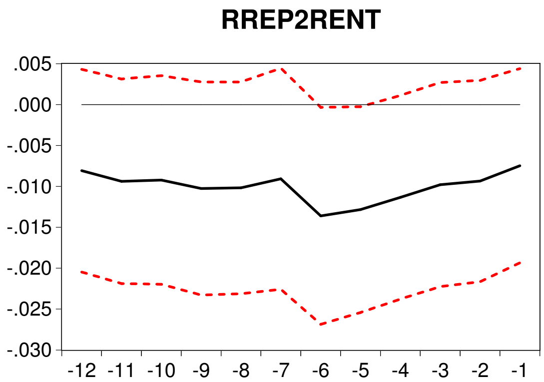
(a) Credit-to-GDP gap ($\lambda = 400000$)



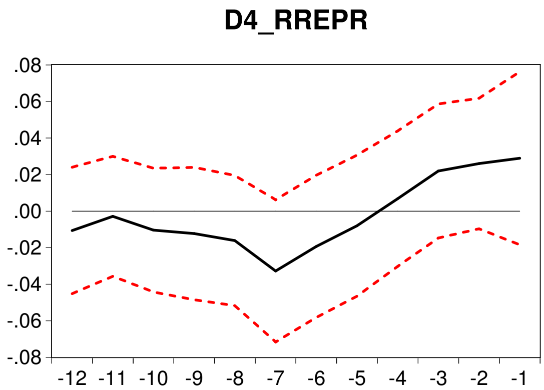
(b) Debt service ratio



(c) Residential property price to rents



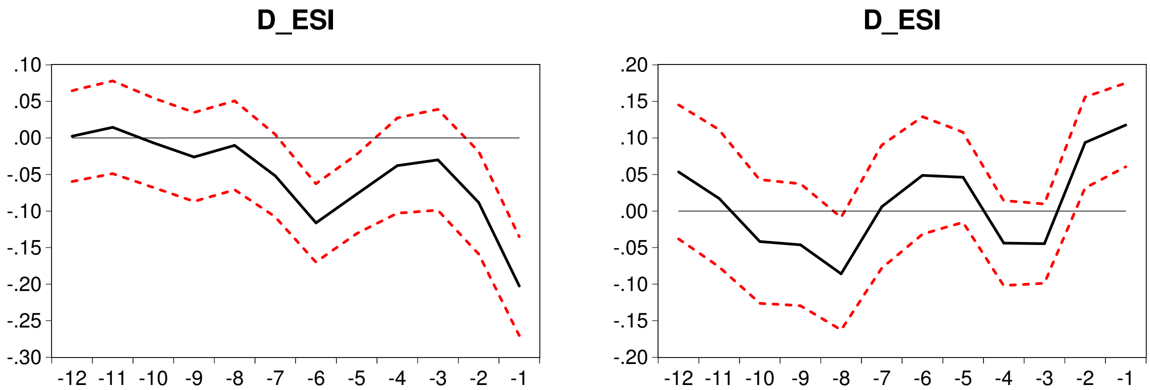
(d) Residential property price growth



Note: This figure shows the parameter values of the different indicators included in the Markov switching (MS) model as leading indicators of the probability to exit financial stress, with up to 12 lags. The solid black line represents the point estimate from the switching probability of the Markov chain, and the dashed red lines provide the 90th percentile confidence interval (+/- 1.65 standard deviations). The MS model includes a switch in the mean. Inflation is controlled for separately so that all other indicators are expressed in real terms.

Figure 5: Parameters for the economic sentiment indicator, up to 12 monthly lags

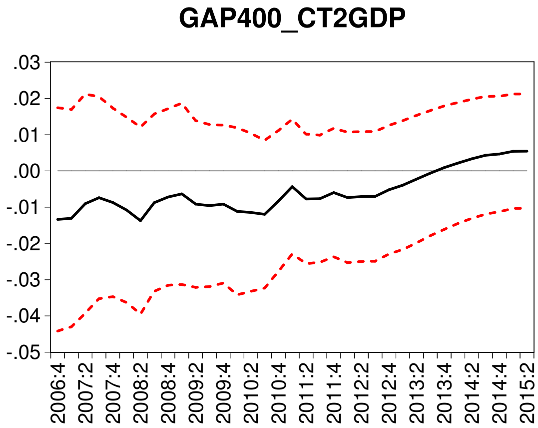
(a) Probability to enter | **(b)** Probability to exit



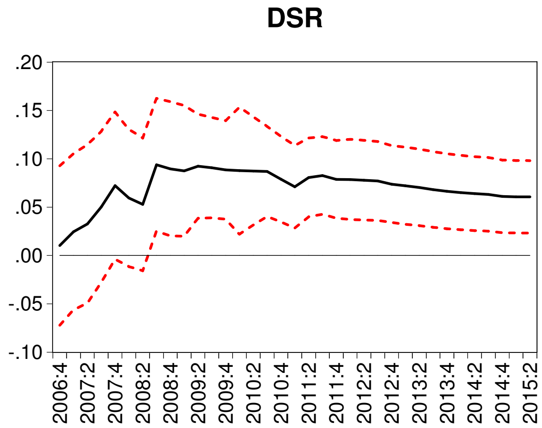
Note: This figure shows the parameter values of the economic sentiment indicator (ESI) when included as a leading indicator in the Markov switching (MS) model with up to 12 lags. The solid black line represents the point estimate from the switching probability of the Markov chain, and the dashed red lines provide the 90th percentile confidence interval (+/- 1.65 standard deviations). The MS model includes a switch in the mean and considers only the ESI as leading indicator. Because of the shorter time span for which the ESI is available, it is considered separately from other candidate leading indicators.

