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Jakob Fiedler[1], Josef Ruzicka[2], Thomas Theobald[3]

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[1] University Duisburg-Essen and Deutsche Apotheker- und Ärztebank, Germany. Mail jakob.fiedler@uni-due.de (corresponding author).
[2] Universidad Carlos III de Madrid, Spain.
[3] Macroeconomic Policy Institute (IMK), Düsseldorf, Germany.

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Jakob Fiedler* Josef Ruzicka† Thomas Theobald ‡

July 22, 2019

Abstract

We integrate newly created financial stress indices (FSIs) into an automated real-time recession forecasting procedure for the Euro Area and Germany. The FSIs are based on a large number of financial indicators, each of them potentially signaling financial stress. A subset of these indicators is selected in real-time and their stress signal is summarized by principal component analysis (PCA). Besides conventional measures of realized financial stress, such as volatilities, we include variables related to the financial cycle, such as different types of credit growth, for which strong increases may anticipate future financial market stress. Building blocks in our fully automated real-time probit forecasts are then i. the use of a broad set of widely acknowledged macroeconomic and financial variables with predictive power for a real economic downturn, ii. the use of both general-to-specific and specific-to-general approaches for variable and lag selection, and iii. the averaging of different specifications into a composite forecast. As a real-time out-of-sample analysis shows, the inclusion of financial stress leads to an improved recession forecast for the Euro Area, while the results for Germany are mixed. Finally, we also evaluate the predictive power of the change in bank lending (credit impulse) and find that it adds little additional information.

1 Introduction

Since the 1990s recessions have been surrounded and increasingly driven by financial market turbulence (Kindleberger 1993). In light of this development, the forward-looking nature of financial markets and the potential effects of financial conditions on future real-economic activity make it obvious to include financial indicators into recession forecasting exercises. Indeed, the usefulness of individual financial indicators for recession forecasts has been extensively explored. This applies to the interest rate spreads of borrowers with different credit ratings (Bernanke et al. 1990, Mody & Taylor 2004, among others), the slope of the yield curve (Estrella & Mishkin 1998, Ang, Piazzesi & Wei 2006, among others) and stock returns (Birchenhall, Osborn & Sensier 2001, Nyberg 2010, among others). Their predictive power has also been confirmed by studies running real-time forecast regressions (Proaño & Theobald 2014, Schreiber & Soldatenkova 2016).

Other studies started to investigate (in addition) the predictive power of factor variables that condense the information from large sets of financial indicators (Hatzius et al. 2010, Menden

*Corresponding author (jakob.fiedler@uni-due.de). University Duisburg-Essen, Germany, and Deutsche Apotheker- und Ärztebank. This paper reflects the views of its authors, not necessarily those of the affiliated institutions.

†Universidad Carlos III de Madrid, Spain.

‡Macroeconomic Policy Institute (IMK), Düsseldorf, Germany.

& Proaño 2017). Depending on the underlying information matrix, some of these factors are referred to as financial market stress indices (Cardarelli, Elekdag & Lall 2011, Cevik, Dibooglu & Kutan 2013). From our point of view, this strand of the literature lacks an analysis of the predictive power in a comprehensive real-time approach. Such an exercise requires to take into account both data availability as well as data revisions of all the time series involved. Accordingly, in this study, we analyze the predictive power of newly created financial stress indices (FSIs) in a fully automated real-time probit model for economic downturns in Germany and the Euro Area.

The fact that a large part of the FSI-related literature does not take into account the issue of real-time methods (Hatzius et al. 2010, Cardarelli, Elekdag & Lall 2011, van Roye 2014, Islami & Kurz-Kim 2014, Cevik, Dibooglu & Kutan 2013) is often justified by two lines of argument. First, many FSIs are created using solely financial market data that are not revised and are not subject to publication lags. Second, if the analysis aims at analyzing empirical phenomena from an *ex-post* perspective, there might be no need for mimicking the selection of indicators and weights in a real-time setting. But once financial indicators subject to a publication lag, i.e. credit data, are integrated, and if the *ex-ante* role of financial market stress is prioritized, the above-mentioned arguments are of little help. Indeed, we are explicitly interested in the ex-ante predictive power of FSIs with respect to historical recessions. The paper that is closest to this perspective is the one by Levanon et al. (2015). Like our study, the authors include data that is released with publication lags and frequently revised. However, contrary to our study, the variable selection by Levanon et al. (2015) does not change in real-time. Instead, we employ a fully-enriched real-time setting which includes vintage data (as far as available), the consideration of publication lags, variable and lag selection for the probit forecasts and a time-varying selection of the indicators underlying the FSIs.

Following Hollo, Kremer & Lo Duca (2012), financial stress can be interpreted as financial risks that already have materialized. The classical example of a time series following this definition is a stock market volatility index, such as the globally leading VIX (Rey 2015). In addition, other parts of financial risks that have not yet materialised, but describe a latent build-up, can be important for the recession probability forecast. In this way, Borio (2014) uses the interaction of credit and property prices to parsimoniously define a boom-bust cycle, the so-called financial cycle. Its peaks usually coincide with financial market crises and then unfold fatal real economic consequences. Parallely, a strand of the literature has focused on the characterization of the intrinsic dynamics of the financial cycle (Claessens, Kose & Terrones 2011, Claessens, Kose & Terrones 2012, Drehmann, Borio & Tsatsaronis 2012, Strohsal, Proaño & Wolters 2019).

By allowing our automated procedure to add different types of credit and property price growth to the FSI information matrix, if they are among the most statistically relevant indicators, we try to take this risk perspective into account. By doing so, we are facing the challenge that most credit and house price series are subject to data availability lags. A similar issue arises when incorporating financial indicators for which data histories are relatively short. The TARGET2 balances of the European System of Central Banks may serve as an example here. We resolve this issue by employing an imputation procedure as part of the real-time forecast process(Josse & Husson 2016).

The two concepts of financial risk and their respective proxy variables differ in several ways. First, conventional indicators capture risks that are perceived by financial market participants. Such indicators, like stock market volatility, often tend to move abruptly, while the financial cycle indicators, like credit growth, tend to behave more slowly. Second, different indicators may not always move synchronously. Especially if risk behavior of economic agents changes over time and stability breeds instability, one might expect a low level of financial risk perception, while indicators of risk build-up might indicate high levels of risk (Minsky 2008).

A further aspect that has been rarely discussed in the literature using real-time forecasts is the ambivalent role of credit. This ambivalence is evident from the fact that strong credit growth in the perspective of the financial cycle leads to different real economic consequences than those one receives if credit growth is merely seen as a financial reflection of real economic expenditure and thus real economic activity. For the latter case, the change in credit growth, the so-called credit impulse, is preferred for reasons of flow consistency. With respect to the financial cycle, as already mentioned, the most common representation is based on asset price and private credit growth[1] (Drehmann, Borio & Tsatsaronis 2012). Here, the rationale behind the inclusion of the credit variable is that strong credit growth increases an economy's vulnerability to financial crises and hence reduces future economic activity (Schularick & Taylor 2012, Drehmann, Juselius & Korinek 2018). On the other hand, as argued by Biggs, Mayer & Pick (2010), there exists a tight relationship between the change in credit growth and the growth of real economic activity. Here, the intuition is that private households and firms finance a significant part of their spending by loans. As the first and second derivative of the credit stock as a function of time - credit growth and the credit impulse - are usually correlated, regressions of economic activity only on credit growth might yield spurious results (Pick 2016). To control for this effect we test the predictive power of the change in the flow of net bank lending as an additional regressor in our probit forecasts, while different types of credit growth - mortgage, consumer credit, and corporate credit growth - are allowed to influence the results of the financial stress indices.

Along these lines of research, this paper aims to contribute to the literature in the following dimensions. First, we integrate information about the financial cycle into an FSI capturing a large number of different financial market variables. Second, using a PCA-based imputation method, our FSI approach is capable of incorporating indicators with missing values and short data histories. Third, both the creation of the FSIs and the estimation of the probit models are designed in a fully-automated real-time setting including variable selection. Fourth, we test the credit impulse as an additional potentially powerful predictive variable.

Our results can be summarized as follows: Similar to the results of Levanon et al. (2015) for the US, the inclusion of financial stress leads to improved recession forecasts for the Euro Area, while the results for Germany are mixed. Furthermore, the credit impulse adds little additional information and does not improve the out-of-sample forecasting performance. Overall, our results suggest that financial stress can considerably improve recession forecasts, especially since the model is capable of automatically including and excluding variables whose relation to financial stress may change over time. Thus, even though we do not find a clear improvement of the forecasting performance in the German case, considering financial stress can be valuable during future episodes of uncertainty. The remainder of this paper is organized as follows: Section 2 briefly summarizes the existing literature on the information content of financial stress on real activity. Section 3, describes the data and the empirical model employed in our real-time analysis. The results are presented in Section 4. Section 5 concludes.

2 Literature Overview

In the aftermath of the financial crisis several FSIs have been developed both in academia and in the financial sector.[2] In addition to the aim of measuring and monitoring financial stress, a strand of this literature has focused on its effects on real economic activity and in particular on its forecasting power with respect to economic downturns.

[1]Alternatively, in order to compare credit growth relative to GDP growth, macroprudential authorities usually consider a non-positive change in the credit-to-GDP ratio or a negative credit-to-GDP gap as stable.

[2]See Darracq Pariès, Maurin & Moccero (2014) for an overview.

van Roye (2014) extracts an FSI using a dynamic factor model based on 19 financial variables reflecting dynamics in the banking sector, on capital markets and foreign exchange markets. Applying a threshold autoregressive model, he shows that economic activity decelerates significantly after the FSI exceeds the estimated threshold (high-stress regime), while below this threshold activity remains mostly unaffected. Dovern & van Roye (2014) construct variance- and CDF[3]-weighted FSIs based on 6 financial variables for 20 major economies. These variables are stock market returns and the volatility of returns on general firm equity, bank equity, exchange rates, government bond yields, and money market instruments. Running a global vector autoregression (GVAR), they find that financial stress has a significantly negative effect on industrial production, with the maximum impact being reached with a lag of approximately 6 months. In an analysis of the Euro Area, Islami & Kurz-Kim (2014) construct a variance-weighted FSI consisting of six indicators reflecting financial risk (general CDS spreads, non-financial CDS spreads, volatilities of the exchange rate and future oil price, the earnings-price ratio minus 10-year interest rate and the 3-month interest minus the overnight rate). They estimate its information content on industrial production using correlation analysis and find that the FSI provides significant predictive power over a horizon of four months. Duprey, Klaus & Peltonen (2017) create country-specific financial stress indices for EU countries based on the correlations of financial indicators reflecting the stock market, bond market and foreign exchange market stress. They find that periods of high financial market stress combined with real-economic downturns are in many cases consistent with episodes that are identified as (banking) crises by experts. Hatzius & Stehn (2018) focus on the US and create an FSI using interest rates, the exchange rate, equity valuations, and credit spreads weighted by their estimated impact on real GDP growth. Based on VAR estimations they find that financial conditions summarized in this way have a significantly negative impact on the output gap with the maximum effect reached after 7 quarters.

In contrast to the aforementioned studies, which measure financial stress and its predictive power from an ex-post and in-sample fashion, Levanon et al. (2015) take a real-time, quasi-out-of-sample perspective. Using principal component analysis, they construct an FSI for the US-based on 6 financial indicators.[4] Estimating probit models, they then find that the inclusion of the FSI leads to considerably improved recession forecasts compared to a benchmark model based on standard macroeconomic variables. From a real-time perspective, our study transfers this approach to European data. Moreover, as the underlying financial indicators in each study are different, we try to cover as many indicators as possible.

Another strand of non-real-time literature selects their variables according to the definition of the financial cycle and then analyzes the predictive power with respect to economic downturns. An early study taking into account the information content of both the financial cycle and materialized financial stress is Cardarelli, Elekdag & Lall (2011) who construct FSIs using an equal-variance-weighted average of seven financial market variables for seventeen advanced economies. They show that only half of the peak episodes in financial stress are followed by economic downturns. When reducing the sample to financial stress episodes that are related to high credit growth and rapidly increasing house prices, i.e. peaks in the financial cycle, the likelihood of subsequent economic downturns significantly increases. Menden & Proaño (2017) extract dynamic factors from a sample of 32 indicators related to the financial cycle. Using a probit model which only includes the dynamic factors and a term spread as explanatory variables, they show that the factors significantly improve one-quarter-ahead in-sample forecasts of recessions in the US. In a real-time setting Borio, Drehmann & Xia (2018) construct financial cycle variables

[3]Here, CDF stands for the cumulative distribution function.

[4]The indicators that have been selected by Levanon et al. (2015) are 2-year swap spreads, 3-month LIBOR less the 3-month Treasury bill yield spread, debit balances at margin accounts at broker-dealers, investors sentiments, survey-based credit conditions to large and medium firms and liabilities-security repurchases.

for 16 advanced economies by applying a bandpass filter to inflation-adjusted credit volumes, credit-to-GDP ratios, and property prices. They then average the filtered series. Estimating panel probit models also in real time, they find that their financial cycle index outperforms the predictive power of models using only the term spread, especially in longer-term horizons of 2 and 3 years. Our study goes beyond these probit specifications mentioned by using a broader set of control variables, not just term spreads, so that the additional predictive power of the FSI cannot be attributed to the omission of individual indicators.

In parallel to the growing literature on the financial cycle, there has been increased attention to the credit impulse and its relation to real economic activity, especially in the applied research of financial sector institutions.[5] In the academic literature, in contrast, the inclusion of the credit impulse in forecasting economic activity has been rare. Ermişoğlu, Akçelik & Oduncu (2013) show that the credit impulse provides valuable input in nowcasting Turkish GDP growth. Seitz, Baumann & Albuquerque (2015) use the credit impulse in a VAR approach to forecast US GDP growth and find that it adds predictive power in 1-to-8-quarter out-of-sample forecasts. To our knowledge, so far there exists no study which includes the credit impulse in real-time recession forecasts.

3 Data and Methodology

In the following sections, we describe how FSIs are built and integrated into a real-time out-of-sample forecast procedure. The full sample consists of monthly data starting in January 1991 and ending in December 2018. The monthly real-time out-of-sample estimations begin in January 2007 and take into account all available data starting in January 1991 until the respective vintage month. As the cut-off date for the creation of the respective vintage data set, we chose the 15th calendar day of the subsequent month.

3.1 Construction of the financial stress indices

The FSIs presented here are based on a large number of financial indicators, 58 for Germany and 52 for the EMU, which potentially provide information regarding financial market risks. As already mentioned, an innovative feature of our FSIs is the inclusion of both conventional indicators reflecting *financial risk realization*, like the volatility of asset prices, and the financial cycle indicators in the spirit of Borio (2014) - reflecting the *build-up of financial risks*. Our data sets comprise a broad range of indicators including i.a. house and stock price returns, credit and term spreads, Credit Default Swap spreads, different types of volatilities, survey data on financial conditions, and (bank) loan growth for various categories. See the Tables 5 and 6 in the appendix for a full list of indicators and Figures 13 to 16 for an illustration. Data are retrieved in - and if necessary interpolated to - monthly frequency. For each vintage, 2007/01 to 2018/12, the following steps are taken:

1. **Creation of the vintage data set:** A vintage data set starting the observations in January 1991 is constructed for each of the publications from January 2007 on. This vintage data takes into account the variables' publication lags. In contrast to the explanatory variables used in the probit estimations, the underlying series in the FSI information matrix are generally not subject to data revisions.[6]

[5] Research notes analyzing credit impulses are regularly provided i.a. by Deutsche Bank, Pictet Asset Management, BCA Research, and Bloomberg.

[6] Bank loans are a rare exception. To the best of our knowledge, there is no publicly available real-time database for credit data. At the same time, our own records only go back to vintages since 2014. Overall, as the FSIs

2. **Variable selection:** To reduce both the ex-post selection bias and the potential noise due to uninformative indicators, for each vintage the data set is selected based on the indicators' correlation with a monthly published reference series for financial stress. For Germany, we use the respective country level of financial stress constructed by Duprey, Klaus & Peltonen (2017) as the reference series and for the EMU we use the average of the respective indices for Germany, France, Italy, and Spain. For each series, the correlation to the reference series is calculated and then the 20 series with the highest correlations are selected. To ensure that the indicators are only included in an economically meaningful way, we impose sign restrictions. See Tables 5 and 6 in the Appendix.

