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What Predicts Financial (In)Stability? A Bayesian Approach

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Abstract

This paper contributes to the literature on early warning indicators by applying a Bayesian model averaging approach. Our analysis, based on Austrian data, is carried out in two steps: First, we construct a quarterly financial stress index (AFSI) quantifying the level of stress in the Austrian financial system. Second, we examine the predictive power of various indicators, as measured by their ability to forecast the AFSI. Our approach allows us to investigate a large number of indicators. The results show that banks' share price growth and cross-border lending are among the best early warning indicators.

Wie lässt sich Finanzmarktstabilität prognostizieren? Ein Bayesianischer Ansatz

Zusammenfassung

In dieser Arbeit wird ein bayesianischer Ansatz zur Bestimmung von Frühwarnindikatoren für Finanzkrisen beschrieben. Unsere Analyse basiert auf österreichischen Daten und teilt sich in zwei Schritte auf: Im ersten Schritt entwickeln wir einen vierteljährlichen Index zur Messung des Stresses im österreichischen Finanzsystem (Austrian Financial Stress Index, AFSI). Im zweiten Schritt überprüfen wir die Vorhersagekraft verschiedener Indikatoren für den AFSI. Unser Ansatz erlaubt die Überprüfung einer großen Anzahl an Indikatoren. Die Ergebnisse zeigen, dass die Renditen von Bankaktien und grenzüberschreitende Kredite die besten Frühwarnindikatoren sind.

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JEL Classification: G01, G28

I. Introduction

The huge costs of financial crises are well-known. In many cases, total costs (resulting from rescue measures and output loss) amount to 10 % of GDP or even more (*Laeven/Valencia* 2008). Moreover, due to high unemployment and resulting poverty, high social costs may occur. Against this background, it is essential to find early warning indicators which help to detect vulnerabilities in the financial system. Furthermore, in order to gain a better understanding of how important different sources of risk are, measures which quantify financial soundness are valuable.

In this paper, we contribute both to the literature on quantifying financial stability and to the literature on identifying early warning indicators. Our paper is based on Austrian data. We choose a two-step approach. In the first step, we construct a composite financial stress index. The index measures the current strength of Austrian financial stability and is called the Austrian Financial Stress Index (AFSI). In the second step, we examine various indicators with respect to their early warning capability, as measured by their power to forecast the AFSI. We use a Bayesian model averaging approach.[1]

The literature has identified a large number of possible early warning indicators. The earlier literature pointed to macroeconomic variables (such as interest rates, balance of current accounts, inflation and development of monetary aggregates) and excessive credit growth (see, for example, *Demirgüc-Kunt/Detriagache* 1998; *Hardy/Pazarbasioglu* 1999). Later papers showed that banks' risk-bearing capacity and asset price development may be relevant as well. Overall, results are often contradictory, which may be due to a differing geographical focus, but also due to different variables included. Most papers consider only subsets of the possible indicators, generally around 10 to 15 variables. We differ from this approach by using Bayesian model averaging. We are able to take into account around 30 variables. By using a much larger set of indicators we can improve indicator selection. In particular, our method delivers more robust results since results reflect a large number of models.

We find that (i) high returns of banks' share prices, (ii) large cross-border lending and (iii) inflation are the most important early warning indicators for

[1] Results stemming from best subset selection mechanism and model averaging were published in the Austrian Financial Stability Report (*Eidenberger* et al. 2013). In this paper, we go beyond the best subset selection mechanism and apply Bayesian model averaging.

Austria. (i) High share returns may be accompanied by high risks, making stress in the financial system more likely. (ii) Large cross-border lending in general increases the vulnerability of the domestic financial system to external shocks. In the case of Austria, banks granted large amounts of loans to borrowers in CESEE countries and were therefore heavily exposed to shocks there. (iii) Inflation may be important since it may affect the real interest rate and banks' real margin. Moreover, an increase in inflation makes also credit market frictions more likely and may impede financial sector activity. Other relevant indicators are the (iv) total credit-to-GDP gap, a prominent indicator for excessive credit growth, as well as the (v) corporate debt-to-profit ratio reflecting the risk bearing capacity of companies. Overall, our findings suggest that indicators on credit development are particularly relevant for predicting financial stress.

We differ in two major respects from the literature. First, as mentioned above, we apply a Bayesian model averaging approach. We search for the models with the highest posterior model probability. Based on the 1,000 most probable models, we present the predictors with the highest model inclusion probability. In doing so, we address the variance versus omitted variable bias tradeoff and we are able to reduce the model uncertainty in a consistent way at the same time. Including (too) many explanatory variables improves the in-sample fit (reduces the residual variance). However, each additional variable may increase the variance of the coefficients and may thereby lead to weak prediction accuracy (especially in the case of high multicollinearity).

Second, in contrast to most of the relevant literature, we do not use a binary variable to classify a crisis, but use a continuous financial stress index capturing the severeness of a stress event. When using a binary variable, the question arises as to where to put the threshold, i.e. which stress events are classified as a crisis and which are not. Stress events just below the threshold are assigned to the same group as calm periods, making the selection of early warning indicators noisier. In addition, there are substantial differences between crisis databases with respect to crisis classification. For instance, the ESCB Heads of Research database contains 26 systemic banking crises up to 2007 (see *Detken* et al. 2014), of which 12 are not classified as a crisis in the *Laeven/Valencia* (2008) dataset. Five events are classified as a crisis, but with a different starting date. Crisis classification issues may have an impact on which indicators have predictive power. We instead use an index, thereby mitigating crisis classification problems.

Our paper is structured as follows. In section II, we describe the construction of our stress indicator which is used as the dependent variable. In Section III, potential early warning indicators (explanatory variables) are discussed and the related literature is reviewed. In Section IV, we explain our estimation methods and present our results. Finally, Section V concludes.

II. Measuring Financial (In)stability with Financial Stress Indices

In this section, we briefly explain the objectives of financial stress indices and review related papers. We then describe the construction of the Austrian Financial Stress Index (AFSI).

1. Financial Stress Indices

The main objective of financial stress indices is to quantify the current state of instability in the financial system, i.e. to summarize the level of stress stemming from different sources into one single (usually continuous) statistic (*Hollo/Kremer/Lo Duca* 2012). Financial stress indices make different stress events comparable. They help macroprudential supervisors to monitor and assess the stress level in the financial system and facilitate decision-making on putting on or off macroprudential instruments.

Developing financial stress indices is a relatively new topic. The seminal paper is *Illing/Liu* (2003), who construct a daily stress index for Canada. Due to the recent financial crisis, monitoring the stress level in the financial system has become much more important over the last years. For this reason, a number of papers has emerged on financial stress indices since 2007 (see, for instance, *Nelson/Perli* (2007) for the US, *Hollo/Kremer/Lo Duca* (2012) and *Islami/Kurz-Kim* (2013) for the euro area and *Jahn/Kick* (2012) for Germany).

Financial stress indices are composite indices covering different segments of the financial system. While financial stress indices differ substantially in the number of segments and variables included, most papers have in common that they use information on equity and bond markets, money market and foreign exchange rates (see, for instance, *Hollo/Kremer/Lo Duca* 2012; *Lo Duca/Peltonen* 2011; *Jakubik/Slacik* 2013). Several papers also include information on financial intermediaries, mostly variables derived from a stock market banking sector index (see, for example, *Illing/Liu* 2003; *Cardarelli/Elekdag/Lall* 2011). Some papers use factor models to derive a composite indicator (see, for instance, *Matheson* 2012; *Hatzius* et al. 2010). Both papers use a wide range of variables. In addition to above mentioned variables, *Hatzius* et al. (2010) also include survey-based indicators and leverage data (e.g. on the volume of bank credit, commercial paper issuance and ABS).

Financial stress indices differ with respect to their frequency (for instance, weekly (e.g. *Nelson/Perli* 2007), monthly (*Cardarelli/Elekdag/Lall* 2011) or quarterly (e.g. *Lo Duca/Peltonen* 2011). To attain a high frequency, almost all indicators are based only on market information. Market-based indicators are suitable for real-time monitoring, as these are published without delay on a daily basis (unlike macroeconomic or supervisory data with their lower frequency and sometimes significant time lags). Obviously, market data have their drawbacks, as they reflect not only the current market situation but market sentiment as well.