Figure 6: Parameters of the probability of entering financial stress for key leading indicators, stability over time

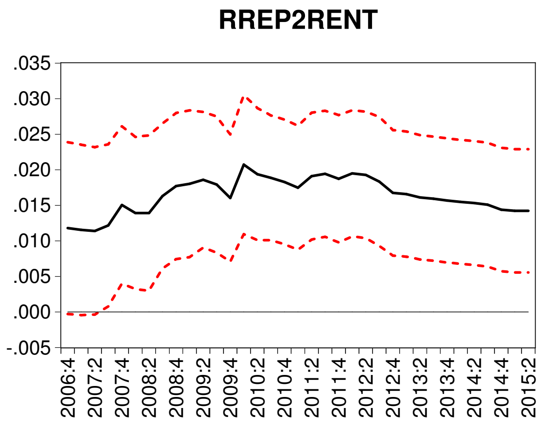
(a) Credit-to-GDP gap ($\lambda = 400000$)



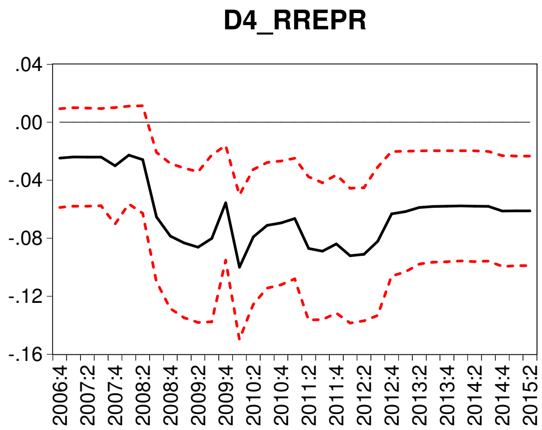
(b) Debt service ratio



(c) Residential property price to rents



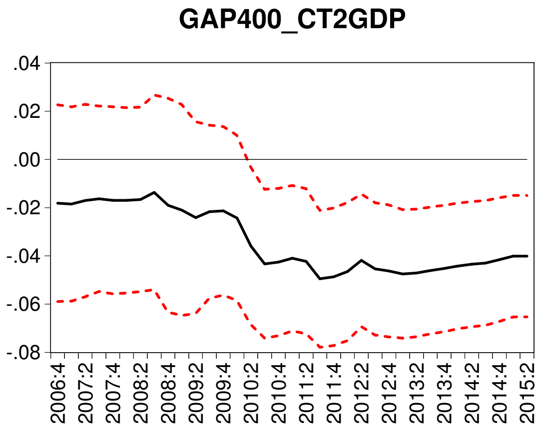
(d) Residential property price growth



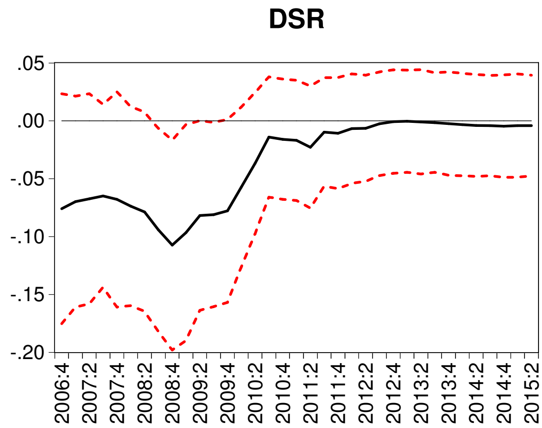
Note: This figure shows the parameter values of the different indicators included in the Markov switching (MS) model as potential explanatory variables for the probability to enter financial stress one period later, estimated on a rolling window starting in 2006Q4. The solid black line represents the point estimate from the switching probability of the Markov chain, and the dashed red lines provide the 90th percentile confidence interval (+/- 1.65 standard deviations). The MS model includes a switch in the mean. Inflation is controlled for separately so that all other indicators are expressed in real terms.

Figure 7: Parameters of the probability of exiting financial stress for key leading indicators, stability over time

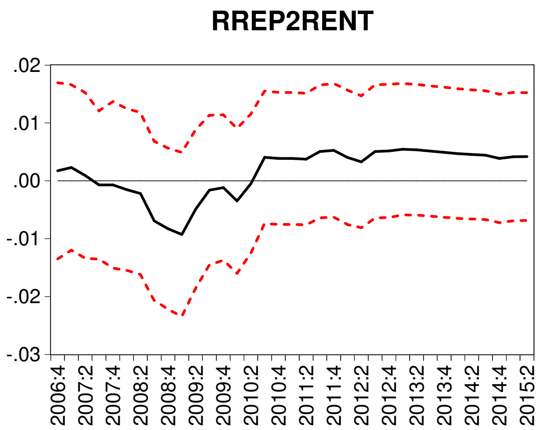
(a) Credit-to-GDP gap ($\lambda = 400000$)