3. **Imputation:** The original data contain missing data both due to indicator-specific publication lags and due to indicator histories that in many cases start after 1991/01. To attain an information matrix of full rank, we fill the data gaps using the PCA-based imputation algorithm of Audigier, Husson & Josse (2013) and Josse & Husson (2016), which imputes missing values minimizing the overall effect on the data set's principal components. An advantage of this approach is high flexibility regarding the potential inclusion of new risk indicators with relatively short data histories.

4. **Principal component extraction:** In the final step, we run a PCA on the data set and use the first principal component as our FSI, which is then scaled such that $min(\text{FSI}) = 0$ and $max(\text{FSI}) = 1$.

The resulting FSIs provide a real-time perspective on the evolution of financial stress.

3.2 Calculation of the credit impulse

The credit impulse is defined as the difference in growth of the outstanding stock of bank lending to the private non-financial sector (Biggs, Mayer & Pick 2010). We compute it as

$$CreditImpulse_t = \Delta \left(\frac{loans_t - loans_{t-3}}{loans_{t-3}} \right), \tag{1}$$

where Δ is the monthly difference and $loans_t$ the stock of outstanding bank loans to the private non-financial sector in month t. See Tables 3 and 4 in the Appendix for a description and data sources. As the registered volume of bank lending on banks' balance sheets usually is affected by loan securitisations and sales to non-banks, we use adjusted series, if available.

3.3 Recession dating

With respect to probit recession forecasts, the identification of previous recessions, i.e. a binary dependent variable, is required. Moreover, from a real-time perspective, this identification should take place only based on information of the respective vintage data. For both Germany and the EMU, we use a centered three-month moving average of industrial production y_t^{3mma} as a reference series proxying the business cycle in monthly frequency. Industrial production is subject to a data availability lag of one month and is frequently revised. See Tables 3 and 4 in the Appendix for a description and data sources.

Following Proaño & Theobald (2014), we apply a modified version of the Bry & Boschan (1971) algorithm to identify business cycle peaks and troughs. A peak is given in a month where the economic activity is higher than in the previous and in the following five months. A

are constructed on a large number of indicators, we suppose that the potential effects of revisions are of minor importance at this point.

trough is defined vice versa. Then, a recession is identified either as a sharp decline in economic activity over a short time or a slower drop of activity over a longer time span. Furthermore, to exclude temporary slumps in industrial production, which are quickly reversed, we require a minimum recession length of four months. Following Harding & Pagan (2002) and using a severity parameter of 0.1, a recession is given if

$$0.1 \leq (y_p^{3mma} - y_\tau^{3mma})/y_p^{3mma} * (\tau - p) \quad \text{and} \quad \tau > p + 3, \tag{2}$$

where a trough is reached in τ and p is the period of the previous peak. For illustration, given the duration of four months, this condition is fulfilled by a decline in activity of at least 2.5%. Alternatively, it can be fulfilled by a decline of at least 0.83% with a duration of 12 months. Accordingly, we define a recession indicator b_t that takes a value of one in periods in which a recession is identified (ranging from $p+1$ to τ) and zero otherwise. Due to the publication lag of one month, the centered three-month moving average (which leads to the exclusion of the first and last observation for each vintage series) and the trough detection (which requires five subsequent observations) the recession ex-post dating ends seven months ahead of the respective vintage's data edge. While this results in fewer observations for the in-sample estimations, it comes with the advantage that the regression coefficients are not influenced by a false (non-)detection of a potential recession near the current data edge.

3.4 Forecasting real-time recession probabilities

We evaluate the predictive power of the FSIs by integrating it into a real-time forecasting procedure that already uses a relatively large set of regressor variables (predictors). This includes individual financial indicators, macroeconomic indicators, and sentiment indicators. Moreover, this real-time procedure comprises a general-to-specific and a specific-to-general model selection as well as a forecast averaging. With respect to the research question, the whole procedure has two advantages. Firstly, we test whether the FSIs provide predictive power on top of the widely acknowledged predictors, thereby reducing the probability of omitted variable biases. Secondly, the automatic model selection and forecast averaging procedures reduce the probability of ex-post selection and misspecification biases. On the other hand, this approach might underestimate the potential predictive power of the FSIs in simpler setups with less competitive predictors, as mentioned in the literature review (Menden & Proaño 2017, Borio, Drehmann & Xia 2018). Therefore, we also investigate the forecasting performance in comparably simple probit models in Section 4.4.3 in order to robustify the results of the main model.

In the literature, pooling of individual forecasts has been widely discussed to increase the predictive power (Bates & Granger 1969, Timmermann 2006). This finding even applies to a composite forecast that includes obviously inferior forecast models, as long as these are based on additional information relative to what is used in the superior forecast models. Correspondingly, our individual forecasts differ in three dimensions: First, specifications differ in the explanatory variables (predictors) used. Second, from each of the potentially very large models, we create two different (reduced) specifications applying either a general-to-specific (gts) or a specific-to-general (stg) variable and lag selection procedure. Third, as several of the predictors are subject to revisions and as there is a trade-off between revision sensitivity and up-to-dateness of the data, we produce two different out-of-sample forecasts for the same target month. The first of the two is based on the most recent data. The other is based on data that has been revised at least once. As we are aiming at the same target month, the latter case requires that the prediction horizon is one period longer than in the case of the forecast with the data up to the current edge. The whole functioning of the forecast procedure is broadly based on Proaño & Theobald (2014). To describe it in more detail, we focus on each of its elements in the following paragraphs:

1. **Probit estimations:** At its core, the forecast procedure consists of probit models where the probability of a recession in time t is given by

$$Prob(b_t = 1) = \Phi(\phi_t), \tag{3}$$

with Φ denoting the cumulative distribution function of a standard normal distribution. The probit specifications take the following general form:

$$\begin{aligned} \phi_t &= \alpha + \sum_{j=0}^{p} \gamma_j \Delta y_{t-j-h-D_y} + \sum_{j=0}^{q} \mathbf{x}'_{t-j-h-D_x} \beta_j + u_t, \\ u_t &\sim N(0,1)\, \forall\, t, \end{aligned} \tag{4}$$

where α is a constant, Δy_t is the one-month log difference of industrial production and $\mathbf{x}_t$ consists of the transformed financial and macroeconomic variables.[7] h stands for the forecast horizon. D_y and D_x denote the variable-specific publication lags. For simplicity of the notation, we assume that the publication lags of the variables in $\mathbf{x}$ are identical, though in the empirical analysis they differ from each other. In the empirical analysis, we set $p = q = 4$, so that for each variable a maximum of five (contemporaneous and lags) is taken into account, depending on the results of the lag selection routines described below.

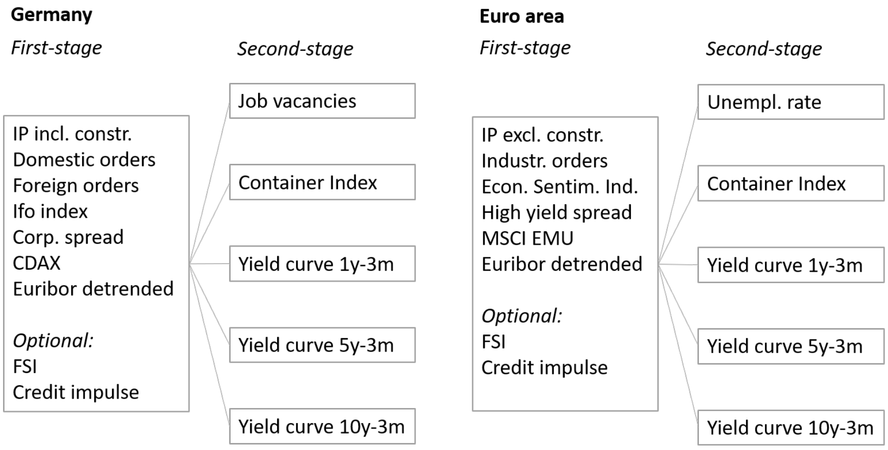
2. **Generating different specifications through first and second-stage variables:** With the aim of creating a variety of models that add different information to the composite forecast, we estimate Equation (4) using different regressor sets. The full set of regressors for each region is split into a group of first-stage regressors - nine for Germany and eight for the Euro Area - and five second-stage regressors. See Figure 1 and Tables 3 and 4 in the Appendix for an overview and description of these variables. Based on this separation, we construct five different specifications each containing all first-stage regressors and one specific second-stage regressor. The FSIs and the credit impulse will be optionally included in the set of first-stage regressors to evaluate their forecast performance.

[7] Alternatively to Equation (4), one could include lagged terms of b_t resulting in a *dynamic* probit specification:

$$\phi_t = \alpha + \sum_{j=0}^{o} \delta_j b_{t-j-h-D_b} + \sum_{j=0}^{p} \gamma_j \Delta y_{t-j-h-D_y} + \sum_{j=0}^{q} \mathbf{x}'_{t-j-h-D_x} \beta_j + u_t, \tag{5}$$

Such a specification can stabilize the forecast performance during recessionary and non-recessionary periods but also because of potential interactions with the remaining regressors. But as the recession dating algorithm applied is capable of identifying recessions only with a delay of seven months, we decided not to include lags of b_t. to avoid a potentially weaker performance at beginnings and ends of recessions (Nyberg 2010, Kauppi & Saikkonen 2008).

Figure 1: Probit specifications



3. **Model selection by gts and stg:** The five basic specifications described in the previous paragraph potentially include several lags of each regressor. To reduce multicollinearity and increase the in-sample fit, we apply a general-to-specific (gts) and a specific-to-general (stg) lag selection algorithm with each of the specifications for each forecast horizon. While the maximum number of lags for each regressor is set to five, we allow for complete rejections of regressors, if all lags are discarded. The decision whether to remove (gts) or add (stg) is based on Likelihood Ratio tests with a critical p-value of 0.05.[8] As we apply two ways of variable and lag selection, this procedure results in ten specifications of the probit model for each forecast horizon.

4. **Forecast averaging:** For each forecast horizon $h = 1, 2, 3, 4$, the $N = 10$ specifications' probability forecasts $\widehat{Prob}$ are averaged with weights negatively depending on their respective difference from the median forecast, thereby putting less weight on outliers:

$$\overline{Prob}_t^h = \sum_{i=1}^{N} \widehat{Prob}_{i,t}^h \frac{\sum_{j=1}^{N} |\widehat{Prob}_{j,t}^h - \widehat{Prob}_{med,t}^h| - |\widehat{Prob}_{i,t}^h - \widehat{Prob}_{med,t}^h|}{(N-1)\sum_{j=1}^{N} |\widehat{Prob}_{j,t}^h - \widehat{Prob}_{med,t}^h|} \tag{6}$$

where $\widehat{Prob}_{med,t}^h$ is the median recession probability forecast for month t with a forecast horizon of h months.

As already mentioned, we also produce forecasts for the same target month with different forecast horizons. This is based on the notion that unrevised observations provide the newest information on a variable, while they might be prone to noise which diminishes their predictive power. Therefore, we add another layer of forecast average by taking into account both forecasts based on information up to the most recent data and up to the data that has been revised at least once. Following Proaño & Theobald (2014), we decide in favor of a double weight on the specifications employing the latest information:

$$\widetilde{Prob}_t^h = 2/3\,\overline{Prob}_t^h + 1/3\,\overline{Prob}_{t-1}^{h+1} \quad , \quad h = \{1, 2, 3\} \tag{7}$$

[8] The potentially large number of regressors in some cases leads to convergence problems of the regression's likelihood optimization. We simply treat these cases as signaling to drop (gts) or not to add (stg) the respective regressor.

Finally, we condense the multiple-horizon forecasts to a single number, i.e. we compute the average recession probability over the next three months:

$$\widetilde{Prob}_t^{\overline{3m}} = 1/3(\widetilde{Prob}_t^{1m} + \widetilde{Prob}_t^{2m} + \widetilde{Prob}_t^{3m}). \tag{8}$$

In the following sections, $\widetilde{Prob}_t^{\overline{3m}}$ will be used to evaluate the out-of-sample performance of the forecast procedure with and without the financial stress index as well as the credit impulse.

4 Results

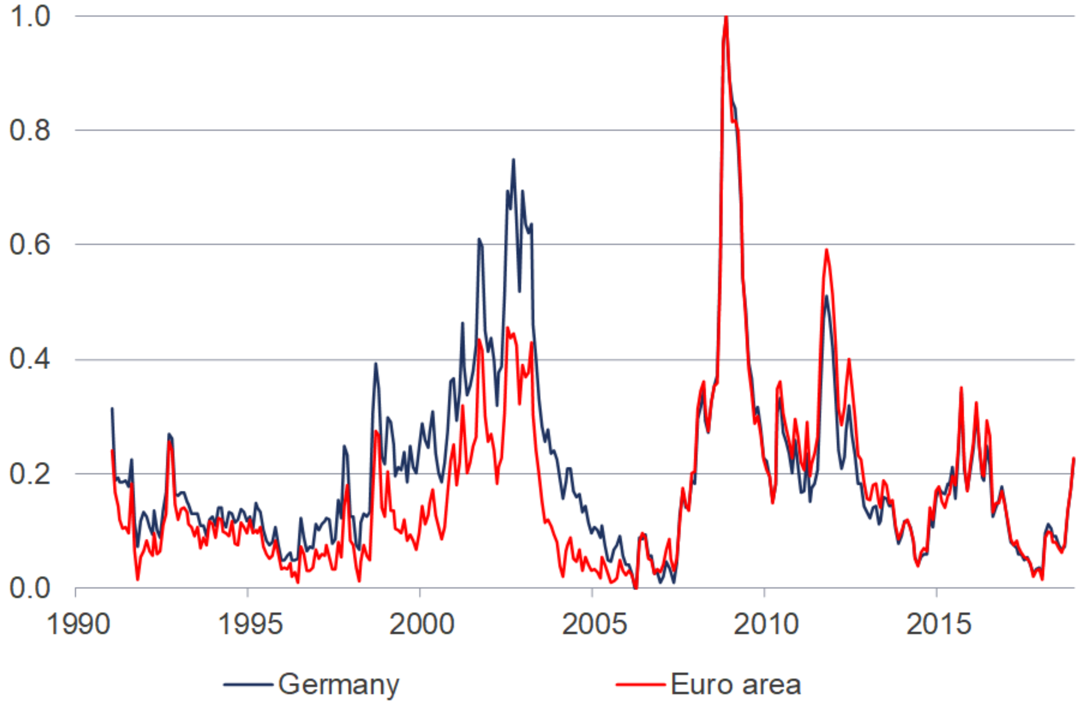
4.1 The financial stress indices

Figure 2 depicts the FSIs for Germany and the Euro Area using the latest vintage data (2018/12). The series clearly reflect historical financial turbulence and are very similar in shape. Both series reach their maximum at the height of the global financial crisis (GFC) in autumn/winter 2008, while lows are around the financially tranquil period of 2006. Furthermore, significant peaks can be observed in the context of the bursting dot-com bubble in 2002, at the height of the euro crisis in 2011, after the Russian debt moratorium and the LTCM collapse in 1998, and during the period of increased concerns regarding a slowdown of the Chinese economy in 2015 and 2016. In contrast, the FSIs only moderately increase during the crisis of the European Monetary System (EMS) in 1992. The latter result can partly be traced back to the fact that the information matrix of underlying indicators does not contain many series related to the Foreign Exchange market. Hence, only few of the underlying indicators show significant patterns during this period. Additonally, for some of the indicators the period is not covered due to data availability. While our FSIs for Germany and the Euro Area are overall quite similar to each other, we find considerable differences in magnitude during specific periods. The Russian debt moratorium in 1998 and the burst of the dot-com bubble in 2002 have a more pronounced impact on the FSI for Germany, while the Euro Area FSI is characterized by higher values during the EMS and the euro crisis. The difference during the burst of the dot-com bubble, where the German FSI peaks at 0.75 and that of the Euro Area only reaches a maximum at 0.45, is predominantly driven by high contributions of the German VDAX volatility index, the implicit volatility of emerging market stocks, and a sharp increase of emerging market sovereign CDS spreads surrounding the Argentinian currency crisis.

4.1.1 Variable selection in real-time

Figures 17 and 18 in the Appendix illustrate the development of the German and the European FSI over time. Looking at the right-hand edge of the heatmap, it can be seen, that the FSI swiftly incorporates new information about financial stress. This is the case even though part of the data is subject to a publication lag and, therefore, has to be imputed. While until 2008 the burst of the dot-com bubble marks the maximum values of the FSIs over the vintages, afterwards this changes to the Global Financial Crisis (GFC). Since then, the pattern across publications is remarkably stable. Although this could be due to a homogeneous selection of the same set of underlying financial indicators over the vintages, this is in fact not the case.