Moreover, indices differ in the aggregation method of the components which have to be standardized before aggregation. Most of the indices are constructed by using a cumulative distribution function (see, for example, *Jakubik/Slacik* 2013), where each observation is transformed according to an ordinal scale. The alternative approach is to normalize variables by variance-equal-weighting where a cardinal scale is used (see, for instance, *Cardarelli/Elekdag/Lall* 2011).

Finally, financial stress indices also differ with respect to correlation between factors being considered or not. While most papers use only levels or growth rates of variables, some papers also take the correlation between the different variables into account (see, for example, *Hollo/Kremer/Lo Duca* 2012).

2. The Austrian Financial Stress Index (AFSI)

Our objective is to construct a contemporary measure of financial soundness for the Austrian financial system. Similarly to the literature, we design the AFSI as a composite index capturing risks for the Austrian financial system in three main segments: (1) the equity market, (2) the money market, and (3) the sovereign bond market. Equal weights are assigned to all three segments. Information on financial intermediaries is considered by a stock market index. A higher AFSI signals periods of imbalances in the financial system, peaking during times of acute financial distress.

Our goal is to design the AFSI to be as simple and narrow as possible. We therefore do not include variables with little or no additional explanatory power for financial distress developments. We examined various variables with regard to their suitability as AFSI constituents to comply with our criterion to best reflect (past) periods of financial distress. In particular, motivated by *Lo Duca/Peltonen* (2011) and *Hollo/Kremer/Lo Duca* (2012), we calculated the effective exchange rate volatility for Austrian firms vis-à-vis their nine most important trading partners (excluding the euro). This measure, however, shows high fluctuations over time without giving clear indications for tense periods. We therefore decided not to consider foreign exchange rate developments.

Our final AFSI consists of the following components. For the equity market, we consider three variables: (i) the yoy return of the ATX[2] index, ii) the realized

[2] The ATX is the leading Austrian equity index; it tracks the price of Austrian blue chips traded at the Vienna stock exchange.

volatility of ATX yoy returns over a horizon of one quarter, and iii), the yoy return of the Datastream Austrian Financials index[3]). Higher equity returns indicate a lower level of tension in the equity market. Hence, the two (normalized) return variables are multiplied by minus 1, so that higher returns decrease the AFSI level. Equity volatilities, however, tend to increase with investors' uncertainty and therefore tend to be higher in stress periods. ATX volatility is therefore positively considered in the AFSI and a higher volatility drives up the measure of distress. All three subindices are weighted equally and jointly make up the equity market segment.

To account for money market distress (2), we include the three-month EURIBOR-OIS spread in the ASFI. The EURIBOR-OIS spread typically increases substantially during periods of stress and is therefore positively related to the AFSI. Finally, as the sovereign bond market represents one key aspect of the overall financial market, we include the spread of Austrian government bond yields over German government bond yields as a measure of market distress associated with the sovereign sector (3).[4] The variable is positively related to the AFSI.

Table 1 gives an overview of the five components included in the AFSI: the ATX yoy return, the Datastream Austrian Financials yoy return, the realized volatility of the ATX[5], the spread of the three-month EURIBOR over OIS and the spread of Austrian ten-year government benchmark bond yields over German ten-year government bond yields.

As mentioned earlier, the literature does not agree on one single method of how to aggregate the variables to a composite index (see *Illing*/*Liu* (2003) for a discussion of the shortcomings of different approaches). One frequently applied option is to use an ordinal scale derived from a cumulative distribution function (CDF). The transformed variable values are unit-free and are in a range between 0 and 1, making interpretation easier. However, the CDF approach implicitly assumes equal distance between any two successively ranked observations. This assumption distorts any subsequent econometric analysis as

[3] The ATX covers a large share of industrial and energy industry corporates. To allow higher weights for financial sector developments, however, we include Datastream Austrian Financials return as a third equity subindex. This time series also covers Austrian financial sector data but is available for a longer time horizon than the ATX Financials series, which has only been available since 2010.

[4] We also examined whether we should include the volatility of the EURIBOR-OIS spread and the volatility of the Austrian government bond spread. However, the AFSI including these two volatility measures shows very high correlation with the AFSI without these measures. Therefore, we do not take account of these volatility subindices.

[5] Together, the first three stock market related components make up one-third of the total AFSI, with each adding one-ninth to its total score.

Table 1

AFSI Components

Segment	*Components*	*Relation*	*Weight*
(1) Equity Market	ATX yoy return	–	1/3
	Datastream Austrian Financials yoy return	–	
	Realized ATX volatility	+	
(2) Money Market	3-month EURIBOR-OIS spread	+	1/3
(3) Sovereign Bond Market	Spread of Austrian 10-year government bond yields over German 10-year government bond yields	+	1/3

the distances of observations of the dependent variable are a major driver of estimation results.[6] This issue is in particular relevant for a stress index, where the difference between peaks and average observations signals the level of tension during a crisis. Furthermore, after a financial crisis, stress may be underestimated since the index components are ranked according to their own data history.

Considering these disadvantages, we choose an alternative approach. In line with *Cardarelli/Elekdag/Lall* (2011) and *Islami/Kurz-Kim* (2013), we use variance-equal weighting to standardize the subindices in the AFSI, i.e. we subtract the arithmetic mean from each variable and divide then the value by its standard deviation.[7] This approach maps the AFSI to an interval scale. Unlike in the case of a CDF transformation, the distance between two observations now carries information.

Figure 1 shows the AFSI development in comparison to the development of the CISS indicator (1999Q1–2015Q3). The CISS index is a prominent measure for financial soundness in the euro area (see *Hollo/Kremer/Lo Duca* 2012). The CISS comprises 15 individual indicators in five market categories: money market[8],

[6] The problem becomes less important with the length of the time series and the range of values covered. However, when dealing with relatively short time periods, this issue is serious and may yield misleading results.

[7] The disadvantage of this approach is that it requires the assumption of normally distributed subindices.

[8] Realized volatility of the 3-month EURIBOR rate, interest rate spread between 3-month EURIBOR and 3-month French T-bills, Monetary Financial Institutions' (MFI) emergency lending at Eurosystem central banks.

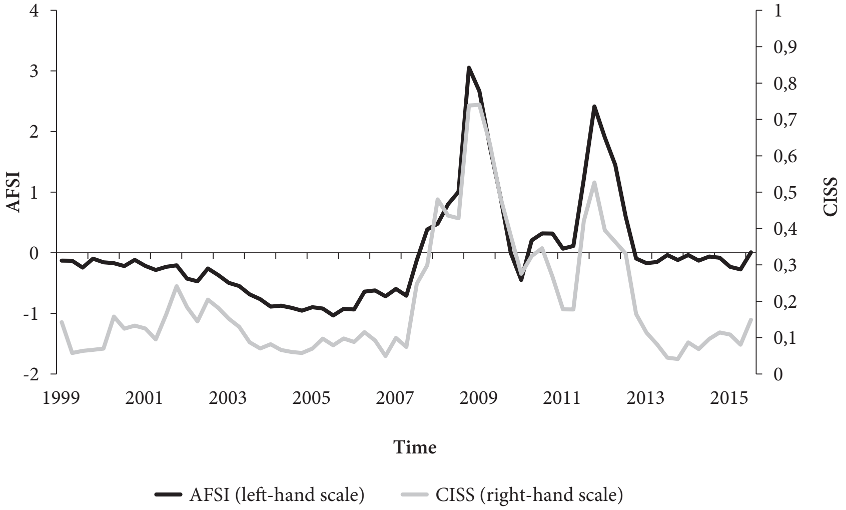

Figure 1: Austrian Financial Stress Index (AFSI) and Composite Indicator of Systemic Stress (CISS)

bond market[9], equity market[10], financial intermediaries[11], and foreign exchange market[12]. We use the CISS index for robustness checks in Section IV. While the AFSI and the CISS differ in their construction and scaling and are therefore comparable only to a limited extent, developments of financial stress are found to be very similar in Austria and the euro area. AFSI and CISS are both measured quarterly for the purpose of this paper.