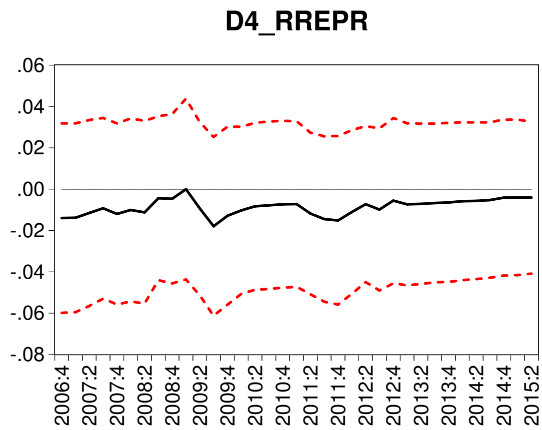
(b) Debt service ratio



(c) Residential property price to rents

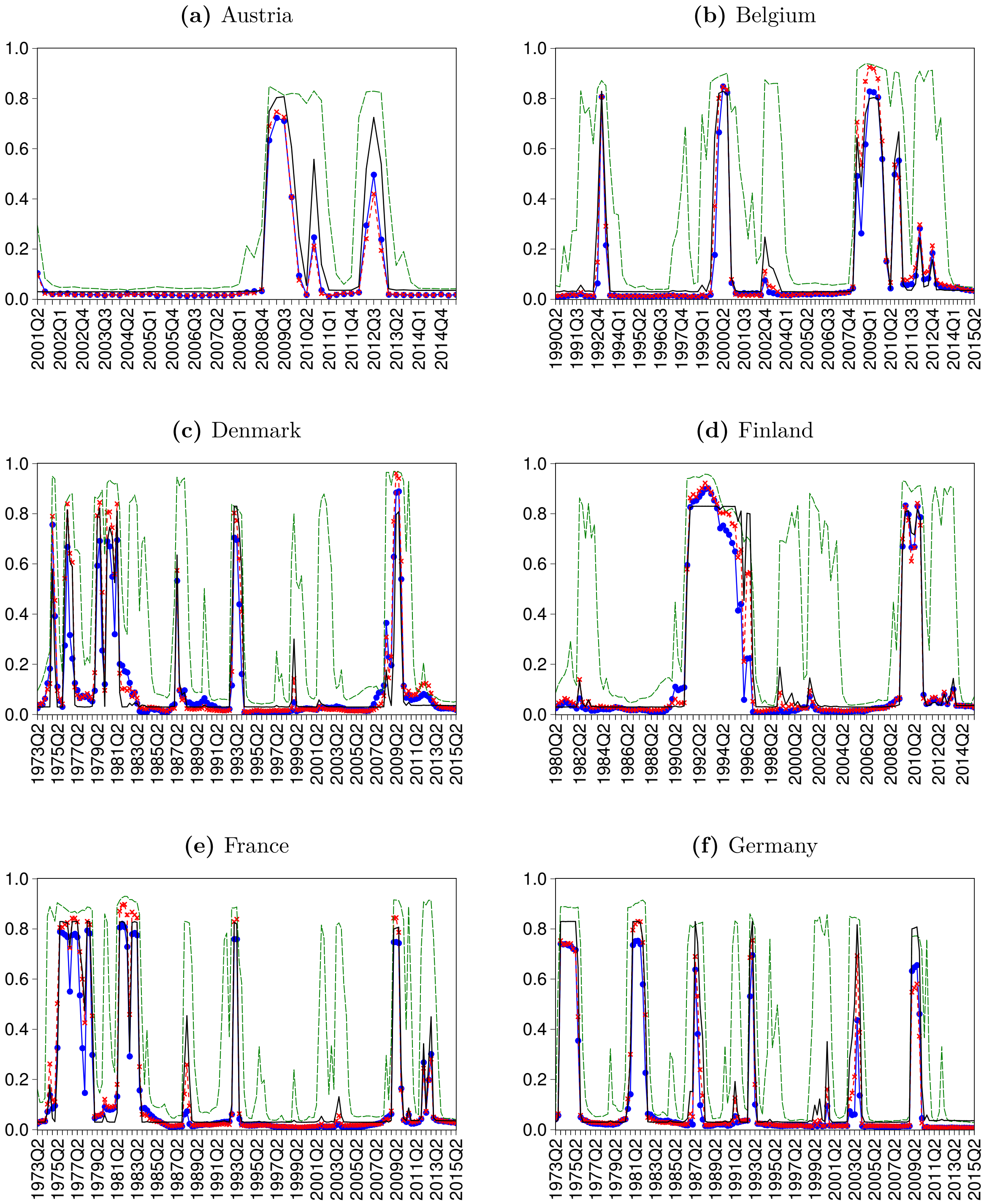


(d) Residential property price growth



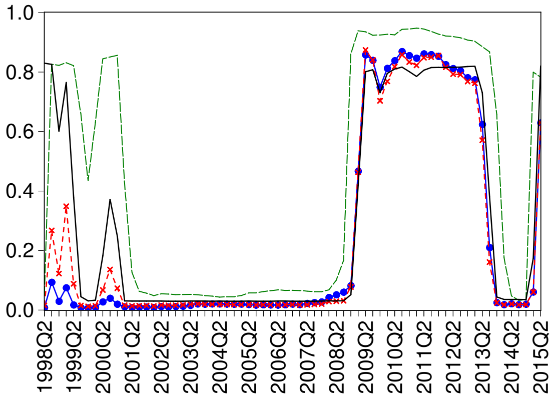
Note: This figure shows the parameter values of the different indicators included in the Markov switching (MS) model as potential explanatory variables for the probability to enter financial stress one period later, estimated on a rolling window starting in 2006Q4. The solid black line represents the point estimate from the switching probability of the Markov chain, and the dashed red lines provide the 90th percentile confidence interval (+/- 1.65 standard deviations). The MS model includes a switch in the mean. Inflation is controlled for separately so that all other indicators are expressed in real terms.

Figure 8: Probability of high financial stress in the next quarter

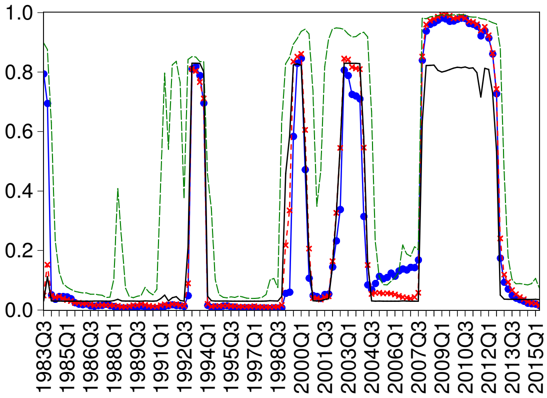


Note: This figure shows the one-step-ahead probability of high financial stress obtained from a Markov switching (MS) model estimated on the quarterly average of the Country-Level Indices of Financial Stress (CLIFS), pooled for all 15 EU countries. High financial stress is defined as the regime with higher mean financial stress. The probabilities are computed either in-sample with a switch in the mean (plain line with blue dots), in-sample with a switch in the mean but excluding all information coming from leading indicators (black line), out-of-sample from 2006 onwards by expanding the estimation window one quarter at a time (red crossed/dotted line), or in-sample with a switch in the mean and variance (green dashed line). The baseline specification includes the following leading indicators: GAP400_CT2GDP, DSR, RREP2RENT, D4_RREPR, D4_CPIP defined in Table 1.