Figure 2: Financial stress indices (vintage 2018/12)



Figures 3 and 4 show the weights by which the individual time series contribute to the first principal component, the so-called factor loadings. The squared loading coefficients add up to 1 and reflect the proportion of the variance of each time series explained by the factor at the time of publication. While some variables are selected in most of the vintages and show a stable positive loading, i.a. asset price volatilities, CDS spreads, and stock market returns, there is also a significant time variation in the selection and in the loadings of other input time series for each region. Recall that, 20 time series with the highest correlation to the monthly published reference series of Duprey, Klaus & Peltonen (2017) serve as an input for the PCA. As will be illustrated in the next section, this does not mean that the resulting financial stress index is identical to the reference series as there are differences in the underlying information matrix and in the methodology applied. Rather in our case, the resulting index is determined by the factor loadings, after a relevant subset of the information matrix has been selected.

The time variation of the loadings underlines the power of this simple, but automatic selection procedure. To illustrate this, consider the German TARGET2 balance as an indicator potentially signaling increased Euro Area fragility. In the meantime, TARGET2 balances partly lost their meaning as a stress indicator because they are to some extent driven by the European Central Bank's large-scale asset purchase programs that started in spring 2015. As shown in Figure 4 (11th series from the bottom), the German TARGET2 balance is only included in the period 2009-2011, in which the increasing balances were clearly reflecting financial stress. This may serve as an example that the methodology presented here allows both for the automatic inclusion of additional risk factors when they become relevant and their exclusion when they lose their relevance.

Figure 3: Factor Loadings Germany. Horizontal axis: vintage months. Blue: significantly positive loading, light grey: loading close to 0, red: significantly negative loading. Only variables shown which are selected at least once. "NEG" denotes variables with negative sign restriction.

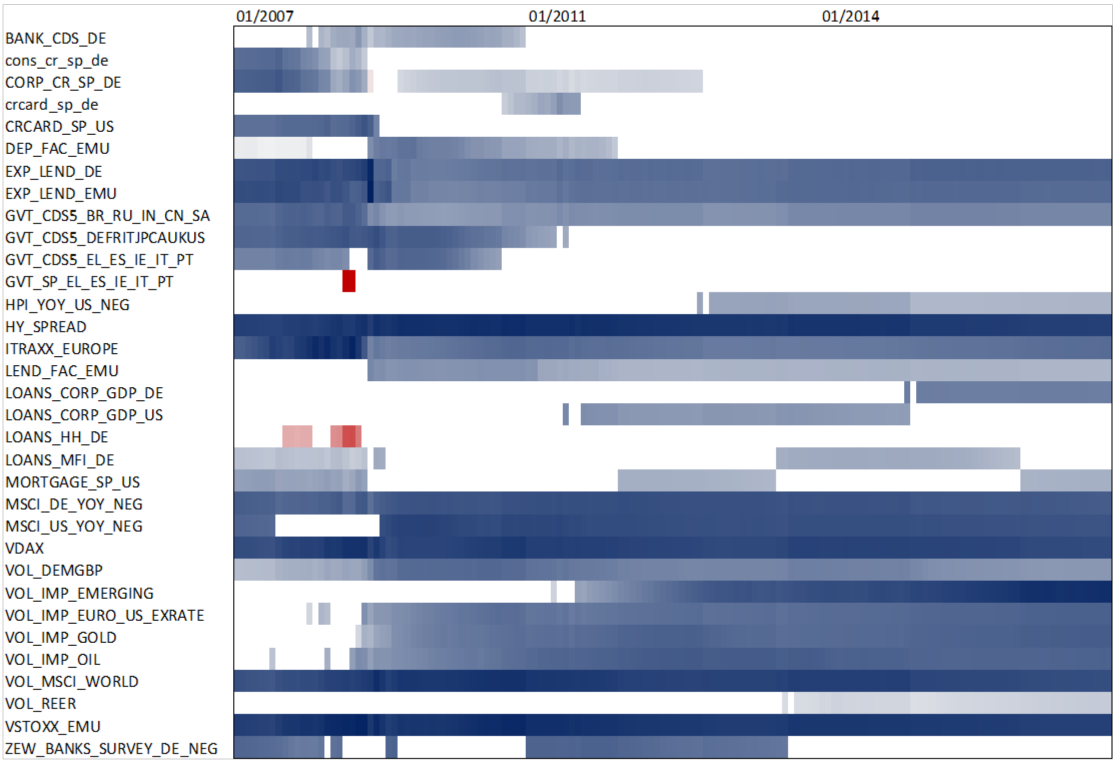
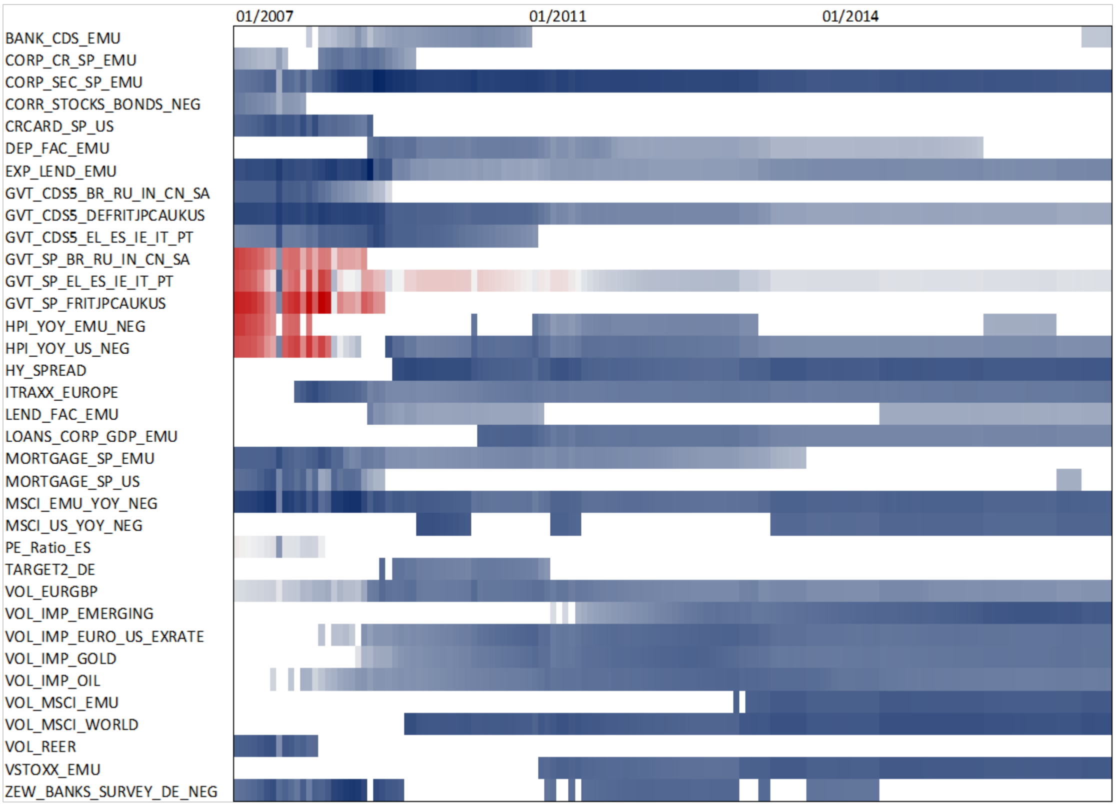


Figure 4: Factor Loadings Euro Area. See the description in Figure 3.



4.1.2 Comparison with results from the literature

When comparing our FSIs to existing ones from the literature, in general, we find a strong co-movement between the series (Figures 5 and 6). In the studies by Duprey, Klaus & Peltonen (2017) and van Roye (2014), the underlying indicators of the FSIs are selected in a discretionary and ex-post manner. At first glance, the strong co-movement may not be surprising as for the automated variable selection we use the correlation of individual indicators with the Country-Level Index of Financial Stress (CLIFS), as provided by Duprey, Klaus & Peltonen (2017). In detail, however, it is worth reflecting on similarities and differences of the financial stress indices.

First, the indices are based on different sets of underlying indicators. Duprey, Klaus & Peltonen (2017) use a relatively small number of variables proxying first and second order developments in three financial market segments (stock market, bond market, foreign exchange market). Also, the indicator set used by van Roye (2014) roughly represents a subset of our database with the distinct difference being our additional consideration of financial cycle variables. As illustrated in Figures 3 and 4, this result does not mean that none of these variables, like credit and house price growth, survive the selection mechanism. Especially corporate loans and US house prices are frequently picked. Rather, it is the case that their contributions to the overall result, i.e. the loadings, are weak relative to those of the conventional stress indicators, in particular to the loading of the stock price volatility (Rey 2015).

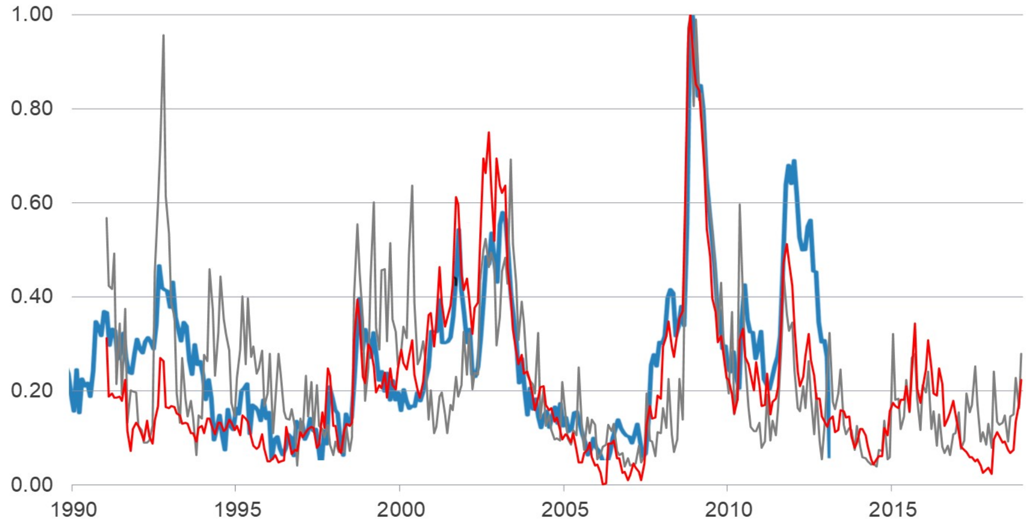
Second, different methodologies are applied. The CLIFS of Duprey, Klaus & Peltonen (2017) are averages of market segment-specific subindices weighted by their respective correlations with each other, while van Roye (2014) applies a dynamic factor model to extract his FSI. Although we use the correlation with the CLIFS indices for the variable selection, the match between our principal component and that of van Roye (2014) is much greater. In this regard, it seems almost irrelevant whether a static or a dynamic factor model is applied.

Despite the general co-movement of the series, there exist considerable differences. On closer inspection, the CLIFS indices are more volatile than our FSIs, including several significant spikes in periods when our FSIs are more tranquil. While the higher sensitivity of the CLIFS might be favorable in some instances, it can provide false signals in others. A good example is the sharp increase of the CLIFS in the context of the *flash crash* of May 2010[9], which might be considered as an idiosyncratic event without systemic or real-economic importance. The FSIs of van Roye (2014) are characterized by a quite similar behavior as ours, while in the German case, the index is considerably more elevated in the period of the EMS crisis. A plausible reason for this difference could be that the EMS crisis was predominantly an exchange rate crisis and not primarily related to asset price bubbles and the financial cycle. Overall, our FSIs do not result in a weaker performance in terms of dating financial market stress than other approaches in the literature. At the same time, we employ a more flexible and automated approach.[10]

[9] Flash crash is the term commonly used to describe an intraday collapse in stock prices. One of the most pronounced events attributed to spoofing algorithms happened 2010 on May 6 and lasted for less than forty minutes during which the Dow Jones Industrial Average lost about 9 % of its value and rebounded rapidly.

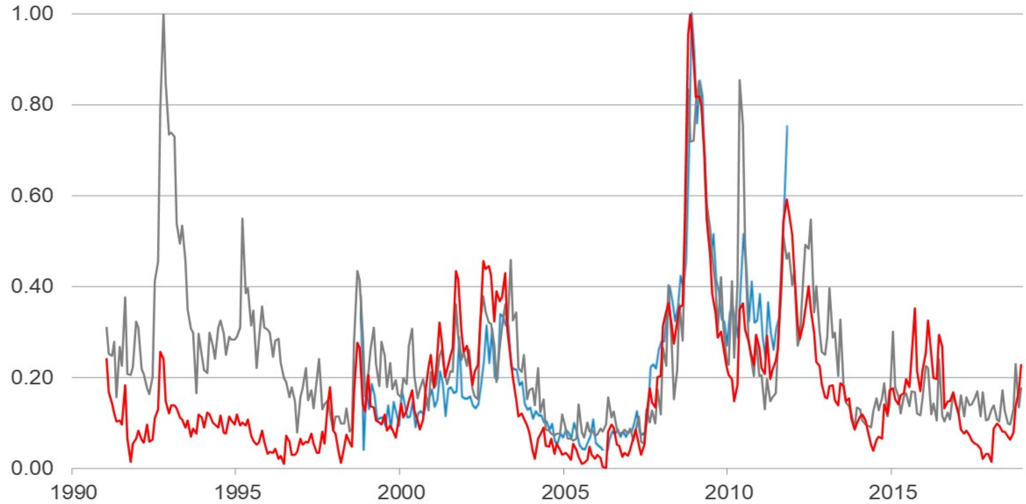
[10] As shown in the previous section, various indicators related to the financial cycle are picked in the correlation based selection procedure and therefore they do affect the shape of the FSI. However, variables related to the realisation of financial stress clearly dominate. We therefore additionally constructed FSIs solely based on financial cycle variables and analysed their predictive content. The results are provided in Section D of the Appendix. In summary, we do not find evidence that narrow FSIs solely based on financial cycle variables improve short-term recession forecasts. However, this might be the case when either analysing longer timespans or country panels which cover a larger number of financial crises as it is done in Borio, Drehmann & Xia (2018) and Lang et al. (2019).

Figure 5: Germany: Comparison of different financial stress indices



Red: our FSI (2018/12 vintage), grey: Duprey, Klaus & Peltonen (2017), blue: van Roye (2014) retrieved from the ECB data warehouse. As we did not have access to the data of van Roye (2014) we included the series using a screenshot. The series are scaled to match each other optimally.

Figure 6: Euro Area: Comparison of different financial stress indices

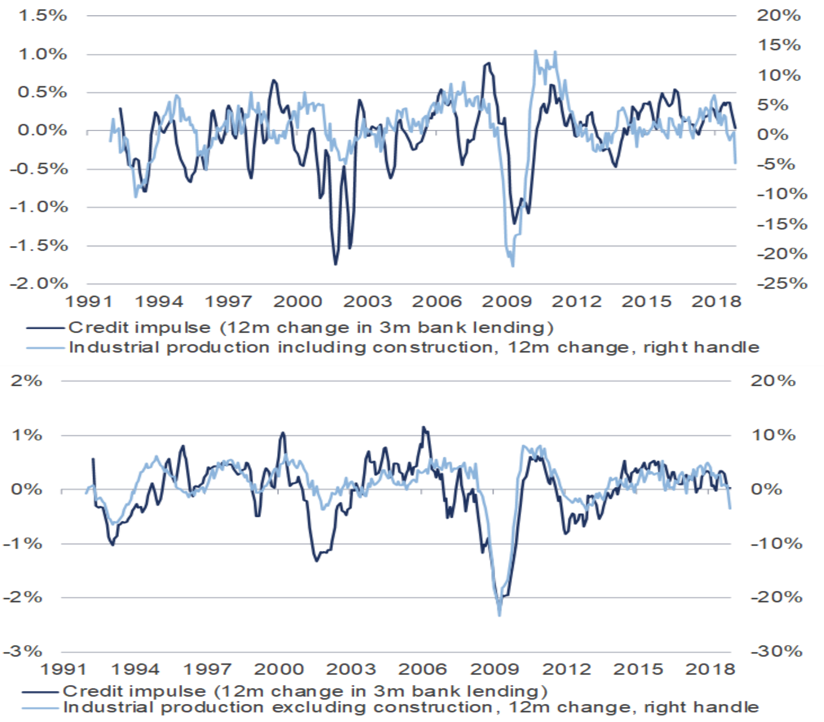


Red: our FSI (2018/12 vintage), grey: simple average of the FSIs for Germany, France, Italy, and Spain from Duprey, Klaus & Peltonen (2017) retrieved from the ECB data warehouse, blue: van Roye (2011). As we did not have access to the data of van Roye (2011) we included the series using a screenshot. The series are scaled to match each other optimally.