For nearly all quarters of the first half of our sample period (1999Q1–2007Q2) both indices are at low levels – indicating no or moderate financial stress. Financial stress starts to build up in the third quarter of 2007. Both indices peak in the fourth quarter of 2008 reflecting market turmoil following the bankruptcy of Lehman Brothers in September 2008. After a short recovery, AFSI and CISS increase again indicating the European sovereign debt crisis. Both indices peak

[9] Realized volatility of the German 10-year benchmark government bond index, yield spread between A-rated non-financial corporations and government bonds, 10-year interest rate swap spread.

[10] Realized volatility of the Datastram non-financial sector stock market index, CMAX for the Datastream non-financial sector stock market index, stock-bond correlation.

[11] Realized volatility of the idiosyncratic equity return of the Datastream bank sector stock market index, yield spread between A-rated financials and non-financials, CMAX interacted with the book-price ratio for the financial sector equity market index.

[12] Realized volatility of the euro exchange rate vis-à-vis the US dollar, the Japanese Yen and the British Pound.

again in the fourth quarter of 2011. Since then a recovery phase has started. Surprisingly, the CISS stress level is considerably lower over the sovereign debt crisis than in late 2008. In addition, the CISS stress level over the sovereign debt crisis is also substantially lower than that of the AFSI over that period. We interpret this as an artifact of the aggregation method of the CISS. Aggregation of the CISS is based on a CDF approach while for the AFSI variance-equal weighting is used (see above).

III. Predicting Financial (In)stability

As follows, we discuss methodologies in early warning models (Subsection 1). Besides that we give a literature overview of early warning indicators and outline what impact indicators are expected to exert on financial stability (Subsection 2). For the purpose of this study, we group potential early warning indicators into five risk channels. Finally, the data base is described (Subsection 3).

1. Methodologies in Early Warning Models

The empirical literature on early warning indicators follows three approaches: (1) the signal extraction approach, (2) discrete choice models and (3) the index-based approach. The approaches mainly differ in two respects: First, whether financial stress is measured by a binary variable or a continuous indicator. Second, whether the approaches are univariate or multivariate.

The signal extraction approach (1) was made popular by *Kaminsky*/*Reinhart* (1999). They analyze twin crises – the links between currency and banking crises. The authors use a dummy variable to classify a banking crisis. A banking crisis is defined by the emergence of bank runs, the closure, merging or takeover of important financial institutions or large-scale government interventions. Similar criteria are applied in other papers using the signal extraction approach (see, for example, *Borio*/*Drehmann* 2009; *Alessi*/*Detken* 2009) or in discrete choice models. The signal extraction approach evaluates indicators based on their noise-to-signal-ratio.[13] A shortcoming of the signal extraction approach is that only the univariate forecasting power is considered.

Most of the literature on early warning indicators applies the second approach, discrete choice models, which are multivariate models. For instance, *Demirgüç-Kunt*/*Detragiache* (1998) estimate the probability of a banking crisis for 65 countries using a static logit model. While the earlier literature focused on de-

[13] The noise-to-signal-ratio combines information on type 1 and type 2 errors. It is defined as the fraction of false alarms (over all non-crisis episodes) relative to the fraction of correctly predicted crises (over all crisis episodes).

veloping countries, later papers, such as *Barrell* et al. (2010) investigate banking crises in industrial countries. *Lund/Jensen* (2012) design a dynamic model that monitors systemic risk on the basis of real-time data.

In contrast to the signal extraction and discrete choice models, the index-based approach (3) defines a crisis not by a binary variable but by using a composite index. This index is then explained by (potential) early warning indicators. *Lo Duca/Peltonen* (2011) evaluate the joint role of domestic and global indicators in a panel framework for 28 emerging market economies and advanced economies. *Jakubík/Slacík* (2013) choose a similar approach for nine CESEE countries.

2. *Expected Impact of Early Warning Indicators*

There is a broad range of risks to financial stability. We assign possible risks and correspondent indicators to five risk channels: (1) risk-bearing capacity of financial institutions, companies and households, (2) mispricing of risk (measured by asset prices), (3) excessive growth of on- and off-balance sheet positions, (4) macroeconomic development and (5) interconnectedness of banks. Our list of indicators is summarized in Table 2.

The literature so far has considered variables on the risk channels (1) to (4). Strictly speaking, there are two strands in the literature (see *Karim* et al. 2013): the first class of models, studying primarily banking crises in developing countries, concentrates on macroeconomic developments and excessive credit growth (risk factors (3) and (4)). The second class of models, examining banking crises in industrial countries, appends new variables to the traditional set of variables. These new variables refer to banks' risk-bearing capacity and asset price development (risk factors (1) and (2)). For our analysis, we supplement the variables of these two literature strands with information on interconnectedness.

The first group of variables is the risk-bearing capacity (1). A higher risk-bearing capacity of financial institutions, corporates and households increases their individual ability to withstand stress and mitigates the propagation of shocks in the financial system. Due to the lack of data, there are only a few papers that consider information in this respect. *Barrell* et al. (2010) and *Karim* et al. (2013) show that low bank capitalization and low bank liquidity positions have a strong predictive power for crises. Both papers use data for OECD countries. The impact of profitability is, however, less clear: According to *Drehmann* et al. (2011), profits typically peak two years ahead of a crisis and then start to decline, i.e. the sign of profitability turns. This is in accordance with the idea that high profits are positively correlated with high risks which increase probability of crises in the long run (also consistent with *Behn* et al. 2013). However, in a medium to short term perspective, a higher profitability improves banks' capitalization and helps banks to withstand crises.

We use information on average banks' rating (as an aggregate measure for banks risk-bearing capacity), their funding (loan-to-deposit ratio) and different variables on their profitability (return on equity, interest margin) as well as on their capitalization (Tier 1 capital ratio)[14]. Furthermore, we also capture the risk-bearing capacity of households and companies. We use the ratio of corporate debt to profit and the ratio of household debt to disposable income (both year-on-year growth rates).

The second group of indicators is mispricing of risk variables (2), captured by different asset price variables. Collective mispricing of risk (signaled by high returns and low spreads) may lead to a buildup of significant systemic imbalances and asset price bubbles. The (often) quick unraveling of mispricings through large movements in asset prices may result in major distortions in the financial system.

There is strong evidence of house price growth having high predictive power for banking crises in advanced economies (see, for example, *Barrell* et al. 2010; *Roy*/*Kemme* 2011; *Detken* et al. 2014). There is also some, albeit less convincing evidence that equity market prices may serve as predictors: Equity price growth is positively significant in *Lo Duca*/*Peltonen* (2013) and *Detken* et al. (2014), while it is not significant in *Behn* et al. (2013). Moreover, *Bush* et al. (2013) show that low volatility on equity markets is a crisis predictor.

We proxy equity price growth by using two indicators: the return of the EURO STOXX Banks index and the return of the MSCI Eastern Europe index. The EURO STOXX Banks subindex is probably superior to a general index since it can be supposed to better reflect mispricings with respect to banks than a general index. We use the European banks index since a measure for share price development of Austrian financials is already included in the AFSI. Moreover, we also consider the price development on the Eastern European stock market as Austria is closely connected with this region. We use volatility on the stock market by using the VIX index.[15] In addition, we take account of the pricing on the corporate bond market by including the spread between European AAA corporate bond yields and high-yield bonds. We do not consider house price developments since data series for possible measures are too short.[16]

[14] Although ratios on capitalization are more meaningful on a consolidated level, here unconsolidated ratios are used as consolidated balance sheet data is not available before 2004.

[15] The VIX index reflects volatility of the US S&P 500 index. Data series for the VIX is longer than that for the VSTOXX, a measure for volatility on the European stock market. Both measures are highly correlated.

[16] Based on a shorter sample we examined the performance of house price measures for Austria. However, the indicators do not turn out to be relevant for Austria.