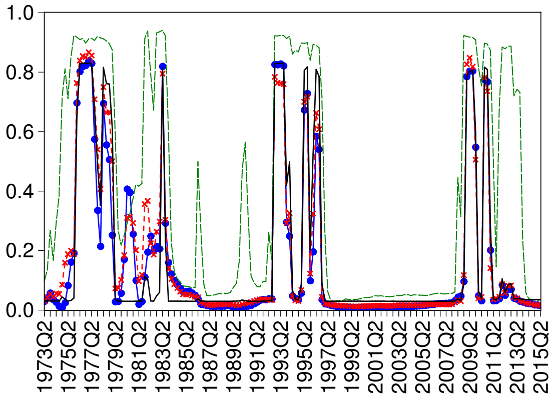
(g) Greece



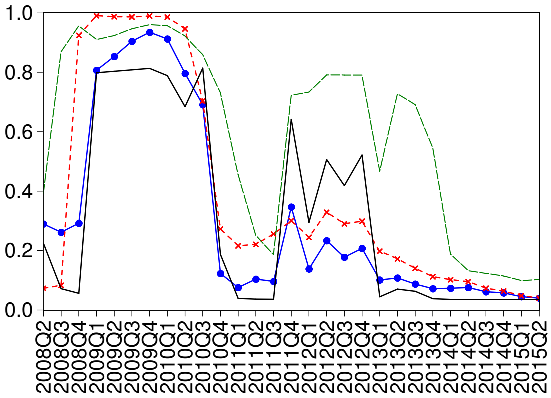
(h) Ireland



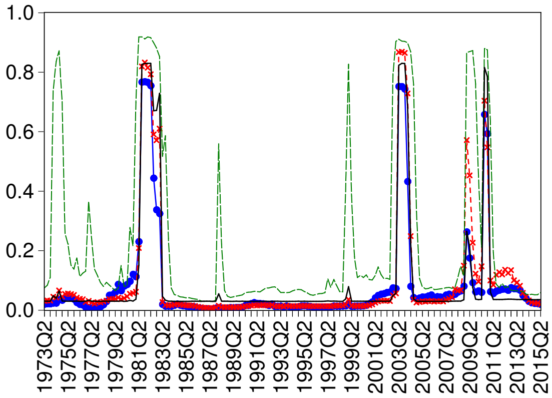
(i) Italy



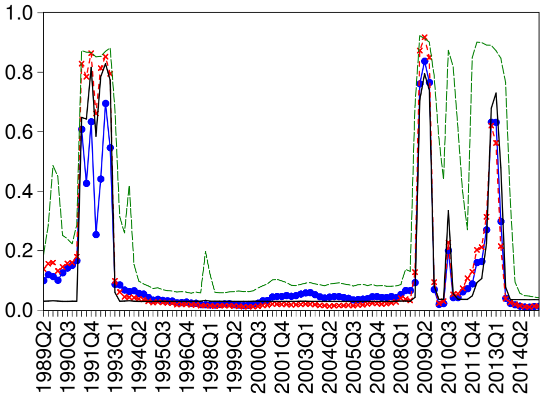
(j) Luxembourg



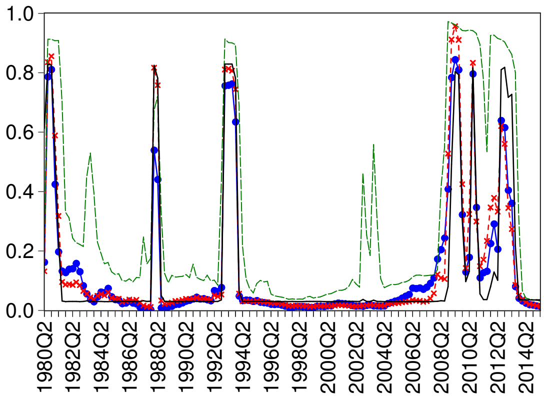
(k) Netherlands



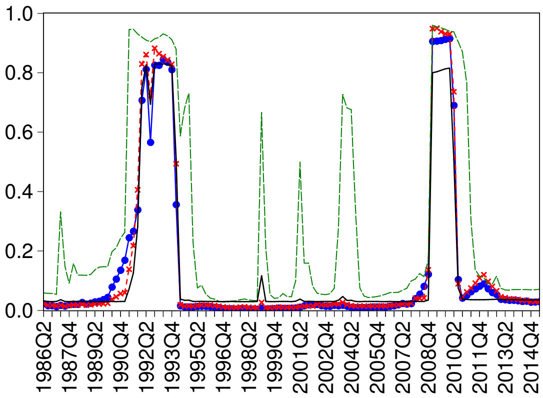
(l) Portugal



(m) Spain



(n) Sweden



(o) United Kingdom

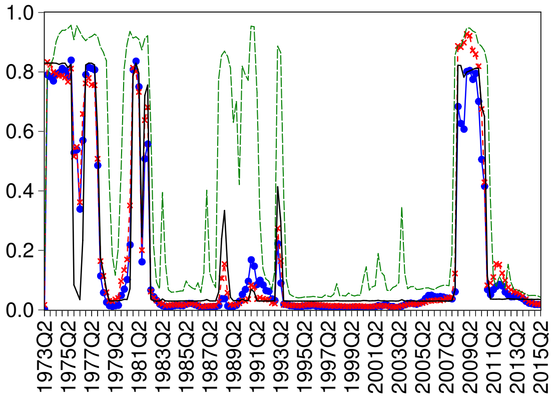
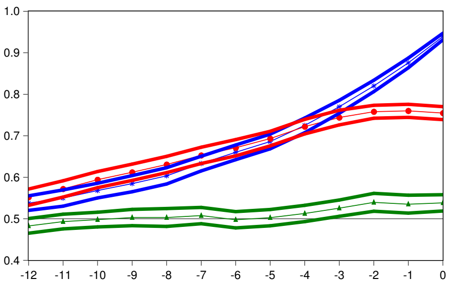
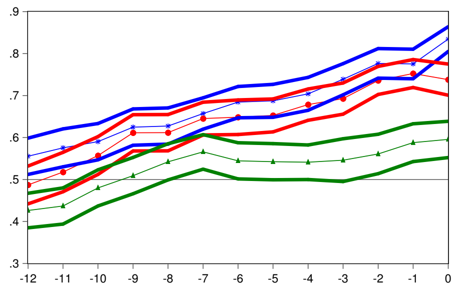


Figure 9: Predictive ability of the logit model versus the Markov switching model