4.2 The credit impulse

Figure 7 shows the relation between the credit impulse and industrial production as a proxy variable of economic activity. The overall high correlation between the time series in both regions, Germany and the Euro Area, justifies the attempt to integrate the credit impulse into a forecasting model. This seems all the more promising as the decline in the credit impulse of German industrial production in the post-reunification recession and after the bursting of the dotcom bubble was leading the production variable. In the Euro Area, this even applies to all dated recessions from the 2000s onwards.

Figure 7: Credit impulse and industrial production, Germany and Euro Area



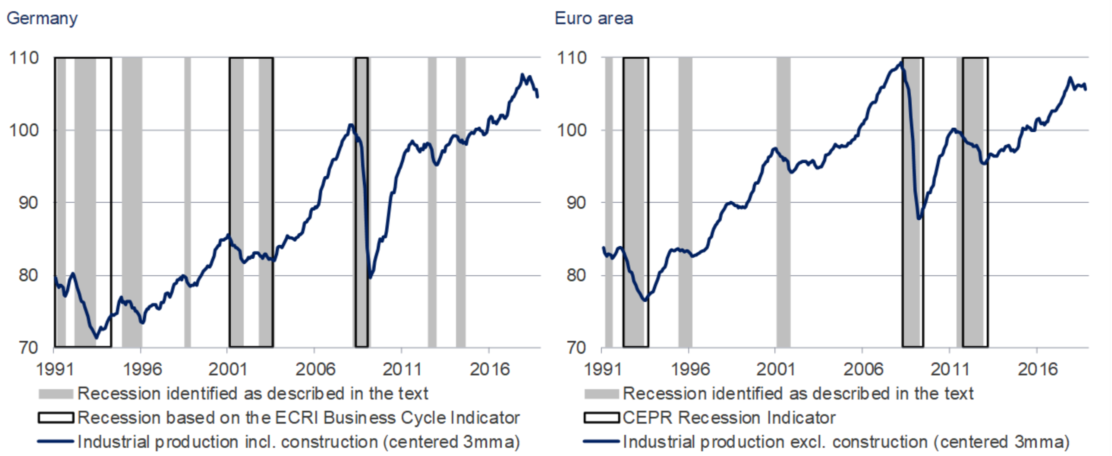
German data (top) and the Euro Area data (bottom). In contrast to the illustration, the probit regressions uses the monthly change of the three-month flow in bank lending.

However, the cross-correlation between credit impulse and industrial production is far from stable. This is illustrated by the fact that there are also periods in which the credit impulse was lagging behind industrial production. This is particularly true in Germany for the time of the Great Recession and, to a lesser extent, for the stagnation phase from 2003 onwards and the technical recession of 2012. Of course, a vintage-dependent correlation analysis does not automatically imply good out-of-sample properties in a multivariate regression. One reason could be that the information content of the credit impulse for real economic spending, especially for investment goods, is already covered in a similar way by other explanatory variables. These may include new manufacturing orders and the sentiment indices that consider managers' propensity to invest.

4.3 Recession dating

Figure 8 shows the results of the recession dating algorithm presented in Section 3.3. Over the whole sample and using vintage data as of 2018/12, our recession dating algorithm identifies nine recessions for Germany and six for the Euro Area.[11] When comparing the results with the respective recession dates provided by ECRI (2019) and CEPR (2019), which each report three recessions, our estimates are significantly more sensitive to economic downturns. For those recessions identified by the aforementioned institutions, we find a high congruence with our results, though on several occasions our recession indicator marks an earlier beginning and end of the recessions. Especially if considering a recession that was erroneously not dated as more important than one that was erroneously dated (asymmetric loss function), the results of the recession dating algorithm can be generally regarded as adequate.

Figure 8: Recession dating (vintage 2018/12)



Though the recession dating based on the industrial production overall coincides very well with the development of economic activity, there is one example that shows that the absence of data measuring service sector economic activity at the monthly frequency can be misleading: From January to September 2014 the three-month moving average of the German industrial production decreased by 1.28% which is slightly higher than the threshold of 1,25% given by Equation 2 for a duration of eight months from peak to trough. This period is therefore flagged as a recession. However, the summer of 2014 was marked by an unusual simultaneity of German Länder-specific holidays which contributed to a slump of industrial production of 3.4% in August followed by an increase of 2.3% in September. As this development does not reflect an economy-wide weakness, we will ignore this signal in the following.

4.4 Real-time out-of-sample recession forecasts

Figure 9 shows real-time out-of-sample recession probability forecasts combined with the ex-post identified recession periods. The red lines plot the estimated three-month-ahead recession probability based on all explanatory variables excluding the FSI and the credit impulse (basic

[11] As the recession dating algorithm is applied in real-time based on the respective vintage data of the industrial production, the identified periods potentially - and actually - change with respect to the different vintage months. Here, as the results do not change materially, only the results of the latest vintage (2018/12) are shown. The full real-time matrices of the binary recession indicators are available from the authors upon request.

specification). The blue lines plot the forecast of the specification augmented with the FSI. This line is also plotted in Figure 10, while here the red line illustrates the forecast specification that additionally includes the credit impulse.

In principle and in comparison to the literature, the basic specification provides satisfactory results. By construction, the results of our basic specification are close to those from Proaño & Theobald (2014), which show that the selected prediction mechanism is competitive with other approaches from the literature, such as Dueker (1997), Estrella & Mishkin (1998) and Nyberg (2010). Nevertheless, the econometric designs differ in some details[12] which implies that the basic specification of the presented forecasting procedure tends to produce slightly higher recession probabilities than in Proaño & Theobald (2014). See Appendix E (Figure 21) Looking at (conventional) forecast evaluation measures, the higher recession probability results in a worse performance because the erroneous deviations of an actual 0-percent probability is given the same weight as those from the actual 100-percent probability. If, on the other hand, one chooses an asymmetric loss function, which puts double weight on the later case, the presented forecasting procedure slightly outperforms the one in Proaño & Theobald (2014). See Appendix E (Table 9). Overall, the paper at hand is less concerned with optimizing the predictive power of the basic specification. Rather, the focus is on whether the FSI unfolds additional predictive power in real-time. This is analyzed relative to the basic specification. In this regard, Figure 9 largely shows a match between the basic and the FSI specification. Only for some vintages, there are remarkable differences. Here, taking the FSI into account tends to improve the results.

In the German case (Figure 9, the left-hand side), there are several events increasing the predicted recession probability so that it even exceeds the 50% threshold, i.e. where a recessionary period was more probable than a non-recessionary one. In particular, the recessions 2008/3-2009/3 and 2012/7-2013/1 are well captured by the forecast. However, especially at the dawn of the Global Financial Crisis (GFC), the inclusion of the FSI does not have a considerable effect on the predicted recession probability. A possible explanation for this result might be that, in contrast to other economies, Germany did not experience a domestic housing bubble and was mainly affected indirectly through trade linkages and banking sector contagion. After 2012 some differences between the basic and the augmented specification can be observed. Still, there are strong co-movements, but the peaks of the basic specification are considerably higher than those of the augmented one. Most of these peaks during non-recessionary phases in GDP, which might be considered as false positives, were indeed accompanied by considerable drawdowns of industrial production (Figure 9, bottom part). Here, the low level of financial stress during these times helps to slightly improve the forecast.

Turning to the results for the Euro Area (Figure 9, the right-hand side) we find both fewer episodes of an increased recession probability and, at the same time, a stronger impact of the inclusion of the FSI on the forecast results. Especially at the beginning of the recession related to the GFC (2008/4-2009/4), the predicted probability of the augmented model steeply increases at the end of 2007, reaching a level of nearly 100% two months before the recession starts and remaining above 65% until March 2009. In contrast, after increasing at the beginning of the recession the predicted probability of the basic specification drops below 20% in July 2008 only rebounding at the height of the GFC in September 2008. Hence we conclude that the FSI considerably increases the model's predictive power.

The recession related to the Euro crisis (2011/5-2012/12) is only reflected in an increased recession probability three months after its start. In fact, the level of industrial production was plateauing during this timespan before beginning its downturn in autumn. Still, the FSI's

[12] E.g.: In contrast to the analysis by Proaño & Theobald (2014), we detrend the 3-month interest rate (Euribor) by subtracting its 2-year trailing moving average. Due to its long-run decrease over the sample period, the 3M-Euribor is clearly nonstationary and this trend should not influence business cycle turning points.

inclusion leads to a significantly stronger signal at the start of the recession. Also, the peak of the predicted recession probabilities in early 2016, when the fear of a severe weakening of the Chinese economy led to global financial market turbulence, is slightly higher when including the FSI. Overall, we do not find considerable false positives in the case of the Euro Area for both specifications.

Figure 9: Real-time out-of-sample recession probabilities including the financial stress index

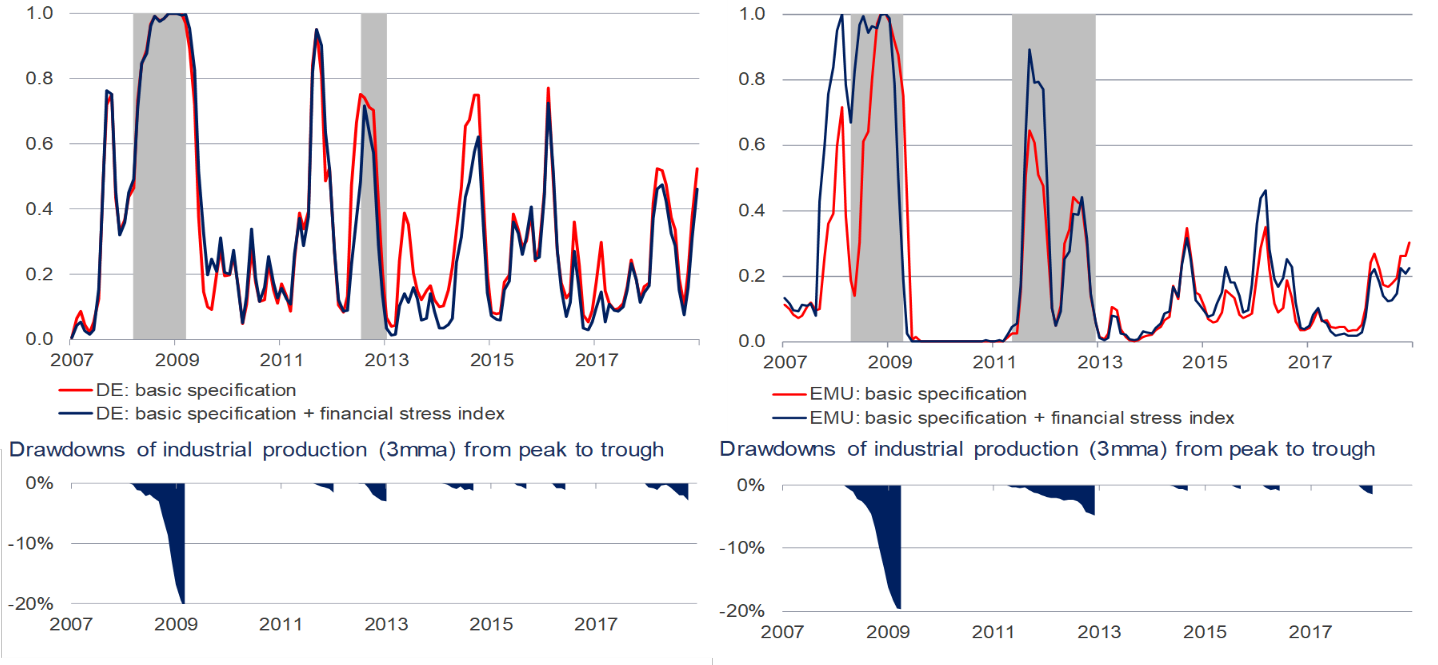
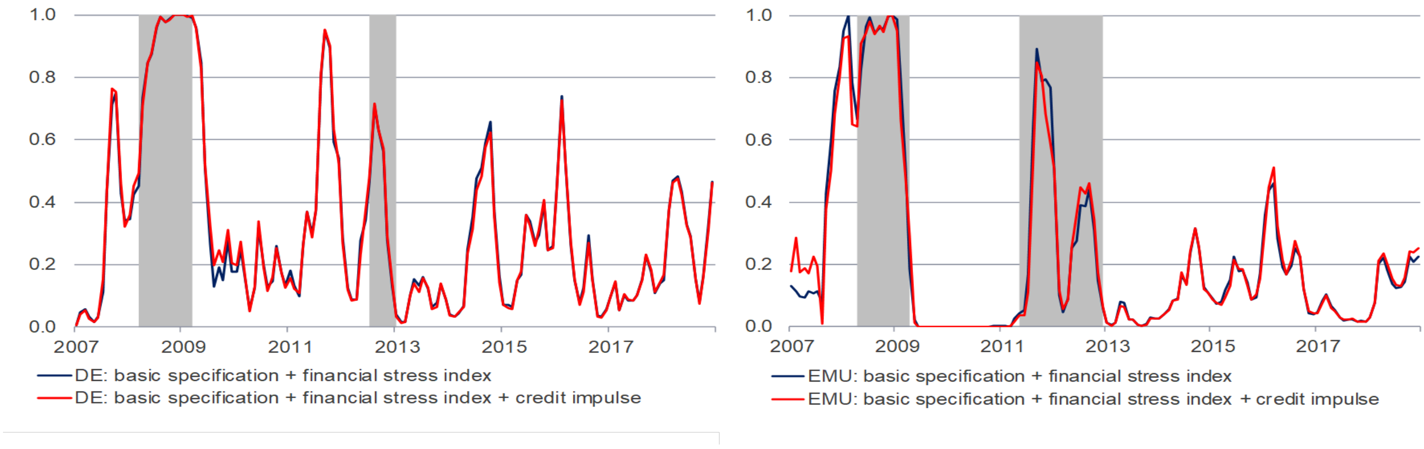


Figure 10: Real-time out-of-sample recession probabilities including the credit impulse



Result for the specification including the credit impulse as an additional predictor are illustrated in Figure 10. We find that the inclusion of the credit impulse leads to minimal, although non-zero, deviations from the specifications including only the FSI. Therefore, although the credit impulse is frequently selected by the general-to-specific (gts) and specific-to-general (stg) variable selection routines (Appendix C, Tables 6 and 7), its contributions to the out-of-sample forecasts are negligible.

4.4.1 Variable selection in real-time

Tables 6 and 7 in the Appendix C summarize the variable selection results of the gts- and stg-routines for the publications 2007/1-2010/12. We choose this period as an example because it includes the GFC and the subsequent economic recovery, which, at least for Germany, restored the pre-crisis production level. The last row of the tables shows average values over the vintages. A value of 50% means that at least one of the lags of a certain regressor variable is not rejected by the respective likelihood-ratio test in half of the potential specifications.[13] As a general result, all of the predictive variables are frequently selected in the regressions. Note, however, this is only a necessary condition for a variable to have a significant influence on the forecast result. In this context, the explanatory contributions of the variables (the size of standardized coefficients) are to be seen as sufficient.[14]

In the German forecast model, foreign orders, the ifo business climate index and the slope of the yield curve (10-year maturity) play a dominant role. On average, they are included in more than 90% of the specifications. But also the FSI, Euribor interest rates, job vacancies and other nodes of the yield curve play an important role. Surprisingly on average, lags of the industrial production, the CDAX stock market index, the spread between corporate and government bond yields (corporate spread) are included in less than half of the specifications. This even more applies to the credit impulse, to domestic orders and to the RWI container index, which is a monthly proxy variable for world trade volumes. The credit impulse is included in most specifications during the recession period in 2008/09 but not so much in the period afterward, while domestic orders are selected more often from this time on. In the Euro Area forecast model, the variables are included more homogeneously. On average, the industrial orders, the MSCI stock market index and the RWI container index are considered in less than one-third of the specifications. All other variables are included in over 60% of the possible cases, on average.