Mispricing of risks is typically accompanied by high, unsustainable growth rates of the correspondent assets. Excessive growth of on- and off-balance sheet assets (in particular of credit) (3) may therefore also serve as a predictor for financial crises. Excessive credit growth is normally measured either by simple credit growth rates or in relation to GDP as credit-to-GDP gap (i. e. gap between the ratio of credit to GDP and its long term trend). Both variables display a good forecasting performance (see, for instance, *Demirgüc-Kunt/Detriagache* 1998; *Jorda* et al. 2011), although there is evidence that the credit-to-GDP-gap is superior (see *Drehmann* et al. 2011; *Detken* et al. 2014). According to *Drehmann* (2013) it is important to note that excessive growth should not only be analyzed in standard loans but in all kinds of on- and off-balance debt. Moreover, *Behn* et al. (2013) show that global credit development outperforms domestic credit variables. This result, however, may be driven by the current global financial crisis which dominates crises episodes in their sample. *Karim* et al. (2013) find evidence that, in addition to excessive credit growth, banks' off-balance sheet activity is a good crisis predictor in advanced economies.

We use several variables to measure excessive credit growth. We apply narrow measures (e. g. customer loans growth) as well as broad ones (e. g. total credit growth, credit-to-GDP gap). We also consider cross-border lending. Moreover, we include total asset growth and growth of off-balance sheet assets.

Macroeconomic developments (4) also constitute a substantial source of systemic risk. In our case, Austria is affected not only by domestic developments, but as a small open economy it is also prone to external macroeconomic shocks. In the literature, the most important predictor among macroeconomic variables is information on external imbalances, such as the current account balance, where a high deficit signals a crisis (see, for instance, *Detken* et al. 2014; *Kauko* 2014). For advanced economies, other macroeconomic variables reflecting domestic developments are often not relevant, particularly when information on the risk-bearing capacity and mispricing of risk is included (see *Barrell* et al. 2010; *Karim* et al. 2013). For example, interest rates turn out to be a good predictor in a number of papers (see, for example, *Jorda* et al. 2011; *Roy/Kemme* 2011; *Bordo/Meissner* 2012). However, interest rates are not significant in *Karim* et al. (2013) and *Barrell* et al. (2010) who control for bank capital and liquidity positions as well as for house price growth.

Motivated by the literature, we include Austrian GDP, inflation, interest rates (for household and corporate loans), current account-to-GDP ratio and exchange rate volatility. To include more forward-looking information, we use a sentiment indicator for the Austrian business climate.[17] We also consider banks' total assets-to-GDP-ratio (as a measure for financial development and over-

[17] The sentiment indicator is the so-called total industry COF indicator from Eurostat.

banking) as well as competition in the banking sector[18] (by estimating Lerner indices)[19]. Moreover, to proxy for macroeconomic developments outside Austria, we take into account GDP growth in the EU-28 and in CESEE countries.

Finally, we also consider information on the interconnectedness (5) of the financial system. Interconnectedness captures the contagion risk arising from actual or perceived interlinkages in the financial system. Via these interlinkages, a (small) shock in one part of the system may be transmitted into other parts of the system – without direct exposure to the initial shock – eventually threatening wider financial stability. The most prominent example in the literature are default cascades in banking systems resulting from connections in the interbank market. We use the share of interbank assets as a simple proxy for linkages via the interbank market. The sign of the variable is, however, unclear: On the one hand, in line with the reasoning we have just presented, we expect interbank assets to increase financial stress. On the other hand, interbank assets may also be an indicator of sentiment at the interbank market. A high level of interbank assets may then reflect a well-functioning interbank market and a low stress level.

3. *Data*

Our data set of early warning indicators consists of regulatory reporting data, market data (provided by Datastream and Bloomberg) and macroeconomic data (see Table 2). Given our objective of identifying indicators with an early warning capability, we use lagged variables in our estimations. We opt for a minimum lag of at least four quarters, as this takes data publications lag into account and would still grant time for macroprudential authorities to set corrective policy decisions. We lag market variables by four and eight quarters, all remaining variables by four quarters (for data availability reasons).

Our data set runs from the first quarter of 1999 to the second quarter of 2015, yielding $T = 66$ time periods. The sample consists of 29 indicators. All indicators are tested for stationarity. For non-stationary variables we calculate their growth rates. All explanatory variables are demeaned and divided by their standard deviations to make results comparable.

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[18] The impact of competition on financial stability is not clear. On the one hand, competition may decrease margins of banks and lead to higher bank risk-taking (see e.g. *Allen/Gale* 2004). On the other hand, higher competition reduces interest rate costs of borrowers. Borrowers may therefore choose safer projects which ultimately generates safer banks (see *Boyd/De Nicolo* 2005).

[19] We use 3-stage-least-squares to estimate the Lerner Index as suggested in *Angelini/Cetorelli* (2003). Based on a Cournot oligopoly, the first order conditions of a revenue and cost equation are estimated simultaneously (see *Gunter* et al. (2013) for more details).

IV. Estimation and Results

1. Estimation Method

In this section we outline the economic theory and estimation procedure behind the multivariate models used to explain the AFSI. As a starting point for modeling the AFSI, we look at a set of predictors K in a linear regression model.

$$y_t = \beta_0 + \sum_{j \in K} x_{j,t} \beta_j + \in_t$$

where y is the AFSI, K is the number of observable explanatory variables and $t \in \{1, 2,.., T\}$ constitutes the time index; x_j is the j-th transformed predictor.

As noted above, the theoretical and empirical literature on how to select the most important predictors $K^* \in K$ is inconclusive. In previous work on this topic, predictors have been selected by mere qualitative reasoning. To deal with the variance versus omitted variable bias tradeoff in a non-heuristic way, we partly depart from these approaches and consider a fully probabilistic approach, namely the Bayesian model averaging approach (BMA).[20] We search the most important predictors by applying the methods developed in *Feldkircher/Zeugner* (2009). They implemented a BMA procedure that builds on the work of *Zellner* (1986). The literature standard is to use a Bayesian linear regression model with a specific prior structure called Zellner's g prior. Zellner's g prior is a hyper parameter that defines the variance of β.

$$\beta \mid g \sim N\left(0, \sigma^2 \left(\frac{1}{g} X'X\right)^{-1}\right)$$

The prior mean of β is set to zero and the variance-covariance structure of β is set such that it is broadly in line with that of the data X. Under these assumptions the hyperparameter g embodies how certain we are that coefficients are zero: A small g implies small prior coefficient variances for the predictors in β and therefore implies the researcher is quite certain (or conservative) that the coefficients are indeed zero. In contrast, a large g would mean that there is high uncertainty that coefficients are zero.

We set Zellner's g to the benchmark prior suggested by *Fernandez* et al. (2001): $g = \max(T, K^2)$, where K is the total number of covariates. With this option the

[20] Major contributions to the BMA framework can be found in *Raftery* (1995) and *Hoeting* et al. (1999).

Table 2

List of Variables Used for AFSI Prediction

Indicators	*Description*	Source
(1) Risk-bearing capacity		
Bank ratings	average stand-alone rating of 6 Austrian banks (ratings from Moody's; high value corresponds to low rating)	Bloomberg
Net interest margin	net interest income divided by total assets (all Austrian banks)	Supervisory Data
ROE (banks)	average return on equity before tax (all Austrian banks)	Supervisory Data
Loan-to-deposit ratio	average loan-to-deposit ratio (all Austrian banks)	Supervisory Data
Tier 1 ratio	tier 1 capital ratio (all Austrian banks)	Supervisory Data
Corporate debt-to-profit ratio	ratio of Austrian corporate debt to corporate profit, yoy growth	BIS, OeNB
Household debt-to-income ratio	ratio of Austrian household debt to household disposable income, yoy growth	BIS, OECD, OeNB
(2) Mispricing of risk		
EURO STOXX Banks return	yoy return of EURO STOXX Banks index	Datastream
MSCI Eastern Europe return	yoy return of MSCI Eastern Europe	Bloomberg
VIX	volatility index of S&P 500	Datastream
High yield bond spread	spread between European AAA corporate bonds and high yield corporate bonds	Datastream

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(Table 2: Continued)