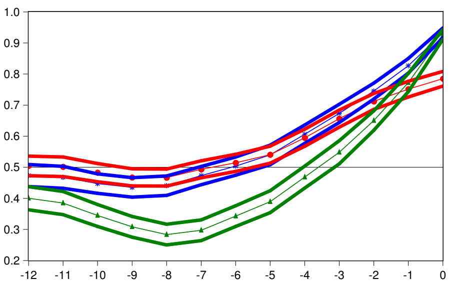
(a) Switch in mean, in-sample



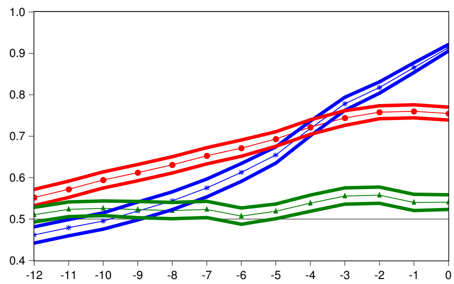
(b) Switch in mean, in-sample, adjusted



(c) Switch in mean, out-of-sample

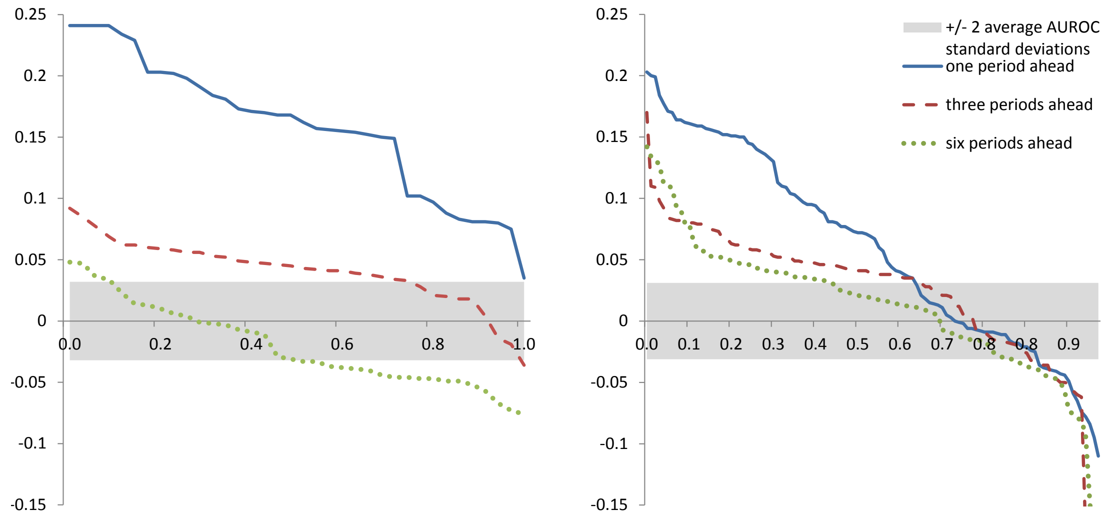


(d) Switch in mean/variance with AR(1), in-sample



Note: This figure shows the non-parametric area under the receiver operating curve (AUROC) of the one-quarter-ahead probability of high financial stress estimated from the Markov switching (MS) model (solid blue line with stars), from the fixed transition probability MS model that excludes all explanatory variables (solid green line with triangles), and from the logit model (solid red line with circles), for different time horizons ranging from 0 to 12 quarters prior to the start of the high-financial-stress episode. The AUROC is computed using financial stress dates defined as the episodes above the 90th percentile of the distribution of the Country-Level Indices of Financial Stress (CLIFS) that last at least two quarters. The AUROC is computed either on the whole dataset (subgraph a and d); or on a restricted dataset (subgraph b) that includes only 20 quarters prior to each high-financial-stress episode, removes the quarters after the start of the high-financial-stress episode, and excludes the four quarters after each high-financial-stress episode; or starting in 2006 as the out-of-sample probabilities are computed recursively from 2006 onwards by adding one quarter of information at a time (subgraph c). Conversely, in-sample estimation means that the model parameters for the computation of the probabilities are estimated on the whole sample. The financial stress episodes are defined as periods during which the level of financial stress exceeds the 90th percentile of its annual moving average. An AUROC above 0.5 signals that the respective indicator has predictive power, with higher AUROC values indicating a better predictive ability. The baseline specification includes the following leading indicators: GAP400_CT2GDP, DSR, RREP2RENT, D4_RREPR, D4_CPIP defined in Table 1. The 95% bootstrapped confidence bands are displayed.

Figure 10: Distribution of ΔAUROC across different model specifications and forecast horizons



Note: This figure shows the distribution of the difference between the non-parametric area under the receiver operating curve (AUROC) computed for the Markov switching (MS) model and for the logit model ($\Delta AUROC_{h,s} = AUROC_{MS,h,s} - AUROC_{logit,h,s}$) computed for many specifications s over different predictive horizons h. A positive value shown on the y-axis implies that the AUROC is higher for the MS model than for the logit model for the given forecast horizon, i.e. the forecasting power of the MS model for the respective forecast horizon is higher. The x-axis refers to the share of models, out of the total number of estimated models. The solid blue line corresponds to the one-quarter-ahead forecast of the high-financial-stress episode, the dashed red line corresponds to the three-quarter-ahead forecast and the dotted green line to the six-quarter-ahead forecast. Each point corresponds to a different estimation, with either a different structure of the MS model or a different definition of high financial stress. The grey area represents the average 95% confidence interval.
Twenty different specifications s for our benchmark set of controls (GAP400_CT2GDP, DSR, RREP2RENT, D4_RREPR, D4_CPIP defined in Table 1) are considered: a switch in the mean, a switch in the mean with an autoregressive term, a switch in the mean and variance, a switch in the mean and variance with an autoregressive term, a switch in the mean, variance and autoregressive term. Each of these specifications is estimated either with the benchmark computation of the Country-Level Indices of Financial Stress (CLIFS), or (i) with the CLIFS adjusted for a cross-country-relative ranking, (ii) with country dummies, or (iii) with four lags in the leading indicators. The forecast horizon h refers to the predictive ability of the model h-quarters ahead of the high-financial-stress periods. For the subgraph on the left, the AUROC is computed using financial stress periods defined as the episodes above the 90th percentile of the distribution of the CLIFS that last at least two quarters, with or without adjustment for the stress and post-stress period. As a robustness, for the subgraph on the right, the set of specifications include the AUROC computed using the 90th percentile, but also the 80th percentile, and the systemic financial stress dates of Duprey et al. (2017). Hence, there is a total of 40 model specifications included in the left subgraph and 120 model specifications on the right subgraph.

Table 1: List of potential leading indicators, quarterly frequency

Variable name	Description	Source
Credit-related:		
D4_CTR	Growth rate of (real) total credit to private non-financial sector (yoy, %)	BIS; SDW
D4_CBR	Growth rate of (real) bank credit to private non-financial sector (yoy, %)	BIS; SDW
D4_CTHHR	Growth rate of (real) total credit to households (yoy, %)	BIS; SDW
GAP26_CT2GDP	Absolute gap (lambda of 26000; starting in 1970; no rolling window) of the ratio of (nominal) total credit to the private non-financial sector to (nominal) GDP	BIS; SDW
GAP400_CT2GDP	Absolute gap (lambda of 400000; starting in 1970; no rolling window) of the ratio of (nominal) total credit to the private non-financial sector to (nominal) GDP	BIS; SDW
GAP400_CB2GDP	Absolute gap (lambda of 400000; starting in 1970; no rolling window) of the ratio of (nominal) bank credit to the private non-financial sector to (nominal) GDP	BIS; SDW
GAP400_CTHH2GDP	Absolute gap (lambda of 400000; starting in 1970; no rolling window) of the ratio of (nominal) total credit to households to (nominal) GDP	BIS; SDW
DSR	Debt service-to-income ratio, households and non-financial corporations	Various
DSRHH	Debt service-to-income ratio, households	Various
Housing-related:		
D4_RREPR	Growth rate of (real) residential property price index (yoy, %)	OECD
GAP26_RREPR	Absolute gap (lambda of 26000; starting in 1970; no rolling window) of the (real) residential property price index	OECD
GAP400_RREPR	Absolute gap (lambda of 400000; starting in 1970; no rolling window) of the (real) residential property price index	OECD
RREP2RENT	Ratio of (real) residential property price index to rents; rebased such that an index of 100 represents the average of a specific country	OECD
RREP2INC	Ratio of (real) residential property price index to income; rebased such that an index of 100 represents the average of a specific country	OECD
Macro-related:		
D4_CPIP	Growth rate of consumer price index (yoy, %)	SDW
D4_EERR	Growth rate of (real) effective exchange rate (yoy, %)	IMF (IFS)
D4_GDP	Growth rate of (real) GDP (yoy, %)	OECD; SDW
CA2GDPEUR	Current account balance (% of GDP)	SDW
DEBT2GDP	General government consolidated gross debt to GDP	SDW
Market-related:		
MMR3MR	Three-month money market interest rates (real)	SDW
D4_EQPR	Growth rate of (real) stock price index (yoy, %)	SDW

Note: IFS refers to the database International Financial Statistics of the IMF.