4.4.2 Forecast evaluation measures

Forecast evaluation measures with respect to the average three-month-ahead recession probability forecast are reported in Table 1. To account for the forward-looking nature of the estimated recession probabilities we define a binary reference series, b_t^*, as follows:

$$b_t^* = \begin{cases} 1, & \text{if } (b_{t+1} + b_{t+2} + b_{t+3})/3 > 0.66 \\ 0, & \text{else,} \end{cases} \tag{9}$$

where b_t is the recession indicator as described in Section 3.3. With $\overline{\widetilde{Prob}_t^{3m}}$ being the average three-month-ahead recession probability forecasts from $t = 1, \ldots, T$ we calculate the following evaluation measures:

$$\text{Mean absolute error (MAE)} = \frac{1}{T}\sum_{t=1}^{T} |\overline{\widetilde{Prob}_t^{3m}} - b_t^*|, \tag{10}$$

[13]Note that the number of specifications where the variables are potentially included differs for first- and second-stage variables. See Section 3.

[14]Results for the vintage-dependent explanatory contributions are available on request.

$$\text{Root mean squared error (RMSE)} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\widetilde{Prob}_t^{\overline{3m}} - b_t^*)^2}, \tag{11}$$

$$\text{Theil inequality coefficient (Theil)} = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\widetilde{Prob}_t^{\overline{3m}} - b_t^*)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\widetilde{Prob}_t^{\overline{3m}})^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(b_t^*)^2}}. \tag{12}$$

Moreover, AUROC denotes the area under the receiver operator characteristics which can take values between 1 (perfect fit) and 0 (perfectly inverted fit). An AUROC of 0.5 signals no predictive power.[15] To determine correct and false predictions, we use the unconditional ex-post recession probability, i.e. the average of b_t^* over the whole sample starting in 1991, which is 26.1% for Germany and 23.2% for the Euro Area as a threshold that transforms $\widetilde{Prob}_t^{\overline{3m}}$ into a binary series.[16] Based on the comparison of this binary series with b_t^*, we count the number of i. true positives (There was a recession as predicted before), ii. false positives (There was no recession, though it was predicted.), iii. true negatives (There was no recession as predicted before.), iv. false negatives (There was a recession, though it was not predicted.) In addition, we then calculate the following measures:

$$\text{True positive ratio (TPR)} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}, \tag{13}$$

$$\text{False positive ratio (FPR)} = \frac{\text{false positives}}{\text{false positives} + \text{true negatives}}, \tag{14}$$

$$\text{(Hanssen-)Kuipers Score} = \text{TPR} - \text{FPR}. \tag{15}$$

For Germany, when comparing the evaluation measures of the basic specification (BS) versus the specification augmented with the FSI (BS+FSI), we find that BS+FSI performs slightly better with respect to the MAE, the RMSE and the Kuipers score. However, in terms of the Theil coefficient and the AUROC it performs worse. In contrast, for the Euro Area, we find BS+FSI to have a stronger predictive ability than BS based on all of the measures. In summary, the inclusion of the FSI clearly increases the out-of-sample performance in the case of the Euro Area, while the results for Germany are mixed.[17]

Turning to the results for the inclusion of the credit impulse the forecast evaluation measures confirm the message of the graphical analysis. For both regions, we find almost no impact when adding the credit impulse. As already mentioned, there are two possible reasons. First, although the credit impulse might be a relevant indicator of the contemporaneous growth in economic activity, its predictive power relative to other explanatory variables might be low. Second, low explanatory contributions might be driven by a high level of noise diluting the actual signal.

[15] See Fawcett (2006) for more details.

[16] As already mentioned, an alternative threshold would be the 50% value.

[17] To make sure that these results are not driven by the complex setup of the forecasting exercise, we additionally run forecasts based on simpler probit specifications without lag selection and forecast averaging. See Section 4.4.3.

Table 1: Out-of-sample forecast evaluation

	Germany				Euro Area			
	BS	BS + FSI	BS + CI	BS + FSI + CI	BS	BS + FSI	BS + CI	BS + FSI + CI
MAE	0.266	0.258	0.264	0.258	0.210	0.192	0.216	0.197
RMSE	0.345	0.344	0.343	0.344	0.337	0.316	0.336	0.317
Theil	0.422	0.432	0.419	0.430	0.429	0.368	0.410	0.373
AUROC	0.916	0.889	0.922	0.891	0.834	0.848	0.826	0.844
True positives	20	20	20	19	23	25	25	25
False positives	45	42	45	42	14	14	19	17
True negatives	69	72	69	72	87	87	83	85
False negatives	0	0	0	1	10	8	8	8
TPR	1.000	1.000	1.000	0.950	0.697	0.758	0.758	0.758
FPR	0.395	0.368	0.395	0.368	0.139	0.139	0.186	0.167
Kuipers score	0.605	0.632	0.605	0.582	0.558	0.619	0.571	0.591

Notes: BS = basic specification, FSI = financial stress index, CI = credit impulse.
See text for definitions of the evaluation measures.

Table 2: Root mean squared errors for simple real-time out-of-sample probit forecasts

		Germany			Euro Area		
Horizon		BS	BS+FSI	Diff.	BS	BS+FSI	Diff.
1M	eq1	0.440	0.436	-0.004	0.420	0.376	-0.044
	eq2	0.411	0.418	0.007	0.447	0.432	-0.014
	eq3	0.411	0.417	0.006	0.465	0.418	-0.047
	eq4	0.395	0.386	-0.009	0.352	0.304	-0.048
	eq5	0.425	0.427	0.001	0.356	0.308	-0.049
2M	eq1	0.438	0.430	-0.008	0.407	0.355	-0.052
	eq2	0.415	0.416	0.001	0.449	0.408	-0.042
	eq3	0.416	0.415	-0.001	0.459	0.433	-0.026
	eq4	0.403	0.392	-0.012	0.371	0.321	-0.049
	eq5	0.426	0.423	-0.003	0.370	0.322	-0.049
3M	eq1	0.434	0.428	-0.006	0.407	0.367	-0.041
	eq2	0.420	0.420	-0.001	0.473	0.437	-0.036
	eq3	0.422	0.420	-0.002	0.475	0.463	-0.012
	eq4	0.409	0.399	-0.010	0.377	0.342	-0.035
	eq5	0.432	0.430	-0.003	0.381	0.345	-0.036
Average		0.420	0.417	-0.003	0.414	0.375	-0.039

Notes: BS = basic specification, FSI = financial stress index.
Average refers to the simple average of the RMSEs.

4.4.3 Robustification using simple probit models

In addition to the results from the presented forecast procedure, we also analyse the predictive power of the FSIs using simple probit models, where we do not apply lag and variable selection procedures as well as a forecast averaging. For each of the two regions we run 15 different models in a real-time out-of-sample estimation starting from 2007/1. Each specification contains a constant, all of the first stage regressors and one of the five second-stage regressors (see Figure 1). As we do not employ a lag selection procedure, we include only one lag per regressor. We run the forecasts for horizons of one to three months, each time including and excluding the FSI. The RMSEs of this exercise are presented in Table 2. The results are clearcut and confirm those of our main analysis. For Germany, we find that the inclusion of the FSI leads to very small but rather insignificant improvements for the majority of the models and the average RMSE. In case of the Euro Area, the inclusion of the FSI leads to significant improvements for all of the models. Consequently, the average RMSE is 3.9 percentage points smaller than the average one of the basic specification.

5 Conclusion

While term spreads and stock price returns have been incorporated into recession forecasting models for some time, a specific focus on the real-time information content of the level of financial stress is a relatively new development. We contribute to this literature by evaluating the real-time predictive power of newly constructed financial stress indices for Germany and the Euro Area covering the time span 1991/01 to 2018/12. The indices are based on a principal component analysis of a large number of indicators, each of them potentially signaling financial stress. Apart from typical measures of perceived risk, we also include indicators related to the financial cycle, such as different types of credit growth, which aim at capturing the build-up of financial risks. Missing-data imputation and a variable selection are also conducted in real-time. While this approach allows a high degree of flexibility, our results show a strong correlation to existing FSIs from the literature. Future research may, therefore, try to adapt the methodology, e.g. by multi-factor models, in order to further strengthen the influence of the financial cycle variables.

To evaluate the real-time predictive power of the FSIs, we create a fully automated composite probit model forecasting recession probabilities in line with the literature. Individual forecasts are generated by different regressor sets, variable selection methods, and forecast horizons. Using this instrument, we also evaluate the predictive power of the credit impulse, as loans not only reflect an increased vulnerability of the economy along the financial cycle but also capture the synchronous relation of bank lending and economic activity.

Our real-time out-of-sample exercise shows an overall satisfying forecast performance of the basic model. Additionally considering the financial stress index leads to improved recession forecasts for the Euro Area, while the results for Germany are mixed. In contrast, the credit impulse adds little predictive power. Overall, our results suggest that the inclusion of financial stress in recession forecasting models can considerably improve the predictive power, especially since the model is capable of automatically including and excluding variables whose relation to financial stress may change over time. This is particularly important as the characteristics of financial crises leading to recessions may also change. Therefore, the approach presented here is suitable to serve as an early warning system for future recessions which may guide policymakers to decide on counterbalancing measures at an early stage.

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A Data description and sources

Table 3: Variables used in the probit model for Germany

Name	Description	Raw data source	Transform.	Publ. lag	Comment
First-stage regressors					
IP_inc_constr	Industrial production including construction	Bundesbank	Log diff.	1	Vintage data
FSI	see text				
credit_imp	3-month percentage change in the stock of bank credit to HH and NFC	Bundesbank, ECB	3-month moving average of the monthly log diff.	1	Seasonally adjusted using X13. Before 2003: Corrected for 9 major outliers, 3-month trailing MA to reduce remaining noise. After 2003: Adjusted for sales and securitisations. One major outlier removed in 2007/12.
Dom_ord	Domestic manufacturing orders	Bundesbank	Log diff.	1	Vintage data
For_ord	Foreign manufacturing orders	Bundesbank	Log diff.	1	Vintage data
Ifo	Ifo Business Climate Index	Ifo	Log diff.	0	Vintage data. Until 2005 old version of Ifo index, scaled to match new series.
crp_sprd	Corporate bond spreads vs. govt. bonds	Bundesbank	-	0	Yields corresponding to respective average maturities of outstanding bonds.
cdax	CDAX stock market index	Datastream	Log diff.	0	
eubor_3m_detrend	3-Month interest rate, deviation from trailing 2y moving average	Datastream	see description	0	Before 1999 FIBOR, afterwards EURIBOR
Second-stage regressors					
jobvac	Job vacancies	Bundesbank	Log diff.	0	
cui_tdr	Container Throughput Index	RWI/ISL	Log diff.	1	Since 2012/03 vintage data, before earliest available
yc1y	Spread of 1y govt. bond yields vs. 3m interest rate	Datastream	-	0	3m interest rate: before 1999 FIBOR, afterwards EURIBOR
yc5y	Spread of 5y govt. bond yields vs. 3m interest rate	Datastream	-	0	see above
yc10y	Spread of 10y govt. bond yields vs. 3m interest rate	Datastream	-	0	see above

Note: If available the series are working-day and seasonally adjusted.

Table 4: Variables used in the probit model for the Euro Area

Name	Description	Raw data source	Transform.	Publ. lag	Comment
First-stage regressors					
IP_ex_constr	Industrial production excluding construction	ECB and Datastream	Log diff.	1	Vintage data
FSI	see text				
Credit_imp	3-month percentage change in the stock of bank credit to HH and NFC	ECB	Diff.	1	Since 2003 adjusted for sales and securitisation
ESI	European Commission Economic Sentiment Index	ECB and EU Commission	Log diff.	0	Vintage data
Ind_orders	Industrial orders	ECB and Destatis	Log diff.	1	Before 1995 German manufacturing orders
hy_sprd	Spread of BofA ML High Yield index vs. 5y swap rates	Datastream	-	0	Since 1998 euro high yield, before US high yield. Before 1999 DEM swap rate
msci_emu	MSCI EMU	Datastream	Log diff.	0	
eubor_3m_detrend	3-Month interest rate, deviation from trailing 2y moving average	Datastream	-	0	Before 1999 FIBOR, afterwards EURIBOR
Second-stage regressors					
unempl	Unemployment rate	ECB and Datastream	Diff.	0	Vintage data
cui_tdr	Container Throughput Index	RWI/ISL	Log diff.	1	Since 2012/03 vintage data, before earliest available.
yc1y	Spread of 1y vs. 3m interest rate	Datastream	-	0	3m: see eubor_3m. 1y rate: since 1999 euro swap rate, before DEM swap rate
yc5y	Spread of 5y vs. 3m interest rate	Datastream	-	0	see above
yc10y	Spread of 10y vs. 3m interest rate	Datastream	-	0	see above

Note: If available the series are working-day and seasonally adjusted.

Table 5: Variables used for the financial stress index for Germany

Description and transformations	**Raw data source**	**Publ. lag**
MSCI Germany yoy, *(-1)	Datastream	0
MSCI USA yoy, *(-1)	Datastream	0
12-months forward price-earnings ratio of the DAX	Datastream	0
12-months forward price-earnings ratio of the S&P 500	Datastream	0
Nominal house price index Germany yoy log diff, linear interpolation of quarterly data, *(-1)	OECD	Q+5
Case-Shiller National Home Price Index USA yoy, *(-1)	Datastream	2
Outstanding loans to non-financial corporates, yoy	ECB	1
US commercial and industrial loans outstanding, yoy	Federal Reserve	0
Germany bank loans to households and non-profit orgs. yoy	ECB	1
EMU bank loans to non-financial corporates yoy	ECB	1
EMU bank loans to households and non-profit orgs. yoy	ECB	1
US consumer loans outstanding yoy	Federal Reserve	0
US real estate loans outstanding yoy	Federal Reserve	0
Germany bank loans to households and non-profit orgs. / disposable household income	ECB, Bundesbank	1
Germany bank loans to non-financial corporates / GDP	ECB, Bundesbank	1
EMU bank loans to households and non-profit orgs. / disposable household income	ECB, Eurostat	1
EMU bank loans to non-financial corporates / GDP	ECB, Eurostat	1
US real estate loans outstanding / disposable household income	Fed, BEA	0
US consumer loans outstanding / disposable household income	Fed, BEA	0
US commercial and industrial loans outstanding / GDP	Fed, BEA	0
Spread of BofA ML High Yield index vs. 5y swap rates. Since 1998 euro high yield, before US high yield.	Datastream	0
Average 5y senior USD CDS spreads on 4 German banks	Datastream	0
VDAX volatility index	Datastream	0
ZEW survey: profit situation of German banks, *(-1)	ZEW	0
30-day realized correlation of stocks (DAX) and bonds (REX) performance indices, *(-1)	Macrobond	0
30-day realized correlation of german bank equity index and MSCI Germany	Datastream	0
Bundesbank TARGET2 claims	Datastream	0
Yield spread on corporate bonds (non-MFIs) in Germany over 3m euribor.	Bundesbank	0
Interest rate spread on loans to non-financial corporations in Germany with a maturity of 1 up to 5 years over 3m euribor	Bundesbank	0
Interest rate spread on loans for consumption and other purposes to households in Germany with a maturity of over 1 year and up to 5 years over 3m euribor	Bundesbank	0
Interest rate spread of effective interest rates of German banks on extended credit card debt to households over 3m euribor	Bundesbank	0
Interest rate spread between average effective mortgage lending rates on loans secured by residential real estate with interest rates fixed for 10 years and 3m euribor	Bundesbank	0
Volume of the deposit facility of the Eurosystem	ECB	0
Volume of the lending facility of the Eurosystem	ECB	0
Bank lending survey: credit standards to firms EMU	ECB	Q+1
Bank lending survey: credit standards to firms Germany	ECB	Q+1
Interbank loans EMU	ECB	0
Interbank loans Germany	ECB	0
iTraxx CDS Index	Datastream	0
VSTOXX volatility index, before 1999 30-day realized volatility of the euro stoxx 50	Datastream	0
Volatility of the German real effective exchange rate based on a GARCH(1,1) estimation	OECD	0
30-day implied volatility of MSCI Emerging Markets Index	Macrobond	0
30-day implied volatility of the EUR-USD exchange rate	Macrobond	0
30-day implied volatility of the gold price	Macrobond	0
30-day implied volatility of the oil price	Macrobond	0
30-day realised volatility of the MSCI World	Datastream	0
Average 5y senior USD CDS spreads for Germany, France, Italy, Japan, Canada, UK, and US	Macrobond	0
Average 5y senior USD CDS spreads for Greece, Spain, Ireland, Italy, and Portugal	Macrobond	0
Average 5y senior USD CDS spreads for Brazil, Russia, India, China, and South Africa	Macrobond	0
Average 10y-government bond spreads of Greece, Spain, Ireland, Italy, and Portugal vs. Germany	Macrobond	0
Average 10y-government bond spreads of Brazil, Russia, India, China, and South Africa vs. Germany	Macrobond	0
Average 10y-government bond spreads of France, Italy, Japan, Canada, UK, and US vs. Germany	Macrobond	0
Spread between German 10y and 2y swap rates, *(-1)	Datastream	0
Interest rate spread of commercial bank interest rate on credit card plans in the US over 3m libor	Federal Reserve	0
Interest rate spread of commercial bank interest rate on credit card plans in the US over 3m libor	Federal Reserve	0
30-day realized volatility of the GBP-EUR exchange rate, before 1999 GBP-DEM	Datastream	0
Yield spread of listed federal securities in Germany over 3m euribor *(-1)	Bundesbank	0
Spread on bank debt securities over 3m euribor, *(-1)	Bundesbank	0

Notes: Q+x describes a publication lag of x months following the quarter of the latest observation.
If available we use working-day and seasonally adjusted series.