Indicators	*Description*	Source
(3) Excessive growth & credit development		
Customer loans growth	yoy growth rate of customer loans (all Austrian banks)	Supervisory Data
Total credit growth	yoy growth rate of Austrian total credit (including all sources of credit)	BIS
Total credit-to-GDP gap	difference between total credit-to-GDP ratio and its long term trend (two sided HP filtered credit-to-GDP gap with lamba equal to 400,000)	own calculation (BIS, OeNB)
Cross-border loans	cross-border loans (of banks/institutions in Austria) to total assets	BIS
Total assets growth	yoy growth rate of total assets (all Austrian banks)	Supervisory Data
Off-balance sheet growth	yoy growth rate of off-balance sheet exposures (all Austrian banks)	Supervisory Data
(4) Macroeconomic environment		
GDP Austria	yoy growth rate of Austrian real GDP	Eurostat
Inflation	yoy growth rate of Austrian HICP (harmonised index of consumer prices, overall index)	ECB
Interest rate households	interest rate on mortgage loans minus EURIBOR	ECB
Interest rate corporates	interest rate on corporate loans (< 1 million EUR) minus EURIBOR	ECB
Current account-to-GDP ratio	Austrian current account net balance divided by GDP	OeNB

Indicators	*Description*	Source
Exchange rate volatility	standard deviation of daily nominal effective exchange rate (vis-a-vis 25 most important trading partners)	BIS
Business climate	total industry COF (confidence) indicator for Austria (includes order book and production expectations)	Eurostat
Total assets-to-GDP ratio	Austrian banks' total assets divided by GDP	ECB
Banking sector competition	Lerner Index based on a Cournot oligopoly	own calculation (OeNB)
GDP EU-28	yoy growth rate of EU-28 real GDP	OeNB
GDP CESEE	yoy growth rate of real GDP in CESEE countries (Poland, Czech Republic, Slovakia, Hungary and Romania)	ECB
(5) Interconnectedness		
Interbank assets	share of interbank assets on total assets (all Austrian banks)	Supervisory Data

Averages are weighted by total assets. Supervisory Data are unconsolidated.

posterior model probabilities asymptotically either behave like the Bayesian information criterion (with g = T) or the risk inflation criterion (g = K^2) by *Foster/George* (1994).

Concerning model size we start with models with a prior expected model size of 6 variables and then alter this assumption.

2. Estimation Results

In this section we present the results of our estimation approach. Table 3 shows the results of our baseline specification (prior expected model size of 6 variables). A specified prior expected model size $\bar{k}$ follows *Sala-i-Martin* et al. (2004). This means that each variable has a prior probability $\bar{k}$/K of being included, independent of the inclusion of any other variable. In Table 4, we examine several alternative model size priors: i) $\bar{k}$ = 10 (i.e. expected model size of 10 variables) ii) $\bar{k}$ = 15 iii) a uniform model size prior, i.e. all models are equally probable (K/2 is therefore the most likely model size) and iv) a random model size prior which assumes all possible model sizes are a-priori equally likely (see *Ley/Steel* (2008) for details).

Results across estimations are summarized in the following way: the posterior inclusion probability (PIP) gives the probability that a variable is selected in the 1,000 best models (e.g. 0.99 means that a variable is selected in 990 out of 1,000 models). The conditional posterior mean (Cond. Post Mean) is the average coefficient of variable i conditional on variable i included in the model.[21]

$$\bar{x}_i = \sum_{m=1}^{1000} x_{i,m}\, 1_{\{i \in M_m\}}\, w_m$$

w_m represents the posterior model probability of model m which is proportional to the marginal likelihood of model m.

The conditional posterior standard deviation (Cond. Post SD) is the respective standard deviation of the coefficient of a variable in the considered models. The column conditional positive sign (Cond. Positive Sign) gives the share of positive coefficients of a variable in the considered 1,000 best models. Values close to 1 or 0 indicate a consistent sign across our regressions.

Our results in Tables 3 and 4 indicate that there are three important early warning indicators for Austria: (i) high returns of banks' share prices, (ii) large cross-border lending and (iii) inflation. First, EURO STOXX Banks return (with

21 See *Sala-i-Martin* (1997) for more details.

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Table 3

AFSI Estimation Results (Prior Expected Model Size of 6 Variables)

Variable	*Risk Channel*	*PIP*	*Cond. Post Mean*	*Cond. Post SD*	*Cond. Positive Sign*
EURO STOXX Banks return, lag 8	(2) Mispricing of risk	0.92	0.39	0.18	1.00
Inflation	(4) Macroeconomic environment	0.80	0.22	0.06	1.00
Cross-border loans	(3) Excessive growth	0.63	0.57	0.59	1.00
Corporate debt-to-profit ratio	(1) Risk-bearing capacity	0.55	0.20	0.08	1.00
Total credit-to-GDP gap	(3) Excessive growth	0.39	0.20	0.10	1.00
Loan-to-deposit ratio	(1) Risk-bearing capacity	0.39	0.27	0.20	1.00
Bank ratings	(1) Risk-bearing capacity	0.26	0.12	0.06	0.99
Total assets growth	(3) Excessive growth	0.23	–0.08	0.04	0.00
Net interest margin	(1) Risk-bearing capacity	0.22	0.23	0.25	0.99
Interbank assets	(5) Interconnectedness	0.21	0.07	0.03	1.00
GDP EU-28	(4) Macroeconomic environment	0.21	0.10	0.07	1.00
Interest rate households	(4) Macroeconomic environment	0.17	0.11	0.08	0.97
GDP CESEE	(4) Macroeconomic environment	0.11	–0.04	0.02	0.02
Tier 1 ratio	(1) Risk-bearing capacity	0.08	0.02	0.01	1.00

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(Table 3: Continued)

Variable	*Risk Channel*	*PIP*	*Cond. Post Mean*	*Cond. Post SD*	*Cond. Positive Sign*
MSCI Eastern Europe return	(2) Mispricing of risk	0.08	–0.03	0.01	0.04
ROE (banks)	(1) Risk-bearing capacity	0.08	–0.02	0.01	0.01
MSCI Eastern Europe return, lag 8	(2) Mispricing of risk	0.08	–0.01	0.00	0.01
EURO STOXX Banks return	(2) Mispricing of risk	0.07	–0.02	0.01	0.02
Total credit growth	(3) Excessive growth	0.06	0.01	0.01	0.89
VIX	(2) Mispricing of risk	0.05	0.01	0.00	1.00
GDP Austria	(4) Macroeconomic environment	0.05	0.01	0.00	0.96
Business climate	(4) Macroeconomic environment	0.04	0.01	0.00	0.92
VIX, lag 8	(2) Mispricing of risk	0.03	0.00	0.00	0.99
Household debt-to-income ratio	(1) Risk-bearing capacity	0.02	0.00	0.00	0.08
Current account-to-GDP ratio	(4) Macroeconomic environment	0.02	0.00	0.00	0.28
Total assets-to-GDP ratio	(4) Macroeconomic environment	0.02	0.00	0.00	0.33
Banking sector competition	(4) Macroeconomic environment	0.02	0.00	0.00	0.02
Customer loans growth	(3) Excessive growth	0.02	0.00	0.00	0.37
Interest rate corporates	(4) Macroeconomic environment	0.02	0.00	0.00	0.62

Variable	*Risk Channel*	*PIP*	*Cond. Post Mean*	*Cond. Post SD*	*Cond. Positive Sign*
High yield bond spread	(2) Mispricing of risk	0.01	0.00	0.00	0.71
Exchange rate volatility	(4) Macroeconomic environment	0.01	0.00	0.00	0.96
Off-balance sheet growth	(3) Excessive growth	0.01	0.00	0.00	0.60

The table includes summary statistics over the 1,000 best models. The estimations are carried out using the benchmark prior suggested by *Fernandez* et al. (2001) (g = BRIC). Prior expected model size is equal to 6 variables. The table shows the posterior inclusion probability (PIP), i.e. the probability that the variable is selected. It also contains the conditional posterior mean (Cond. Post Mean) and the conditional posterior standard deviation (Cond. Post SD), i.e. the average coefficient and the average standard deviation of the coefficient of a variable conditional on inclusion in the model. The column cond. positive sign gives the share of positive coefficients of a variable in the considered 1,000 best models. Values close to 1 or 0 indicate a consistent sign across our regressions. All variables are lagged by 4 quarters unless otherwise stated.