Table 2: List of potential leading indicators, monthly frequency

Variable name	Description	Source
Credit-related:		
D12_BCG	Growth rate of bank credit (yoy, %)	SDW (BSI)
D12_BCGHH	Growth rate of bank credit to households (yoy, %)	SDW (BSI)
D12_BCGNFC	Growth rate of bank credit to non-financial corporations (yoy, %)	SDW (BSI)
Housing-related:		
D12_GLHP	Growth rate of loans for house purchases (yoy, %)	SDW (BSI)
D12_RENT	Growth of rents (yoy, %)	SDW (ICP)
MORTR	Bank lending rates on new loans to households for house purchases	SDW (MIR)
Market-related:		
D12_EQPI	Growth rate of equity price index (yoy, %)	Datastream
EQPE	PE ratio (3-month average)	Datastream
D_ESI	Growth rate of the economic sentiment indicator base 100 in 1995 (mom, %)	SDW (SUR)
Banking-related:		
D12_BAG	Growth rate of MFIs total assets (yoy, %)	SDW (BSI)
LEV	Leverage ratio	SDW (BSI)
LTDR	Loan to deposit ratio	SDW (BSI)
MFIFX	FX exposure of MFIs (% of total assets)	SDW (BSI)
SMICE	Foreign currency exposure	SDW (BSI)

Note: The following acronyms refer to databases available in the Statistical Data Warehouse of the ECB: BSI, ICP, MIR and SUR.

Table 3: Testing for individual leading indicators of entering/exiting financial stress, quarterly data

Note: This table reports the coefficients driving the probability of entering or exiting high financial stress in the Markov chain. The Markov switching (MS) model is estimated separately for each indicator on quarterly data (15 EU countries starting in 1970). Financial stress is captured by the Country-Level Indices of Financial Stress (CLIFS) of Duprey et al. (2017). The mean level of the CLIFS is regime-dependent and the switching probability across regimes is governed by a two-state Markov chain. High financial stress is defined as the regime with a higher mean level of the CLIFS. Variables are defined in Table 1.

	(1)		(2)		(3)		(4)		
Model	MS		MS		MS		MS		
Dependent variable	CLIFS, EU15		CLIFS, EU15		CLIFS, EU15		CLIFS, EU15		
Frequency	Quarterly		Quarterly		Quarterly		Quarterly		
Adjusted CLIFS	NO		YES		NO		NO		
Switch in level	YES		YES		YES		YES		
Country dummies	NO		NO		YES		NO		
AR(1) term	NO		NO		NO		YES		
Probability to...	enter	exit	enter	exit	enter	exit	enter	exit	No. obs.
Credit-related:									
D4_CTR	-0.036	-0.017	-0.033	-0.005	0.021**	0.013	-0.061***	-0.068*	2302
GAP400_CT2GDP	0.016*	-0.022**	0.016*	-0.017	0.019**	0.013	0.020***	-0.011	2319
GAP26_CT2GDP	0.013	-0.029*	0.012	-0.021	0.018**	0.013	0.021***	-0.014	2319
DSR	0.026	-0.024	0.028*	-0.008	0.013	0.015*	0.042***	0.002	2078
D4_CTHHR	-0.030	-0.002	-0.002	0.027	0.015*	0.016*	-0.057***	-0.048	1792
GAP400_CTHH2GDP	0.017	0.002	0.036	0.008	0.013*	0.018*	0.022	0.005	1842
GAP26_CTHH2GDP	-0.021	0.005	-0.009	0.014	0.013*	0.017*	-0.005	-0.012	1842
DSRHH	0.071**	-0.054	0.097***	-0.075**	0.041***	0.008	0.059**	-0.051	1224
D4_CBR	-0.029	-0.013	-0.022	-0.002	0.016**	0.019**	-0.028	0.005	2303

* p<0.10, ** p<0.05, *** p<0.01

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Table 3 Continued

	(1)		(2)		(3)		(4)		
Model	MS		MS		MS		MS		
Dependent variable	CLIFS, EU15		CLIFS, EU15		CLIFS, EU15		CLIFS, EU15		
Frequency	Quarterly		Quarterly		Quarterly		Quarterly		
Probability to...	enter	exit	enter	exit	enter	exit	enter	exit	
GAP400_CB2GDP	0.027**	-0.026	0.033***	-0.024	0.018**	0.017**	0.029***	-0.018	2322
GAP26_CB2GDP	0.020	-0.019	0.030	-0.017	0.018**	0.018**	0.030*	-0.030	2322
Housing-related:									
D4_RREPR	-0.092***	0.009	-0.124***	0.016	0.013	0.018**	-0.076***	0.004	2097
GAP400_RREPR	-0.003	0.007	-0.010	0.004	0.012	0.019**	-0.012	-0.004	2149
GAP26_RREPR	-0.057***	0.023	-0.071***	0.019	0.012	0.018**	-0.058***	0.014	2149
RREP2INC	0.017***	-0.006	0.018***	-0.007	0.017**	0.012	0.018***	0.003	1837
RREP2RENT	0.008*	0.000	0.009*	-0.004	0.019**	0.011	0.007**	0.003	2109
Macro-related:									
D4_CPIP	0.078***	-0.028	0.076***	-0.053*	0.016**	0.017**	0.076***	-0.010	2395
D4_EERR	0.051**	-0.010	0.065**	-0.002	0.022***	0.008	0.031	0.023	2114
D4_GDP	-0.279***	0.04	-0.292***	0.038	0.018**	0.016**	-0.207***	0.033	2395
CA2GDPEUR	-0.058	0.101**	-0.083**	0.126***	0.028**	0.014*	-0.045	0.076	1264
DEBT2GDP	0.002	0	-0.001	-0.002	0.008	0.022*	-0.003	0.010	942
Market-related:									
MMR3MR	-0.037	-0.029	-0.034	-0.059	0.025***	0.019**	-0.039	-0.049	2130
D4_EQPR	-0.034***	0.015***	-0.044***	0.016**	0.017**	0.016**	-0.023***	0.013	2205

* p<0.10, ** p<0.05, *** p<0.01

Table 4: Multiple leading indicators of entering/exiting financial stress, switch in mean, quarterly data

Note: This table reports the results from a Markov switching (MS) model estimated on quarterly data (15 EU countries starting in 1970) with several leading indicators. Financial stress is captured by the Country-Level Indices of Financial Stress (CLIFS) of Duprey et al. (2017). The mean level of the CLIFS is regime-dependent and the switching probability across regimes is governed by a two-state Markov chain. High financial stress is defined as the regime with a higher mean level of the CLIFS. Inflation is controlled for separately so that all other indicators are expressed in real terms. Variables are defined in Table 1.