Table 6: Variables used for the financial stress index for the Euro Area

Description and transformations	**Raw data source**	**Publ. lag**
MSCI EMU yoy, *(-1)	Datastream	0
MSCI USA yoy, *(-1)	Datastream	0
12-months forward price-earnings ratio of the DAX	Datastream	0
12-months forward price-earnings ratio of the CAC 40	Datastream	0
12-months forward price-earnings ratio of the IBEX 35	Datastream	0
12-months forward price-earnings ratio of the FTSE Italy	Datastream	0
12-months forward price-earnings ratio of the S&P 500	Datastream	0
Nominal house price index euro area yoy, linear interpolation of quarterly data, *(-1)	OECD	Q+5
Case-Shiller National Home Price Index USA yoy, *(-1)	Datastream	2
EMU bank loans to non-financial corporates yoy	ECB	1
US commercial and industrial loans outstanding, yoy	Federal Reserve	0
EMU bank loans to households and non-profit orgs. yoy	ECB	1
US consumer loans outstanding yoy	Federal Reserve	0
US real estate loans outstanding yoy	Federal Reserve	0
EMU bank loans to households and non-profit orgs. / disposable household income	ECB, Eurostat	1
EMU bank loans to non-financial corporates / GDP	ECB, Eurostat	1
US real estate loans outstanding / disposable household income	Fed, BEA	0
US consumer loans outstanding / disposable household income	Fed, BEA	0
US commercial and industrial loans outstanding / GDP	Fed, BEA	0
Spread of BofA ML High Yield index vs. 5y swap rates. Since 1998 euro high yield, before US high yield.	Datastream	0
Average 5y senior USD CDS spreads on 19 euro area banks	Datastream	0
30-day realized volatility of the MSCI EMU	Datastream	0
ZEW survey: profit situation of German banks	ZEW	0
30-day realized correlation of stocks (MSCI EMU) and bonds (Barclays Euro Aggregate) performance indices.	Macrobond	0
30-day realized correlation of german bank equity index and MSCI Germany	Datastream	1
Bundesbank TARGET2 claims	Datastream	0
Yield spread of BofA ML euro corporate bond index against 5-year swap rate. Before 1996: Yield spread on corporate bonds (non-MFIs) in Germany over 5y swap rate	Datastream, Bundesbank	0
Interest rate spread of composite cost of borrowing indicator for non-financial corporations over 5y swap rate	Datastream, ECB	0
Interest rate spread of composite cost of borrowing indicator for consumer loans over 5y swap rate	Datastream, ECB	0
Interest rate spread of composite cost of borrowing indicator for housing loans over 5y swap rate	Datastream, ECB	0
Volume of the deposit facility of the Eurosystem	ECB	0
Volume of the lending facility of the Eurosystem	ECB	0
Bank lending survey: credit standards to firms EMU	ECB	Q+1
iTraxx CDS Index	Datastream	0
VSTOXX volatility index, before 1999 30-day realized volatility of the euro stoxx 50	Datastream	0
Volatility of the German real effective exchange rate based on a GARCH(1,1) estimation	OECD	0
30-day implied volatility of the MSCI Emerging Markets Index	Macrobond	0
30-day implied volatility of the EUR-USD exchange rate	Macrobond	0
30-day implied volatility of the gold price	Macrobond	0
30-day implied volatility of the oil price	Macrobond	0
30-day realised volatility of the MSCI World	Datastream	0
Average 5y senior USD CDS spreads for Germany, France, Italy, Japan, Canada, UK, and US	Macrobond	0
Average 5y senior USD CDS spreads for Greece, Spain, Ireland, Italy, and Portugal	Macrobond	0
Average 5y senior USD CDS spreads for Brazil, Russia, India, China, and South Africa	Macrobond	0
Average 10y-government bond spreads of Greece, Spain, Ireland, Italy, and Portugal vs. Germany	Macrobond	0
Average 10y-government bond spreads of Brazil, Russia, India, China, and South Africa vs. Germany	Macrobond	0
Average 10y-government bond spreads of France, Italy, Japan, Canada, UK, and US vs. Germany	Macrobond	0
Spread between German 10y and 2y swap rates	Datastream	0
Interest rate spread of commercial bank interest rate on credit card plans in the US over 3m libor	Federal Reserve	0
Interest rate spread of commercial bank interest rate on credit card plans in the US over 3m libor	Federal Reserve	0
30-day realized volatility of the GBP-EUR exchange rate	Datastream	0

Notes: Q+x describes a publication lag of x months following the quarter of the latest observation.
If available we use working-day and seasonally adjusted series.

B Illustrations

Figure 11: DE probit variables other than FSI. Vintage 2018/12. Shown untransformed. See Table 3 for description and sources.

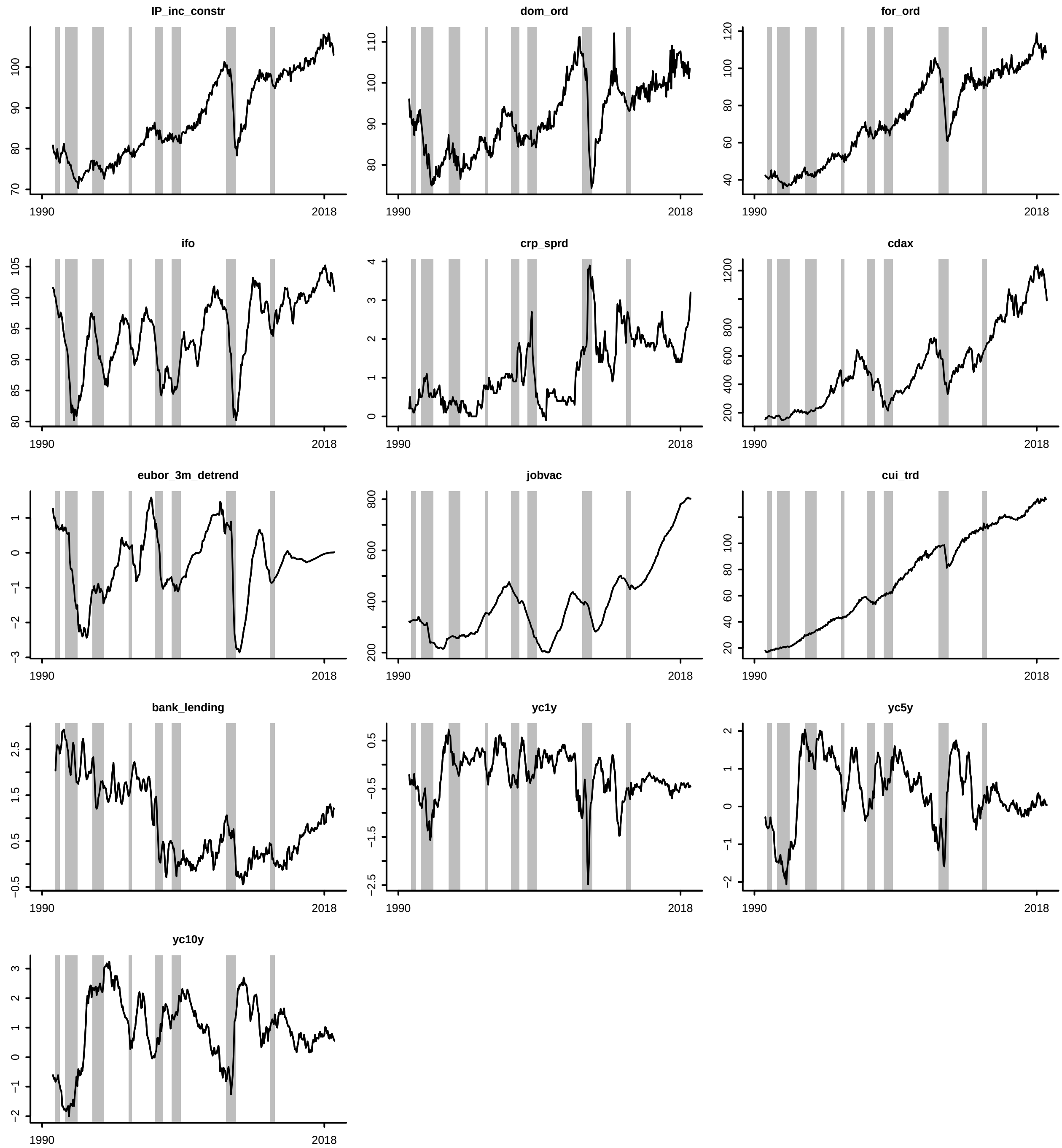


Figure 12: EMU probit variables other than FSI. Vintage 2018/12. Shown untransformed. See Table 4 for description and sources.

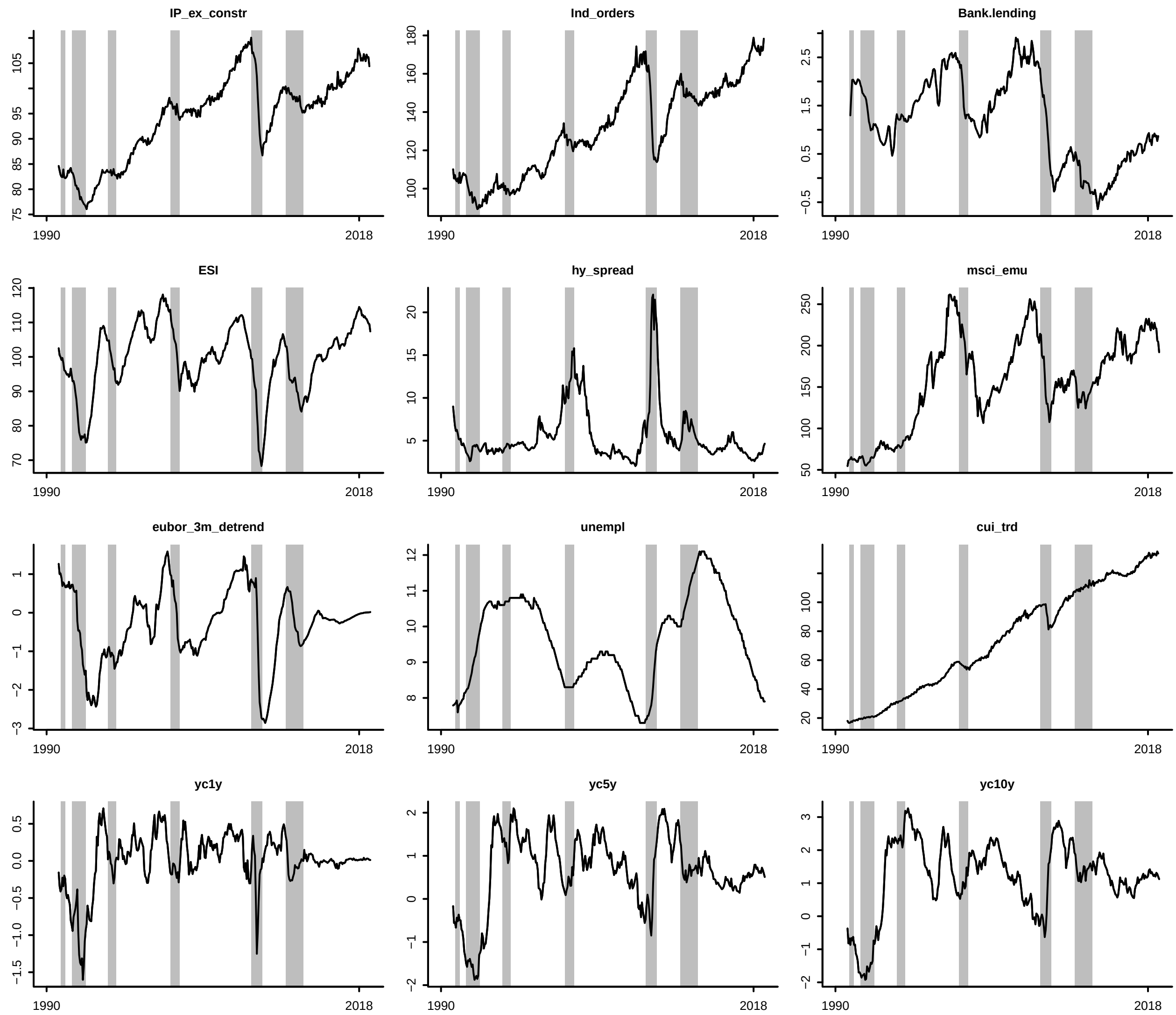
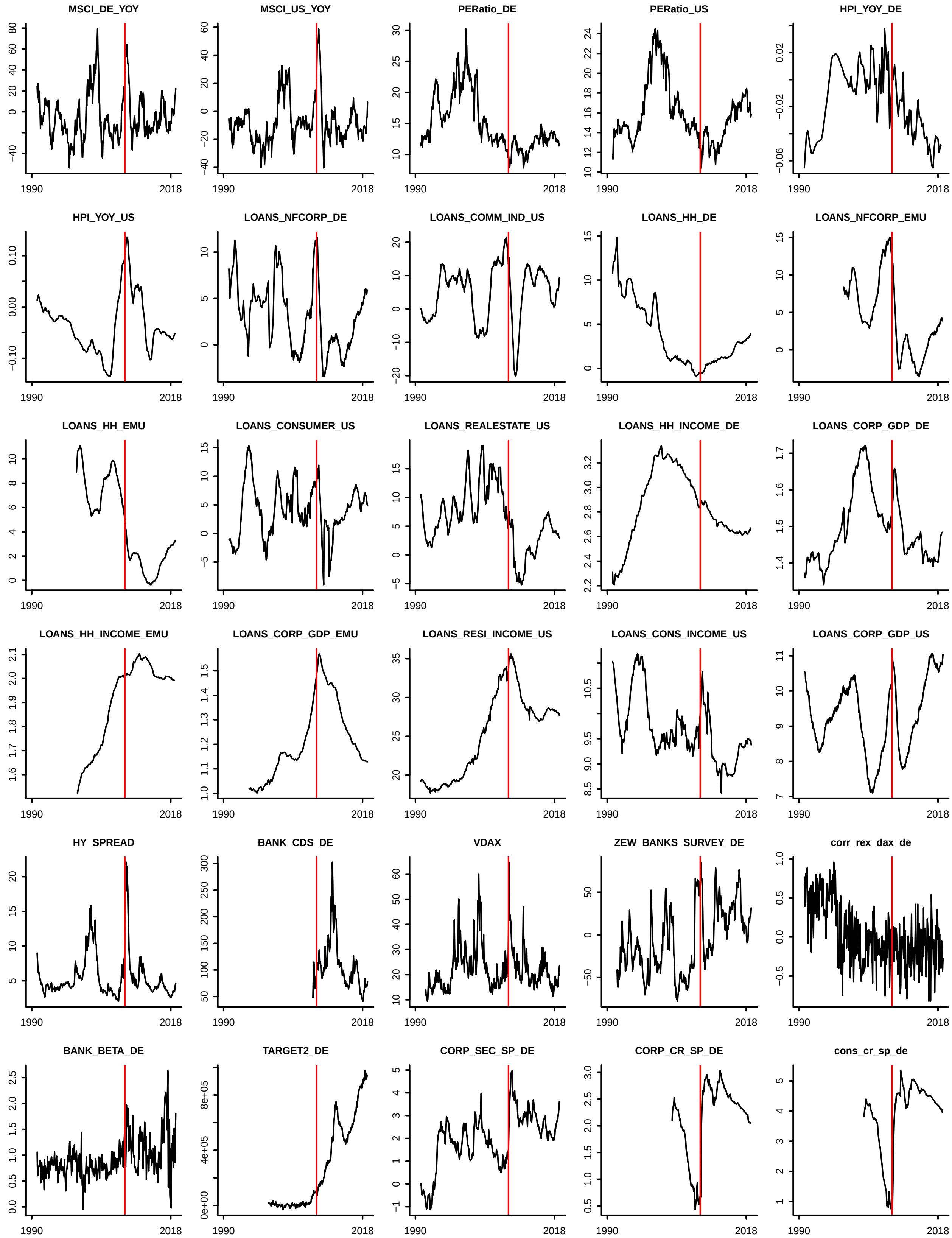
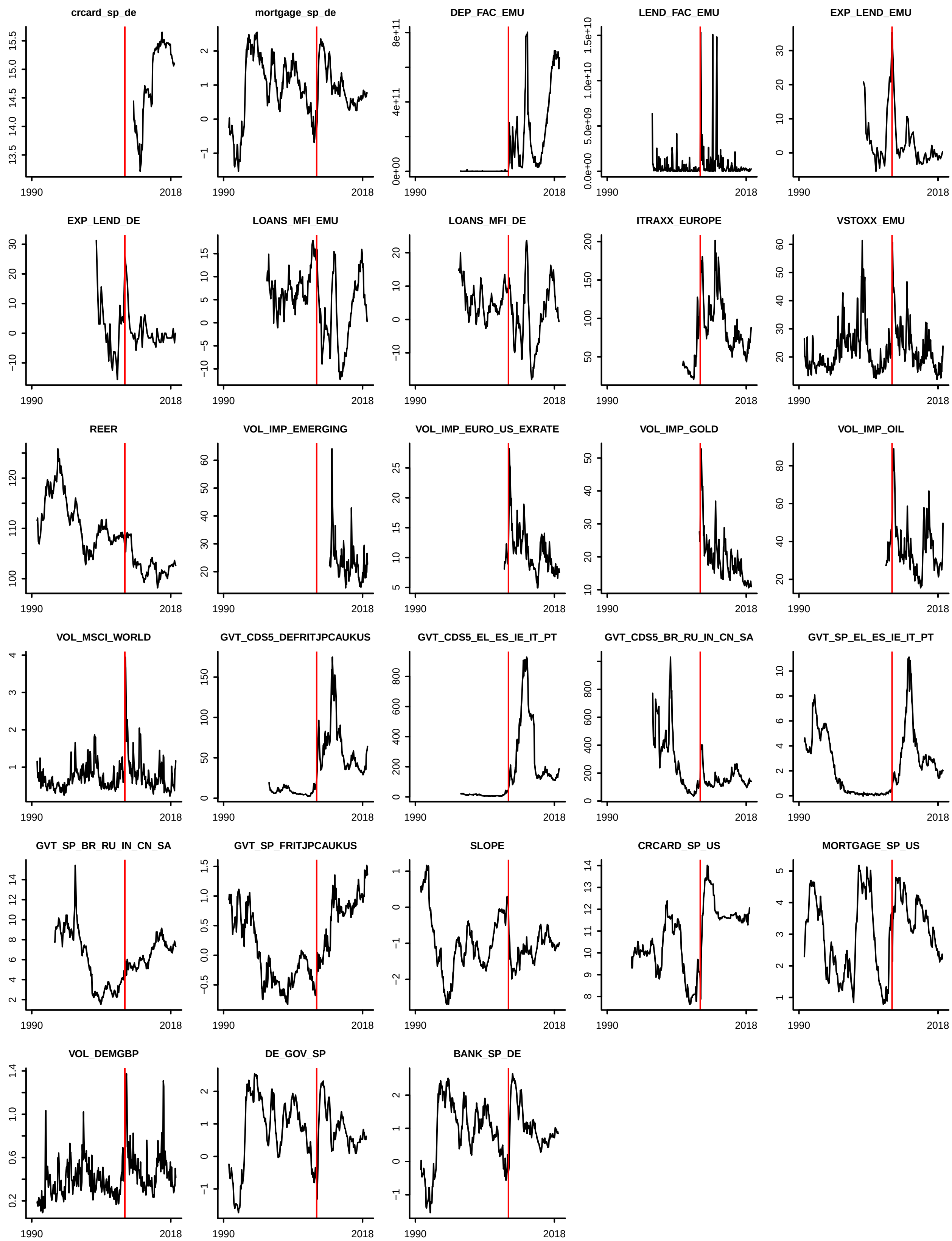