Table 4

AFSI Estimation Results (with Alternative Model Size Priors)

	BRIC Uniform		*BRIC Random*		*BRIC Fixed 10*		*BRIC Fixed 15*	
	PIP	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*
EURO STOXX Banks return, lag 8	0.97	0.37	0.91	0.39	0.94	0.37	0.97	0.37
Cross-border loans	0.94	0.92	0.66	0.56	0.83	0.78	0.94	0.90
Inflation	0.92	0.28	0.79	0.22	0.88	0.26	0.92	0.28

(Continue next page)

(Table 4: Continued)

	BRIC Uniform		*BRIC Random*		*BRIC Fixed 10*		*BRIC Fixed 15*	
	PIP	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*
Total credit-to-GDP gap	0.68	0.37	0.43	0.20	0.58	0.29	0.69	0.36
Corporate debt-to-profit ratio	0.38	0.10	0.51	0.20	0.42	0.14	0.36	0.11
Loan-to-deposit ratio	0.29	0.11	0.38	0.29	0.25	0.13	0.26	0.10
Bank ratings	0.35	0.16	0.27	0.12	0.33	0.15	0.35	0.16
Interest rate households	0.48	0.29	0.20	0.12	0.32	0.19	0.46	0.28
GDP EU-28	0.44	0.18	0.23	0.10	0.31	0.13	0.42	0.18
Total assets growth	0.31	–0.12	0.21	–0.08	0.28	–0.11	0.30	–0.12
Interbank assets	0.31	0.11	0.19	0.07	0.25	0.09	0.29	0.11
Net interest margin	0.27	0.26	0.24	0.22	0.29	0.30	0.28	0.27
VIX	0.22	0.03	0.06	0.01	0.11	0.02	0.20	0.03
MSCI Eastern Europe return	0.22	–0.06	0.09	–0.03	0.16	–0.05	0.22	–0.06
Total assets-to-GDP ratio	0.19	–0.12	0.03	–0.01	0.06	–0.02	0.16	–0.09
ROE (banks)	0.18	–0.04	0.09	–0.02	0.13	–0.03	0.18	–0.04

	BRIC Uniform		*BRIC Random*		*BRIC Fixed 10*		*BRIC Fixed 15*	
	PIP	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*
GDP CESEE	0.17	–0.04	0.12	–0.04	0.11	–0.03	0.16	–0.03
Tier 1 ratio	0.15	0.02	0.09	0.02	0.11	0.02	0.15	0.02
Business climate	0.14	0.03	0.05	0.01	0.08	0.01	0.13	0.02
EURO STOXX Banks return	0.12	–0.01	0.08	–0.02	0.07	–0.01	0.11	–0.01
Household debt-to-income ratio	0.09	0.00	0.03	0.00	0.05	0.00	0.09	0.00
GDP Austria	0.09	0.01	0.05	0.01	0.06	0.01	0.08	0.01
MSCI Eastern Europe return, lag 8	0.09	0.00	0.07	–0.01	0.07	–0.01	0.08	0.00
Banking sector competition	0.08	0.00	0.02	0.00	0.04	0.00	0.07	0.00
Customer loans growth	0.08	0.00	0.02	0.00	0.03	0.00	0.07	0.00
Total credit growth	0.07	0.00	0.05	0.01	0.06	0.01	0.07	0.00
VIX, lag 8	0.07	0.00	0.03	0.00	0.04	0.00	0.06	0.00
Interest rate corporates	0.07	–0.01	0.02	0.00	0.03	0.00	0.06	–0.01
Current account-to-GDP ratio	0.05	0.00	0.02	0.00	0.03	0.00	0.05	0.00

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(Table 4: Continued)

	BRIC Uniform		*BRIC Random*		*BRIC Fixed 10*		*BRIC Fixed 15*	
	PIP	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*
Off-balance sheet growth	0.05	0.00	0.01	0.00	0.02	0.00	0.04	0.00
High yield bond spread	0.04	0.00	0.02	0.00	0.02	0.00	0.04	0.00
Exchange rate volatility	0.04	0.00	0.01	0.00	0.02	0.00	0.04	0.00

The table shows PIP values and average conditional coefficients for different model size priors: i) Uniform means that all possible models are equally probable. ii) Random corresponds to the assumption that all model sizes are a-priori equally likely. iii) Fixed 10 and fixed 15 denotes a prior expected model size of 10 and 15 variables, respectively. All estimations are carried out using the benchmark prior suggested by *Fernandez* et al. (2001) (g = BRIC). PIP denotes the posterior inclusion probability, i.e. the probability that the variable is selected. Cond. Post Mean is the average coefficient of a variable conditional on inclusion in the model. All variables are lagged by 4 quarters unless otherwise stated.

a lag of 8 quarters) is selected in nearly all models (PIP of at least 91 %). The variable shows a positive sign. Equity boom phases seem to be correlated with high risks which increase probability of crises some years later.

Second, cross-border loans are also an important early warning indicator for Austria. While the posterior inclusion probability (PIP) is lower than that of EURO STOXX Banks return (ranges between 63 % and 94 %), the standardized coefficient is substantially larger (see in particular Table 4). In line with expectations, the variable is found to be positively related to the AFSI. Austrian banks held large cross-border loans (especially in Central and Eastern European countries) making them vulnerable to shocks abroad.

The third robust indicator is inflation. In Tables 3 and 4, the PIP ranges between 79 % and 92 %, i. e. the variable in included in the vast majority of all models. Inflation exhibits a positive sign. Inflation is often a significant early warning indicator in emerging countries where high inflation occurs (*Kauko* 2014). But even in a low inflation environment (as in the case of Austria), there may be inflation forecasting errors that may increase with inflation. In this way, real interest rates may be affected and banks' margins and profitability may decline. Moreover, *Boyd*/*Levine*/*Smith* (2001) argue that credit market frictions get more likely with increasing inflation, even for low inflation values. They show, for low to moderate rates of inflation, that there is a strong negative association between inflation and financial sector activity.

With respect to our classification of risk channels, results in Tables 3 and 4 suggest that information on credit development and excessive growth is particularly important. In addition to cross-border loans, the total credit-to-GDP gap, a prominent indicator for excessive credit growth, is also often included (PIP between 39 % and 69 %). In line with expectations, the variable displays a positive sign. However, customer loans growth and off-balance sheet growth, are not relevant. In contrast to the total credit-to-GDP gap, customer loan growth builds on a more narrow definition of credit and considers only bank loans. The reason why off-balance sheet growth does not play a role may be that Austrian banks were much less active in derivatives business than other international banks.

Some variables on the risk-bearing capacity also appear to be, to some extent, relevant to predict financial stress. In particular, the corporate debt-to-profit-ratio, reflecting the indebtedness of companies, is included in many cases (55 % in Table 3, around 40 % in Table 4). The variable is positively associated with the AFSI indicating that high firm leverage makes companies more vulnerable and financial crises more likely. The loan-to-deposit ratio and bank ratings are both selected in around 30 % of all models considered in Tables 3 and 4. Bank ratings are an aggregate indicator for banks' creditworthiness. There is a positive relation between bank ratings and financial stress which indicates that lower ratings of banks precede financial stress.[22] Moreover, we find for the loan-to-deposit ratio a positive sign suggesting that bank funding based on stable deposits contributes to financial stability. This result is in line with evidence from the recent financial crisis of how important funding issues are. By contrast, the risk-bearing capacity of households (as measured by the ratio of household debt to disposable income) does not seem to be relevant at all. Domestic households have not represented a vital source of risk for the Austrian banking system so far, probably due to low household indebtedness in Austria.

Interconnectedness (measured by interbank assets) plays only a minor role in predicting financial stress. In Tables 3 and 4, the PIP lies in the range between 19 % and 31 %. Interbank assets are found to be positively related to the AFSI indicating that contagion via the interbank market may amplify financial stress.

Moreover, with the exception of inflation, the variables covering the macroeconomic environment and the structure of the banking sector either appear not to be relevant (e.g. current-account-GDP-ratio, banking sector competition) or they show a counterintuitive sign (e.g. GDP EU-28). As previously discussed, this statement does not hold for inflation. The lower importance of macro variables is in line with evidence for advanced economies (see Section III.2.). Finally, with the exception of EURO STOXX banks return, variables on asset price development and volatility (as indicators for mispricing of risk) do not reveal good early warning properties. Due to shorter time series, we have not included information on real estate prices in Austria in our regression models.[23] However, monitoring real estate developments will likely gain importance in the future.

Figure 2 compares the estimated AFSI (baseline specification of Table 3) and the realized AFSI. Differences can be observed, in particular, in 2009 and since 2013. Overall, the estimation fits, however, well.