	(1)		(2)		(3)		(4)	
Model	MS		MS		MS		MS	
Dependent variable	CLIFS, EU15		CLIFS, EU15		CLIFS, EU15		CLIFS, EU15	
Frequency	Quarterly		Quarterly		Quarterly		Quarterly	
Adjusted CLIFS	NO		YES		NO		NO	
Switch in level of dependent variable	YES		YES		YES		YES	
Country dummies	NO		NO		YES		NO	
AR(1) term	NO		NO		NO		YES	
Stress regime...	low	high	low	high	low	high	low	high
Constant	0.110***	0.344***	0.114***	0.362***	0.127***	0.352***	0.031***	0.203***
Standard deviation	0.069***		0.072***		0.067***		0.044***	
AR(1)							0.696***	
Probability to...	enter	exit	enter	exit	enter	exit	enter	exit
Constant	-6.632***	-1.184	-6.479***	-0.154	-6.645***	-0.859	-6.101***	-0.226
GAP400_CT2GDP	0.005	-0.040***	0.013	-0.032**	0.006	-0.039***	0.008	-0.024
DSR	0.061***	-0.004	0.048**	0.019	0.061***	-0.007	0.063***	0.029
RREP2RENT	0.014***	0.004	0.014**	-0.007	0.014***	0.001	0.012***	0.006
D4_RREPR	-0.061***	-0.004	-0.095***	0.029	-0.058**	0.007	-0.045***	0.034
D4_CPIP	0.151***	-0.049	0.131***	-0.108**	0.157***	-0.061	0.137***	-0.009
BIC criterion	-2.175		-2.115		-2.165		-2.971	
LR test against fixed transition MS	53.920		58.016		51.362		59.914	
No. of observations	1902		1902		1902		1902	

* p<0.10, ** p<0.05, *** p<0.01

Table 5: Multiple leading indicators of entering/exiting financial stress, switch in mean and variance, quarterly data

Note: This table reports the results from a Markov switching (MS) model estimated on quarterly data (15 EU countries starting in 1970) with several leading indicators. Financial stress is captured by the Country-Level Indices of Financial Stress (CLIFS) of Duprey et al. (2017). The mean level of the CLIFS as well as its variance is regime-dependent and the switching probability across regimes is governed by a two-state Markov chain. High financial stress is defined as the regime with a higher mean level of the CLIFS. Inflation is controlled for separately so that all other indicators are expressed in real terms. Variables are defined in Table 1.

	(1)		(2)		(3)	
Model	MS		MS		MS	
Dependent variable	CLIFS, EU15		CLIFS, EU15		CLIFS, EU15	
Frequency	Quarterly		Quarterly		Quarterly	
Adjusted CLIFS	YES		YES		YES	
Switch in level of dependent variable	YES		YES		YES	
Switch in variance of dependent variable	YES		YES		YES	
AR(1) term	NO		YES		YES	
Switch in AR(1) term	NO		NO		YES	
Stress regime...	low	high	low	high	low	high
Constant	0.091***	0.268***	0.025***	0.111***	0.026***	0.086***
Standard deviation	0.044***	0.118***	0.031***	0.085***	0.030***	0.082***
AR(1)			0.683***		0.663***	0.783***
Probability to...	enter	exit	enter	exit	enter	exit
Constant	-4.456***	-1.279*	-3.474***	0.089	-3.231***	0.192
GAP400_CT2GDP	0.005	-0.033**	0.004	-0.028*	0.002	-0.026*
DSR	0.045**	0.013	0.037*	0.029	0.037*	0.029
RREP2RENT	0.004	-0.004	0.003	-0.007	0.002	-0.009
D4_RREPR	-0.008	0.042***	-0.009	0.059***	-0.010	0.050**
D4_CPIP	0.114***	-0.087**	0.131***	-0.063	0.151***	-0.040
BIC criterion	-2.367		-3.141		-3.142	
LR test against fixed transition MS	39.790		55.100		54.280	
No. of observations	1902		1902		1902	

* p<0.10, ** p<0.05, *** p<0.01

Table 6: Testing for individual leading indicators of entering/exiting financial stress, monthly data

Note: This table reports the coefficients driving the probability of entering or exiting high financial stress in the Markov chain. The Markov switching (MS) model is estimated separately for each indicator on monthly data (euro area countries from 1998 onwards). Financial stress is captured by the Country-Level Indices of Financial Stress (CLIFS) of Duprey et al. (2017). The mean level of the CLIFS is regime-dependent and the switching probability across regimes is governed by a two-state Markov chain. High financial stress is defined as the regime with a higher mean level of the CLIFS. Variables are defined in Table 2.

	(1)		(2)		(3)		(4)		
Model	MS		MS		MS		MS		
Dependent variable	CLIFS, Eurozone		CLIFS, Eurozone		CLIFS, Eurozone		CLIFS, Eurozone		
Frequency	Monthly		Monthly		Monthly		Monthly		
Adjusted CLIFS	NO		YES		NO		NO		
Switch in level	YES		YES		YES		YES		
Country dummies	NO		NO		YES		NO		
AR(1) term	NO		NO		NO		YES		
Probability to...	enter	exit	enter	exit	enter	exit	enter	exit	No. obs.
Credit-related:									
D12_BCG	0.001	-0.013	0.007	-0.002	0.003	0.014	-0.002	0.015	2478
D12_BCGHH	-0.030	-0.008	-0.023	0.009	0.002	0.014	-0.043***	0.017	2478
D12_BCGNFC	0.010	-0.010	0.017	-0.001	0.003	0.014	-0.010	-0.020	2478
Housing-related:									
D12_RENT	0.025	0.024	0.033	0.065	na	na	-0.079**	0.044	2856
MORTR	-0.012	-0.045	0.003	-0.038	0.009	0.004	0.018	-0.014	4452
D12_GLHP	-0.044**	0.000	-0.026	0.030	0.003	0.014	-0.050***	0.020	2478