Figure 13: FSI variables for Germany 1/2



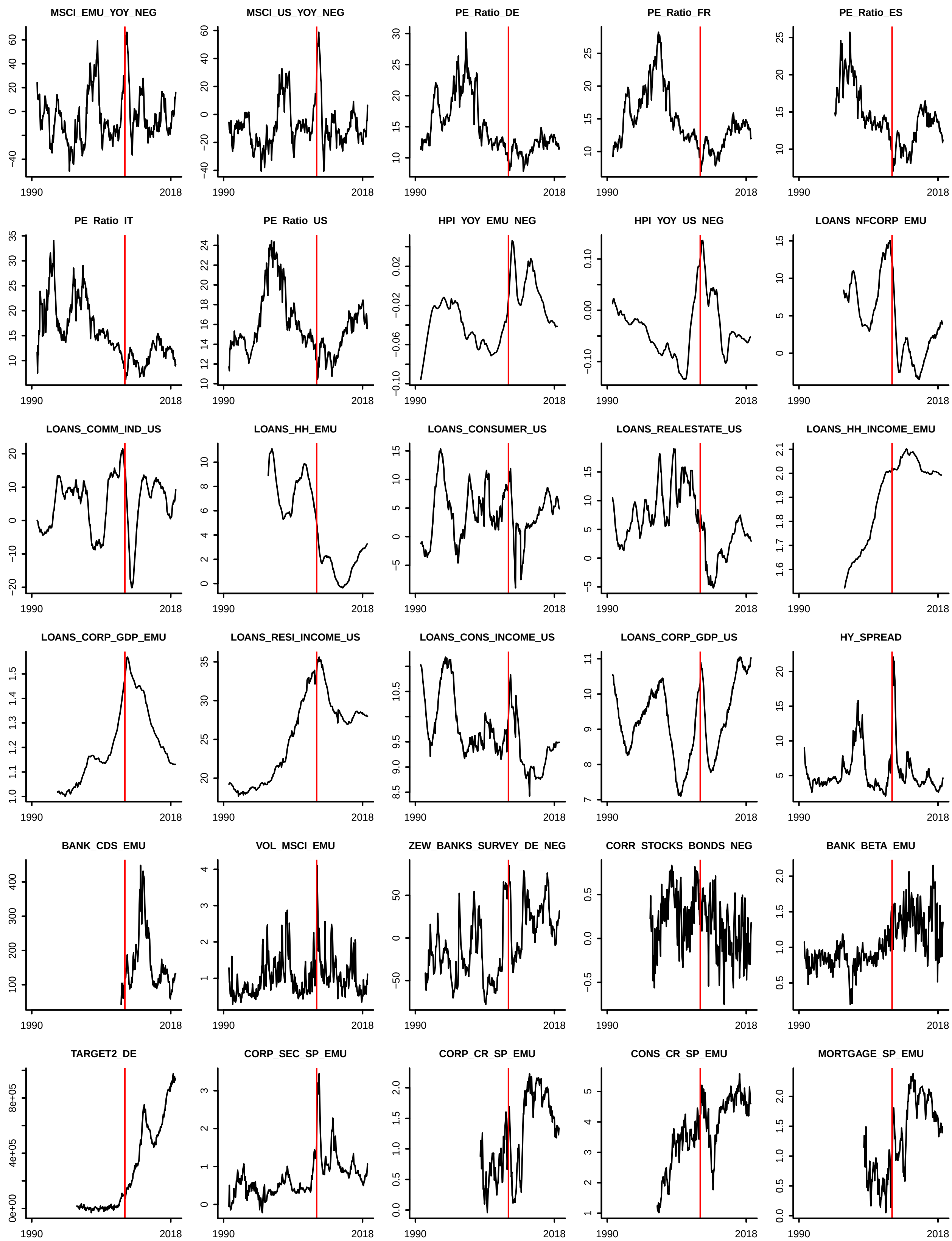
Vertical lines: beginning of banking crisis (09/2008) as defined by Laeven & Valencia (2018).

Figure 14: FSI variables for Germany 2/2



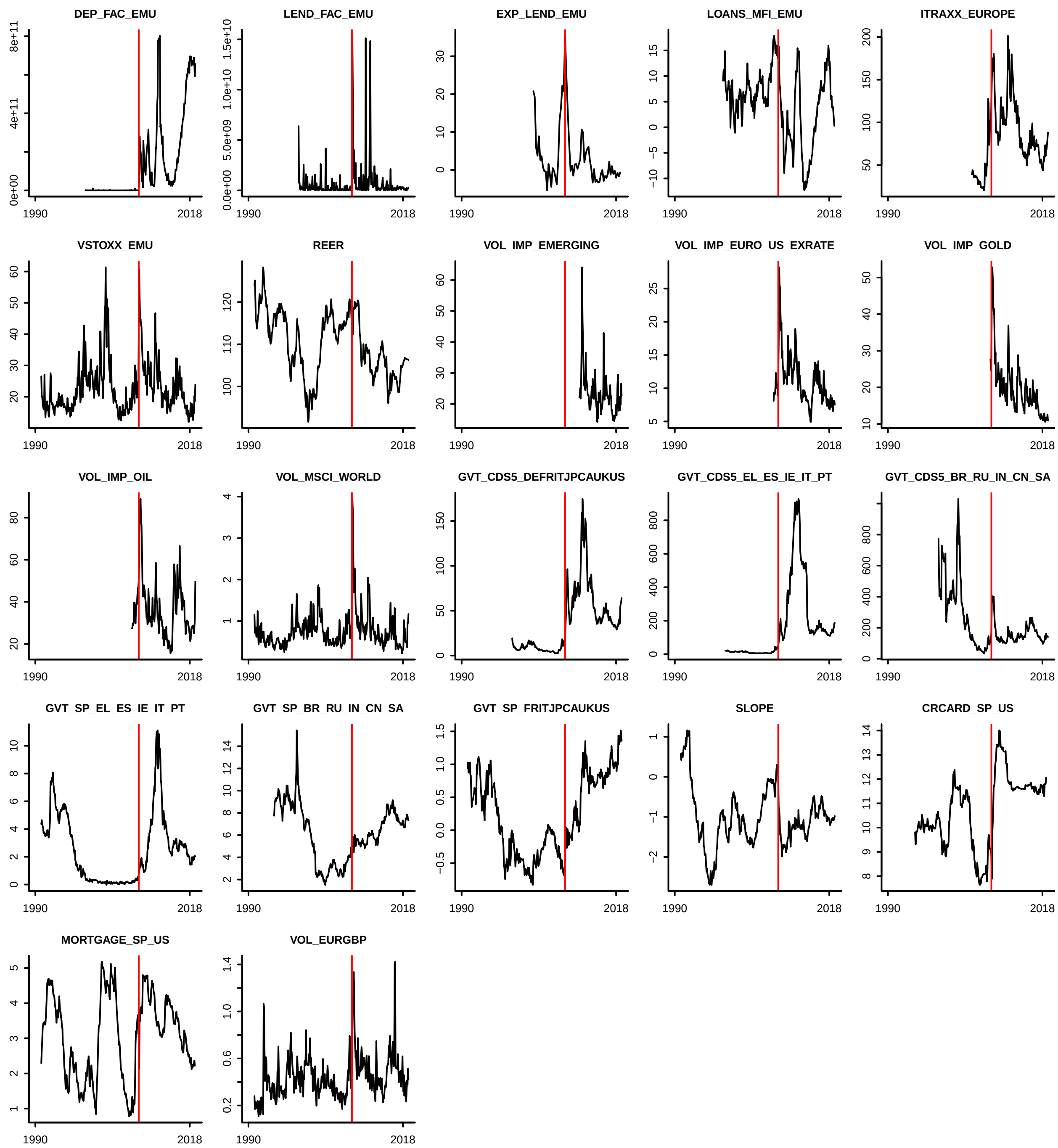
Vertical lines: beginning of banking crisis (09/2008) as defined by Laeven & Valencia (2018).

Figure 15: FSI variables for the Euro Area 1/2



Vertical lines: beginning of banking crisis (09/2008) as defined by Laeven & Valencia (2018).

Figure 16: FSI variables for the Euro Area 2/2



Vertical lines: beginning of banking crisis (09/2008) as defined by Laeven & Valencia (2018).

C Vintage-dependent results

Figure 17: Evolution of the FSI for Germany over time. Dark blue = 1 (maximal financial stress), white = 0 (minimal financial stress).

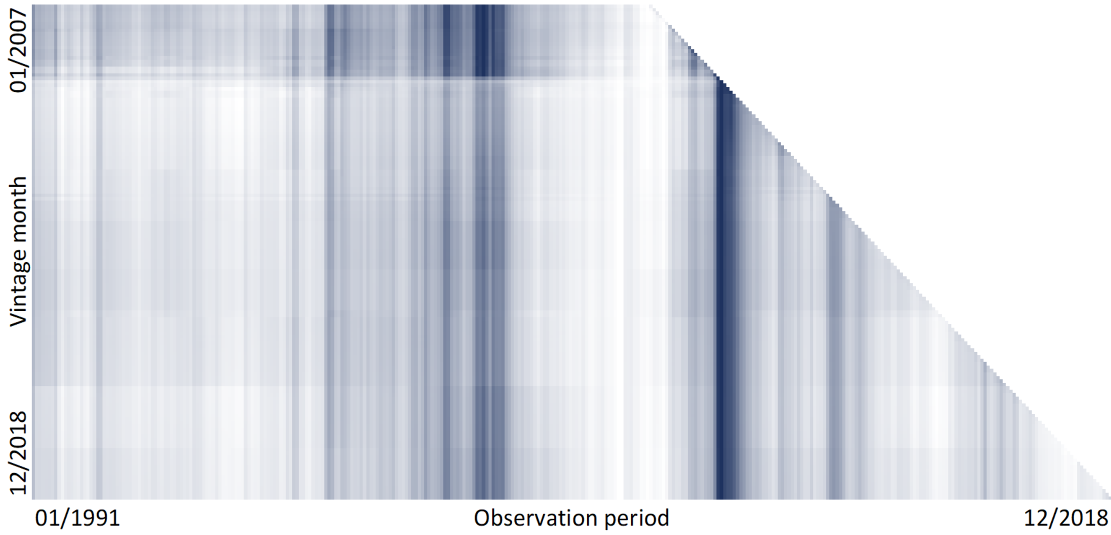


Figure 18: Evolution of the FSI for the Euro Area over time. Dark blue = 1 (maximal financial stress), white = 0 (minimal financial stress).