[22] A high value of the variable bank ratings corresponds to a low rating class.

[23] Based on a shorter sample, variables on real estate prices do not contribute to economically meaningful results so far.

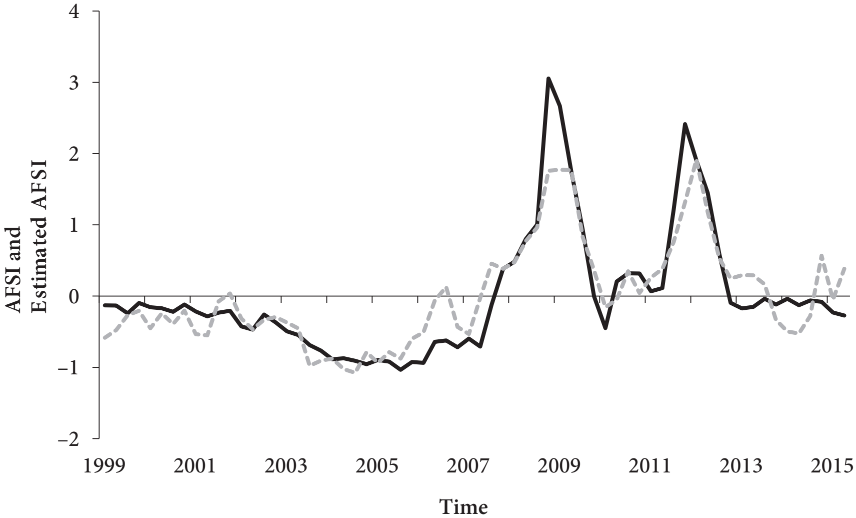

Figure 2: Realized AFSI versus Estimated AFSI

Table 5

CISS Estimation Results

Variable	*PIP*	*Cond. Post Mean*	*Cond. Post SD*	*Cond. Positive Sign*
Total credit-to-GDP gap	0.96	1.30	0.23	1.00
Cross-border loans	0.95	2.08	0.42	1.00
EURO STOXX Banks return, lag 8	0.85	0.76	0.20	1.00
ROE (banks)	0.48	–0.71	0.23	0.00
Inflation	0.36	0.44	0.14	1.00
Loan-to-deposit ratio	0.17	1.23	0.74	1.00
MSCI Eastern Europe return	0.14	–0.64	0.24	0.00
GDP EU–28	0.12	0.74	0.31	0.99
VIX	0.10	0.43	0.19	1.00
EURO STOXX Banks return	0.10	–0.45	0.22	0.00
Net interest margin	0.07	1.62	0.82	1.00

(Continue next page)

(Table 5: Continued)

Variable	*PIP*	*Cond. Post Mean*	*Cond. Post SD*	*Cond. Positive Sign*
Total credit growth	0.06	0.84	0.69	0.79
Business climate	0.06	0.43	0.24	0.98
Household debt-to-income ratio	0.04	–0.32	0.19	0.00
GDP Austria	0.03	0.39	0.32	0.89
Interbank assets	0.02	0.42	0.31	0.95
GDP CESEE	0.02	0.15	0.34	0.71
Interest rate households	0.02	–0.07	0.54	0.48
Total assets-to-GDP ratio	0.02	–0.54	0.65	0.14
Total assets growth	0.02	–0.19	0.25	0.12
Customer loans growth	0.01	–0.07	0.45	0.25
High yield bond spread	0.01	0.19	0.34	0.80
Corporate debt-to-profit ratio	0.01	0.27	0.34	0.78
MSCI Eastern Europe return, lag 8	0.01	0.07	0.25	0.61
Bank ratings	0.01	–0.01	0.35	0.49
VIX, lag 8	0.01	0.12	0.24	0.68
Current account-to-GDP ratio	0.01	0.00	0.48	0.58
Banking sector competition	0.01	–0.13	0.16	0.03
Interest rate corporates	0.01	–0.05	0.37	0.43
Tier 1 ratio	0.01	0.16	0.26	0.78
Exchange rate volatility	0.01	0.07	0.27	0.64
Off-balance sheet growth	0.01	0.02	0.21	0.59

The table includes summary statistics over the 1,000 best models. The estimations are carried out using the benchmark prior suggested by *Fernandez* et al. (2001) (g = BRIC). Prior expected model size is equal to 6 variables. The table shows the posterior inclusion probability (PIP), i. e. the probability that the variable is selected. It also contains the conditional posterior mean (Cond. Post Mean) and the conditional posterior standard deviation (Cond. Post SD), i. e. the average coefficient and the average standard deviation of the coefficient of a variable conditional on inclusion in the model. The column conditional positive sign gives the share of positive coefficients of a variable in the considered 1,000 best models. Values close to 1 or 0 indicate a consistent sign across our regressions. All variables are lagged by 4 quarters unless otherwise stated.

3. *Robustness Checks*

We carry out several robustness checks. First, we replicate our estimations with the CISS index, i.e. we use the Bayesian model averaging method to estimate the CISS index instead of the AFSI. We thereby show that our method also produces meaningful results for an exogenous stress index. Second, we use alternative g-priors from the literature. Third, we augment our set of explanatory variables by adding a lagged dependent variable.

For explaining the CISS index, we use the same set of variables as above although they are Austrian specific (see Table 5). The results for the CISS prediction are overall similar to our AFSI results. Cross-border loans and EURO STOXX Banks return remain important early warning indicators. While inflation (in Austria) is less relevant in predicting the CISS, the total credit-to-GDP gap as well as ROE (banks) gain importance. Although the AFSI is very simple and consists only of 5 variables, results change to a surprisingly limited extent when using the CISS which is much more sophisticated.

Next, we investigate whether our results (in particular the posterior inclusion probability (PIP)) are influenced by the choice of the g-prior. In our regressions above, we set $g = \max(T, K^2)$ as suggested by *Fernandez* et al. (2001). In addition to this criterion, we now examine five alternative priors. We apply

(i) the EBL g-prior that estimates a local empirical Bayes g-parameter as in *Liang* et al. (2008)

(ii) $g = \log(N)^3$ which asymptotically mimics the Hannan-Quinn criterion[24]

(iii) the g-prior by *Koop/Potter* (2004) (i.e. $g = \log(T)$)

(iv) the risk inflation (RIC) g-prior (i.e. $g = K^2$) of *George/Foster* (1994)

(v) the g-prior $g = N$ of the unit information prior (UIP) model

Table 6 shows the results. With respect to PIP values, all g-priors in Table 6 deliver similar results to our previous results in Tables 3 and 4. Differences can be observed when using the KoopPotter model that assigns a substantially lower posterior inclusion probability to inflation. Moreover, for some alternative g-priors, the PIP value and conditional post mean of cross-border loans are larger than those values derived under a BRIC model and a prior mean model size of 6 variables (as presented in Table 3), but more in line with results found for different model size priors (see Table 4). Overall, our results are relatively robust with respect to different g-priors.

[24] See *Hannan/Quinn* (1979) for the original paper and *Fernandez* et al. (2001) for further details how the criterion can be used in Bayesian model averaging.

Finally, we check the robustness of our regressions by adding the lagged dependent variable to the set of predictors. We use the fourth lag of the AFSI (see Table 7). In comparison to our previous results (see Table 3), output does not change substantially. The lagged AFSI is selected only in 2 % of all models and its coefficient is zero.

Overall, we conclude that in our setting the BMA prodecure is very robust with respect to different g-priors, a-priori model sizes and adding the lagged dependent variable. Moreover, this robustness is not caused by the AFSI construction since CISS estimation also delivers similar results.

V. Conclusion

This paper has two objectives: First, we develop the Austrian Financial Stress Index (AFSI) as a measure of the current financial stability situation in Austria. Second, we identify early warning indicators and risk drivers that have sufficient predictive power to explain the developments in the Austrian financial system as measured by the AFSI. To determine early warning indicators, we apply Bayesian model averaging. We calculate the 1,000 most probable models and search for the indicators which are most frequently included. The Bayesian approach offers the advantage that we are able to investigate a considerably larger set of variables than usually considered. Moreover, results are more robust to model misspecification since they reflect a large number of models.