* p<0.10, ** p<0.05, *** p<0.01

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Table 6 Continued

	(1)		(2)		(3)		(4)		
Model	MS		MS		MS		MS		
Dependent variable	CLIFS, Eurozone		CLIFS, Eurozone		CLIFS, Eurozone		CLIFS, Eurozone		
Frequency	Monthly		Monthly		Monthly		Monthly		
Probability to...	enter	exit	enter	exit	enter	exit	enter	exit	
Market-related:									
EQPE	-0.069	0.006	-0.045	-0.014	0.024***	0.008	-0.067***	-0.056	3163
D12_EQPI	-0.039***	0.009**	-0.033***	0.010**	0.001	0.021***	-0.028***	0.010	3530
D_ESI	-0.219***	0.163***	-0.145**	0.213***	na	na	-0.104***	-0.007	4039
Banking-related:									
D12_BAG	0.013	-0.013	0.026	0.005	0.014	0.003	0.000	0.006	2478
LEV	-0.141*	-0.020	-0.035	-0.040	-0.005	0.019**	-0.105**	-0.001	2622
LTDR	-0.001	0.007	0.003	0.010	-0.007	0.021**	-0.012*	-0.005	2622
MFIFX	0.034	-0.110*	0.021	-0.003	-0.005	0.020**	0.125***	-0.007	2622
SMICE	0.045	-0.128	0.040	-0.010	-0.005	0.020**	0.133***	0.051	2622

* p<0.10, ** p<0.05, *** p<0.01

Table 7: Multiple leading indicators of entering/exiting financial stress, switch in mean, monthly data

Note: This table reports the results from a Markov switching (MS) model estimated on monthly data (euro area countries starting in 1998) with several leading indicators. Financial stress is captured by the Country-Level Indices of Financial Stress (CLIFS) of Duprey et al. (2017). The mean level of the CLIFS is regime-dependent and the switching probability across regimes is governed by a two-state Markov chain. High financial stress is defined as the regime with a higher mean level of the CLIFS. Variables are defined in Table 1.

	(1)		(2)		(3)		(4)	
Model	MS		MS		MS		MS	
Dependent variable	CLIFS, Eurozone		CLIFS, Eurozone		CLIFS, Eurozone		CLIFS, Eurozone	
Frequency	Monthly		Monthly		Monthly		Monthly	
Adjusted CLIFS	NO		YES		NO		NO	
Switch in level of dependent variable	YES		YES		YES		YES	
Country dummies	NO		NO		YES		NO	
AR(1) term	NO		NO		NO		YES	
Stress regime...	low	high	low	high	low	high	low	high
Constant	0.087***	0.262***	0.083***	0.252***	0.085***	0.256***	0.019***	0.157***
Standard deviation	0.062***		0.059***		0.061***		0.038***	
AR(1)							0.791***	
Probability to...	enter	exit	enter	exit	enter	exit	enter	exit
Constant	-3.727***	-1.991**	-4.977***	-0.730	-3.920***	-1.524*	-2.367***	-0.523
BCGHH	0.031	-0.035	0.026	-0.009	0.047	-0.015	-0.039	-0.063
D12_RENT	0.141	-0.140	0.109	-0.067	0.066	-0.169	0.121**	-0.162
MORTR	0.377***	0.043	0.378***	-0.252*	0.409***	0.016	0.126	0.142
GLHP	-0.128***	0.029	-0.103**	0.018	-0.130***	0.019	-0.014	0.031
D_ESI	-0.490***	0.124*	-0.414***	0.051	-0.458***	0.125*	-0.230***	0.071
LEV	-0.181*	-0.025	-0.008	-0.119	-0.170*	-0.123	-0.180***	0.175
SMICE	-0.158	-0.034	-0.142	0.115	-0.138	0.065	0.024	0.623*
BIC criterion	-2.45		-2.561		-2.454		-3.278	
LR test against fixed transition MS	81.892		70.184		58.252		65.200	
No. of observations	2325		2325		2325		2325	

* p<0.10, ** p<0.05, *** p<0.01

Table 8: Multiple leading indicators of entering/exiting financial stress, switch in mean and variance, monthly data

Note: This table reports the results from a Markov switching (MS) model estimated on monthly data (euro area countries starting in 1998) with several leading indicators. Financial stress is captured by the Country-Level Indices of Financial Stress (CLIFS) of Duprey et al. (2017). The mean level of the CLIFS is regime-dependent and the switching probability across regimes is governed by a two-state Markov chain. High financial stress is defined as the regime with a higher mean CLIFS. Variables are defined in Table 1.

	(1)		(2)		(3)	
Model	MS		MS		MS	
Dependent variable	CLIFS, Eurozone		CLIFS, Eurozone		CLIFS, Eurozone	
Frequency	Monthly		Monthly		Monthly	
Adjusted CLIFS	YES		YES		YES	
Switch in level of dependent variable	YES		YES		YES	
Switch in variance of dependent variable	YES		YES		YES	
AR(1) term	NO		YES		YES	
Switch in AR(1) term	NO		NO		YES	
Stress regime...	low	high	low	high	low	high
Constant	0.061***	0.200***	0.013***	0.056***	0.015***	0.046***
Standard deviation	0.031***	0.087***	0.019***	0.059***	0.018***	0.057***
AR(1)			0.730***		0.686***	0.777***
Probability to...	enter	exit	enter	exit	enter	exit
Constant	-5.112***	-2.950***	-1.048	0.080**	-0.990	-0.261
BCGHH	0.005	-0.039	0.048	-0.006	0.054	0.000
D12_RENT	0.180*	-0.118	-0.001	-0.277	-0.100	-0.320***
MORTR	0.525***	-0.104	0.263	-0.185	0.267	-0.165
GLHP	-0.084*	0.051*	-0.130	0.024	-0.117***	0.031
D_ESI	-0.317***	0.130**	-0.310	0.033	-0.347***	0.010
LEV	-0.024	0.032	-0.178***	-0.113	-0.180**	-0.092
SMICE	-0.074	0.097	-0.194***	-0.050	-0.197**	-0.064
BIC criterion	-2.878		-3.659		-3.661	
LR test against fixed transition MS	56.960		60.978		58.380	
No. of observations	2335		2335		2335	

* p<0.10, ** p<0.05, *** p<0.01