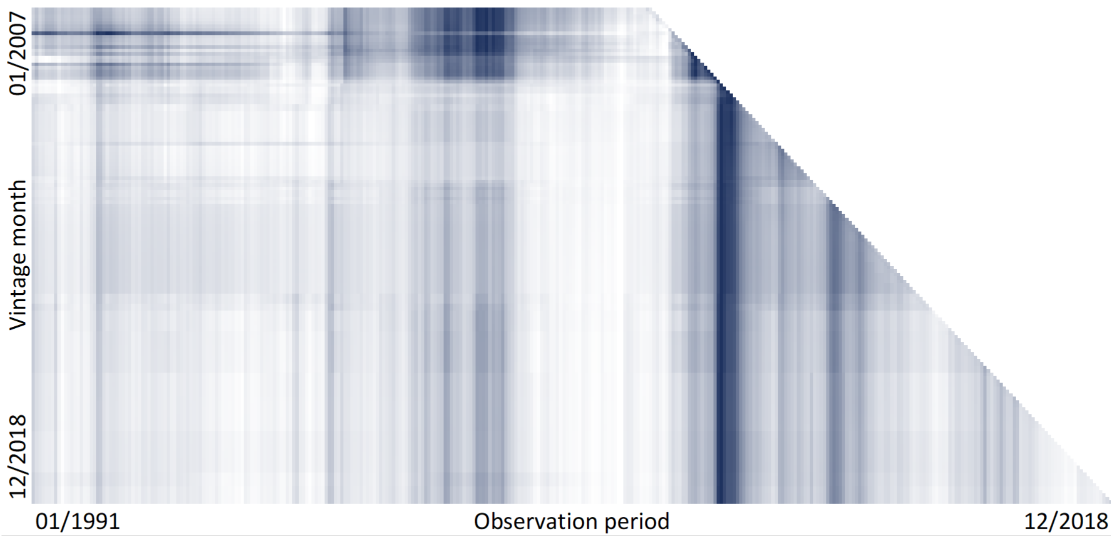


Table 7: Variables included according to the real-time selection process, German forecast model

	IPinc constr	**dom ord**	**for ord**	**credit imp**	**FSI**	**Ifo**	**CDAX**	**eubor 3m**	**crp sprd**	**job vac**	**cui tdr**	**yc1y**	**yc5y**	**yc10y**
2007M01	60%	33%	97%	37%	100%	100%	50%	80%	63%	100%	17%	100%	83%	83%
2007M02	60%	53%	80%	37%	100%	100%	50%	83%	67%	100%	33%	100%	83%	100%
2007M03	57%	17%	83%	33%	100%	100%	50%	73%	43%	100%	50%	100%	100%	100%
2007M04	60%	20%	83%	37%	100%	100%	50%	77%	47%	100%	50%	100%	100%	100%
2007M05	57%	17%	83%	33%	100%	100%	50%	73%	47%	100%	50%	100%	100%	100%
2007M06	43%	10%	83%	33%	100%	100%	50%	73%	50%	100%	50%	100%	100%	100%
2007M07	40%	20%	100%	57%	67%	100%	23%	60%	53%	67%	17%	83%	67%	100%
2007M08	40%	17%	100%	57%	63%	100%	23%	60%	57%	67%	17%	83%	67%	100%
2007M09	33%	7%	100%	47%	63%	100%	20%	57%	53%	50%	17%	83%	67%	100%
2007M10	33%	10%	100%	47%	57%	100%	20%	57%	57%	50%	17%	83%	67%	100%
2007M11	33%	7%	100%	50%	57%	100%	20%	60%	53%	50%	17%	83%	67%	100%
2007M12	33%	7%	100%	50%	53%	100%	20%	60%	57%	50%	33%	83%	67%	83%
2008M01	33%	7%	100%	20%	50%	100%	23%	57%	63%	83%	17%	83%	67%	83%
2008M02	33%	7%	100%	23%	50%	100%	23%	60%	63%	67%	17%	83%	67%	83%
2008M03	33%	3%	100%	23%	50%	100%	20%	60%	60%	67%	17%	83%	50%	83%
2008M04	33%	17%	100%	60%	53%	100%	17%	67%	57%	33%	33%	83%	50%	83%
2008M05	33%	3%	100%	60%	50%	100%	10%	70%	53%	33%	33%	83%	67%	83%
2008M06	33%	13%	100%	53%	53%	100%	17%	70%	57%	33%	33%	83%	50%	83%
2008M07	33%	20%	100%	67%	50%	100%	30%	77%	67%	67%	33%	83%	50%	67%
2008M08	33%	17%	100%	73%	50%	100%	17%	73%	53%	33%	33%	83%	50%	83%
2008M09	33%	17%	100%	73%	53%	100%	13%	73%	47%	50%	33%	83%	50%	83%
2008M10	33%	10%	100%	77%	57%	100%	13%	73%	33%	33%	33%	67%	50%	83%
2008M11	33%	0%	100%	70%	50%	100%	17%	80%	43%	50%	33%	67%	50%	83%
2008M12	50%	3%	83%	70%	53%	100%	20%	87%	40%	50%	33%	67%	50%	83%
2009M01	50%	0%	83%	70%	67%	100%	17%	93%	30%	50%	33%	67%	50%	67%
2009M02	33%	10%	97%	27%	97%	97%	13%	100%	10%	100%	33%	83%	50%	83%
2009M03	37%	10%	97%	27%	100%	97%	7%	100%	17%	67%	33%	83%	50%	83%
2009M04	33%	0%	83%	27%	100%	87%	3%	87%	33%	83%	33%	67%	67%	83%
2009M05	33%	3%	80%	43%	100%	87%	13%	83%	50%	83%	17%	100%	83%	83%
2009M06	33%	3%	63%	47%	100%	83%	10%	83%	57%	100%	33%	67%	67%	83%
2009M07	33%	0%	70%	33%	100%	83%	10%	60%	50%	83%	17%	17%	67%	67%
2009M08	33%	0%	63%	33%	100%	77%	50%	53%	77%	83%	50%	17%	67%	83%
2009M09	0%	0%	57%	3%	100%	97%	23%	30%	90%	100%	0%	50%	83%	100%
2009M10	50%	67%	100%	23%	90%	93%	20%	63%	23%	67%	50%	83%	83%	83%
2009M11	47%	83%	100%	23%	73%	100%	20%	57%	27%	83%	17%	100%	100%	100%
2009M12	57%	77%	93%	23%	80%	100%	13%	63%	20%	100%	33%	100%	100%	100%
2010M01	57%	77%	90%	30%	77%	100%	20%	60%	20%	100%	50%	100%	100%	83%
2010M02	53%	80%	93%	23%	73%	100%	23%	60%	20%	100%	50%	100%	100%	83%
2010M03	57%	77%	93%	23%	80%	100%	30%	60%	20%	100%	50%	100%	100%	100%
2010M04	57%	77%	97%	23%	80%	100%	30%	63%	17%	100%	50%	100%	100%	100%
2010M05	57%	77%	97%	27%	80%	100%	30%	57%	17%	100%	50%	100%	100%	100%
2010M06	53%	77%	90%	27%	80%	100%	33%	57%	17%	100%	50%	100%	100%	100%
2010M07	57%	77%	93%	23%	87%	100%	30%	50%	13%	100%	50%	100%	100%	100%
2010M08	57%	70%	93%	23%	90%	100%	27%	50%	13%	100%	50%	100%	100%	100%
2010M09	57%	70%	93%	20%	90%	100%	23%	50%	17%	100%	50%	100%	100%	100%
2010M10	57%	70%	93%	20%	90%	97%	23%	50%	13%	100%	50%	100%	100%	100%
2010M11	57%	70%	97%	20%	90%	97%	23%	50%	23%	100%	33%	100%	100%	100%
2010M12	57%	70%	97%	20%	90%	97%	23%	50%	23%	100%	33%	100%	100%	100%
Total	43%	31%	92%	38%	77%	98%	24%	66%	41%	78%	34%	85%	77%	90%

Note: Percentage values stand for the proportion of specifications in which at least one lag of a certain regressor variable plays a role. Red-colored is the percentage range 0% to 33%, grey-colored 34% to 66% and blue-colored 67% to 100%."IP inc constr" is used for the industrial production including construction, "dom ord" for the domestic manufacturing orders, "for ord" for the foreign manufacturing orders, "credit imp" for the credit impulse, "FSI" for the financial stress index, "Ifo" for the ifo business climate index, "CDAX" for the CDAX stock market index, "eubor 3m" for the 3-Month EURIBOR interest rate, "crp sprd" for the corporate bond spread, "job vac" for the job vacancies, "cui trd" for the RWI container index proxying world trade, "yc1y", "yc5y" and "yc10y" for the slopes of the yield curve.

Table 8: Variables included according to the real-time selection process, Euro Area forecast model

	IP ex constr	**ind orders**	**credit imp**	**fin str**	**FSI**	**MSCI EMU**	**eubor 3m**	**hy spread**	**yc1y**	**unempl**	**cui trd**	**yc5y**	**yc10y**
2007M01	50%	13%	87%	60%	67%	20%	93%	90%	83%	100%	50%	83%	83%
2007M02	50%	10%	53%	60%	63%	13%	93%	90%	83%	100%	50%	83%	83%
2007M03	50%	10%	80%	63%	63%	17%	93%	90%	83%	100%	50%	83%	83%
2007M04	50%	10%	83%	63%	63%	17%	93%	90%	83%	100%	50%	83%	83%
2007M05	53%	10%	87%	63%	63%	20%	93%	90%	83%	100%	50%	83%	83%
2007M06	53%	10%	87%	63%	63%	23%	93%	90%	83%	100%	50%	83%	83%
2007M07	57%	37%	83%	70%	67%	20%	93%	93%	83%	100%	67%	67%	83%
2007M08	63%	40%	83%	70%	67%	23%	93%	93%	83%	100%	33%	67%	83%
2007M09	53%	23%	80%	70%	70%	23%	93%	93%	83%	100%	50%	67%	83%
2007M10	60%	30%	83%	70%	67%	23%	93%	90%	83%	100%	50%	67%	83%
2007M11	53%	27%	80%	70%	70%	20%	93%	93%	83%	100%	33%	67%	83%
2007M12	60%	33%	87%	70%	67%	27%	93%	90%	83%	100%	50%	67%	83%
2008M01	63%	30%	80%	70%	67%	23%	93%	90%	83%	100%	50%	67%	83%
2008M02	53%	27%	83%	67%	67%	17%	93%	90%	83%	100%	50%	83%	83%
2008M03	57%	33%	87%	70%	67%	20%	93%	90%	83%	100%	67%	83%	83%
2008M04	60%	20%	87%	67%	70%	33%	93%	90%	83%	100%	17%	83%	83%
2008M05	60%	33%	80%	63%	70%	17%	93%	97%	83%	100%	0%	83%	83%
2008M06	57%	27%	83%	67%	67%	13%	93%	93%	83%	100%	33%	67%	83%
2008M07	57%	17%	73%	60%	63%	13%	93%	93%	83%	100%	0%	83%	83%
2008M08	63%	17%	70%	60%	63%	17%	87%	77%	100%	100%	0%	100%	100%
2008M09	60%	10%	67%	60%	63%	23%	87%	77%	100%	100%	0%	100%	100%
2008M10	67%	20%	80%	60%	70%	30%	87%	73%	100%	100%	0%	100%	100%
2008M11	70%	17%	80%	67%	63%	23%	97%	63%	100%	100%	0%	100%	100%
2008M12	63%	13%	73%	63%	67%	23%	90%	73%	100%	100%	0%	100%	100%
2009M01	67%	17%	80%	70%	67%	27%	93%	73%	100%	100%	0%	100%	100%
2009M02	63%	20%	77%	57%	67%	40%	90%	77%	100%	100%	0%	100%	100%
2009M03	73%	17%	83%	80%	70%	37%	87%	73%	100%	100%	0%	100%	100%
2009M04	67%	17%	80%	83%	70%	40%	83%	80%	100%	100%	33%	100%	100%
2009M05	67%	20%	80%	83%	73%	50%	80%	83%	100%	100%	33%	100%	100%
2009M06	57%	13%	63%	87%	100%	30%	73%	23%	100%	100%	0%	100%	100%
2009M07	63%	17%	93%	83%	70%	23%	87%	87%	100%	100%	17%	100%	100%
2009M08	60%	20%	93%	87%	70%	20%	87%	87%	100%	100%	17%	100%	100%
2009M09	70%	17%	33%	97%	100%	43%	80%	47%	100%	100%	17%	100%	100%
2009M10	63%	67%	87%	87%	70%	20%	97%	50%	100%	100%	17%	100%	100%
2009M11	77%	27%	97%	80%	70%	30%	97%	73%	100%	100%	33%	100%	100%
2009M12	73%	43%	100%	80%	70%	23%	97%	77%	100%	100%	33%	100%	100%
2010M01	70%	43%	97%	77%	67%	10%	97%	80%	100%	100%	50%	100%	100%
2010M02	73%	27%	90%	80%	73%	23%	97%	60%	100%	100%	50%	100%	100%
2010M03	73%	30%	83%	77%	73%	27%	97%	60%	100%	100%	50%	100%	100%
2010M04	77%	37%	83%	80%	77%	43%	93%	57%	100%	100%	50%	100%	100%
2010M05	80%	40%	87%	80%	77%	23%	93%	67%	100%	100%	33%	100%	100%
2010M06	70%	23%	100%	73%	73%	13%	97%	70%	100%	100%	33%	100%	100%
2010M07	67%	33%	100%	80%	77%	20%	97%	73%	100%	100%	50%	100%	100%
2010M08	67%	33%	100%	80%	77%	20%	97%	73%	100%	100%	50%	100%	100%
2010M09	63%	33%	100%	73%	73%	17%	97%	67%	100%	100%	50%	100%	100%
2010M10	63%	50%	100%	77%	70%	17%	97%	67%	100%	100%	50%	100%	100%
2010M11	67%	37%	100%	80%	80%	17%	97%	73%	100%	100%	33%	100%	100%
2010M12	70%	50%	100%	80%	77%	17%	97%	73%	100%	100%	33%	100%	100%
Total	63%	26%	84%	72%	70%	24%	97%	78%	93%	100%	32%	91%	93%

Note: Percentage values stand for the proportion of specifications in which at least one lag of a certain regressor variable plays a role. Red-colored is the percentage range 0% to 33%, grey-colored 34% to 66% and blue-colored 67% to 100%. "IP ex constr" is used for the industrial production excluding construction, "credit imp" for the credit impulse, "FSI" for the financial stress index, "ESI" for the European Commission's economic sentiment index, "eubor 3m" for the 3-Month Euribor interest rate, "hy spread" for the spread between BofA ML High Yield index and 5year swap rates, "unempl" for the unemployment rate, "cui trd" for the RWI container index proxying world trade, "yc1y", "yc5y" and "yc10y" for the slopes of the yield curve.

D Alternative FSIs solely based on financial cycle variables

To analyze the predictive power of the financial cycle variables even more in depth, we run an additional regression for which we construct a FSI only based on the indicators related to the financial cycle. These are house price changes, loan growth and loan to income ratios (16 indicators for Germany and 12 for the Euro Area). We roughly follow the methodology of the broad FSI described in Section 3.1. Due to the smaller number of relevant indicators we resign the variable selection procedure. Furthermore, instead of the imputation methodology described, we simply extrapolate the latest available observations in case of publication lags. The resulting Euro Area FSI is illustrated in Figure 21 for several vintages. The corresponding out-of-sample results are presented in Figure 20. Compare Section 4.1.2, in particular Footnote 11.

Figure 19: Financial cycle FSIs

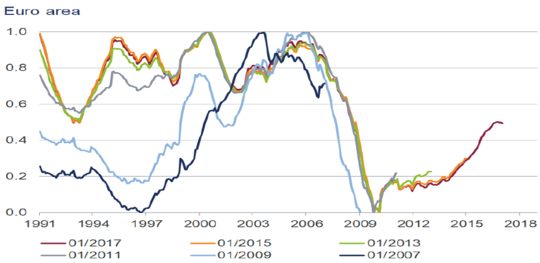
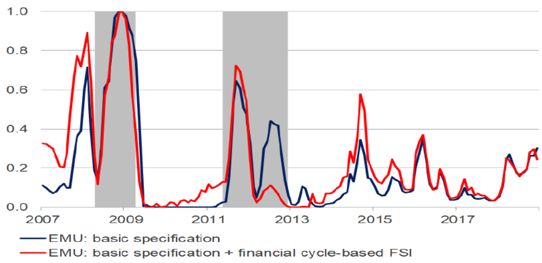


Figure 20: Real-time out-of-sample forecast



E Comparison of the basic forecast with the literature

To compare our basic specification with results from the literature, we refer to Proaño & Theobald (2014). Beside the conventional root mean squared error, we also compute a conditional one, which puts a simple weight on the error of a recession signal and a double weight on the error of a missing recession signal. With the aide of the indicator function $\mathbb{1}_{\{b_t^*=1\}}$ we therefore obtain

$$\text{CRMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(1+\mathbb{1}_{\{b_t^*=1\}})(\widetilde{Prob_t}^{3m} - b_t^*)^2}. \tag{16}$$

As could be expected from the graphical analysis, both specifications produce similar results, while a certain preference depends on the loss function used. Also compare Section 4.4.

Figure 21: Real-time out-of-sample forecast

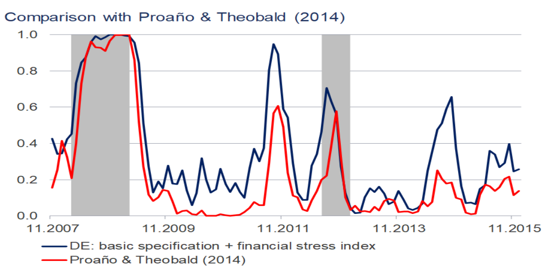


Table 9: Forecast evaluation measures

	Loss Function	German Basic Specification	Proano & Theobald(2014)
RMSE	symmetric	0.356	0.305
CRMSE	asymmetric	0.383	0.384

Notes: CRMSE stands for conditional root mean squared error.

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Phone: +49-211-7778-331, IMK@boeckler.de, http://www.imk-boeckler.de

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