We find that banks' share price growth, cross-border lending and inflation are the most important early warning indicators for Austria. Other relevant indicators are the total credit-to-GDP gap and the corporate debt-to-profit ratio. Overall, our findings suggest that indicators on credit development are particularly relevant for predicting financial stress.

Our approach may also be used for macroprudential supervision. First, our approach measures financial stability on a continuous scale. It does not depend on the judgement behind a dummy variable that classifies a state as a crisis or not. Comparing financial stress events and updating them is therefore easier. Moreover, our approach delivers a ranking of risk factors and helps to identify the relevant areas where macroprudential instruments are needed. Finally, for the design of certain macroprudential instruments, concrete indicators are needed which deliver the signal to put the instrument on or off or to calibrate the size of the instrument. For instance, for the design of the countercyclical capital buffer, our analysis indicates that a broad measure of excessive credit growth is superior to more narrow ones.

Table 6

AFSI Estimation Results (with Alternative g-Priors)

Variable	*BRIC Fixed 6*		*EBL Fixed 6*		*HQ Fixed 6*		*KoopPotter Fixed 6*		*RIC Fixed 6*		*UIP Fixed 6*	
	PIP	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*
EURO STOXX Banks return, lag 8	0.92	0.39	0.96	0.36	0.95	0.36	0.85	0.30	0.91	0.39	0.96	0.36
Cross-border loans	0.63	0.57	0.90	0.86	0.90	0.85	0.73	0.48	0.68	0.57	0.90	0.86
Inflation	0.80	0.22	0.86	0.26	0.89	0.27	0.54	0.17	0.81	0.22	0.89	0.27
Total credit-to-GDP gap	0.39	0.20	0.64	0.34	0.63	0.33	0.46	0.17	0.44	0.20	0.63	0.34
Corporate debt-to-profit ratio	0.55	0.20	0.42	0.11	0.41	0.12	0.47	0.13	0.50	0.20	0.41	0.11
Loan-to-deposit ratio	0.39	0.27	0.31	0.09	0.25	0.10	0.41	0.19	0.35	0.27	0.26	0.10
Bank ratings	0.26	0.12	0.32	0.15	0.32	0.15	0.25	0.08	0.28	0.12	0.33	0.15
Total assets growth	0.23	−0.08	0.34	−0.12	0.32	−0.12	0.34	−0.07	0.21	−0.08	0.32	−0.12
Net interest margin	0.22	0.23	0.27	0.26	0.28	0.28	0.23	0.14	0.24	0.23	0.28	0.28
Interbank assets	0.21	0.07	0.30	0.10	0.29	0.10	0.25	0.05	0.20	0.07	0.29	0.10
GDP EU-28	0.21	0.10	0.43	0.16	0.39	0.16	0.40	0.11	0.22	0.10	0.40	0.16
Interest rate households	0.17	0.11	0.41	0.26	0.40	0.25	0.23	0.11	0.20	0.11	0.40	0.25
GDP CESEE	0.11	−0.04	0.21	−0.03	0.15	−0.03	0.26	−0.05	0.11	−0.04	0.16	−0.03

(Continue next page)

(Table 6: Continued)

Variable	*BRIC Fixed 6*		*EBL Fixed 6*		*HQ Fixed 6*		*KoopPotter Fixed 6*		*RIC Fixed 6*		*UIP Fixed 6*	
	PIP	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*
Tier 1 ratio	0.08	0.02	0.18	0.02	0.14	0.02	0.21	0.02	0.08	0.02	0.14	0.02
ROE (banks)	0.08	–0.02	0.19	–0.04	0.17	–0.04	0.22	–0.03	0.09	–0.02	0.16	–0.04
MSCI Eastern Europe return	0.08	–0.03	0.20	–0.06	0.19	–0.06	0.20	–0.02	0.09	–0.03	0.19	–0.06
MSCI Eastern Europe return, lag 8	0.08	–0.01	0.12	0.00	0.08	–0.01	0.20	–0.01	0.07	–0.01	0.09	–0.01
Total credit growth	0.06	0.01	0.11	0.00	0.07	0.00	0.24	0.02	0.05	0.01	0.08	0.00
EURO STOXX Banks return	0.07	–0.02	0.14	–0.01	0.11	–0.01	0.22	–0.02	0.07	–0.02	0.11	–0.01
VIX	0.05	0.01	0.22	0.03	0.18	0.03	0.21	0.01	0.05	0.01	0.18	0.03
GDP Austria	0.05	0.01	0.12	0.01	0.09	0.01	0.20	0.01	0.05	0.01	0.09	0.01
Business climate	0.04	0.01	0.15	0.02	0.12	0.02	0.18	0.01	0.04	0.01	0.12	0.02
VIX, lag 8	0.03	0.00	0.09	0.00	0.06	0.00	0.17	0.00	0.03	0.00	0.06	0.00
Current account-to-GDP ratio	0.02	0.00	0.07	0.00	0.05	0.00	0.15	0.00	0.02	0.00	0.05	0.00
Total assets-to-GDP ratio	0.02	0.00	0.17	–0.07	0.12	–0.05	0.17	–0.01	0.02	0.00	0.12	–0.06
Household debt-to-income ratio	0.02	0.00	0.13	0.00	0.08	0.00	0.20	0.00	0.02	0.00	0.08	0.00
Banking sector competition	0.02	0.00	0.10	0.00	0.07	0.00	0.15	0.00	0.02	0.00	0.07	0.00

Variable	*BRIC Fixed 6*		*EBL Fixed 6*		*HQ Fixed 6*		*KoopPotter Fixed 6*		*RIC Fixed 6*		*UIP Fixed 6*	
	PIP	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*	*PIP*	*Cond. Post Mean*
Interest rate corporates	0.02	0.00	0.08	–0.01	0.05	0.00	0.15	0.00	0.02	0.00	0.06	0.00
Customer loans growth	0.02	0.00	0.10	0.00	0.06	0.00	0.16	0.00	0.02	0.00	0.07	0.00
High yield bond spread	0.01	0.00	0.07	0.00	0.04	0.00	0.15	0.00	0.01	0.00	0.04	0.00
Off-balance sheet growth	0.01	0.00	0.07	0.00	0.04	0.00	0.13	0.00	0.01	0.00	0.04	0.00
Exchange rate volatility	0.01	0.00	0.06	0.00	0.03	0.00	0.12	0.00	0.01	0.00	0.04	0.00

The table shows PIP values and average conditional coefficients (Cond. Post Mean) derived for different g-priors. Column BRIC contains the correspondent values of table 3 to simplify comparisons. EBL shows the results of the empirical Bayes criterion. HQ refers to the Hannan Quinn g-prios. The KoopPotter column reports the values for the g-prior by Koop and Potter. RIC refers to the risk inflation criterion of George and Foster. Finally, UIP shows the results for the unit information g-prior. All estimations are carried out under the assumption of a prior expected model size of 6 variables. PIP denotes the posterior inclusion probability, i.e. the probability that the variable is selected. Cond. Post Mean is the conditional posterior mean (see Table 3). All variables are lagged by 4 quarters unless otherwise stated.

Table 7

AFSI Estimation Results (Including the Lagged Dependent Variable)

Variable	*PIP*	*Cond. Post Mean*	*Cond. Post SD*	*Cond. Positive Sign*
EURO STOXX Banks return, lag 8	0.79	0.33	0.15	1.00
Cross-border loans	0.70	0.54	0.45	1.00
Inflation	0.66	0.18	0.05	1.00
Total credit-to-GDP gap	0.46	0.20	0.10	1.00
Corporate debt-to-profit ratio	0.36	0.13	0.05	1.00
Loan-to-deposit ratio	0.33	0.23	0.18	1.00
GDP EU-28	0.29	0.21	0.17	1.00
Bank ratings	0.28	0.12	0.05	0.99
EURO STOXX Banks return	0.28	–0.11	0.05	0.00
GDP CESEE	0.20	–0.11	0.06	0.02
Total assets growth	0.17	–0.05	0.02	0.00
MSCI Eastern Europe return, lag 8	0.13	–0.03	0.01	0.00
ROE (banks)	0.11	–0.03	0.01	0.00
Interest rate households	0.09	0.04	0.02	0.95
Interbank assets	0.09	0.03	0.01	0.97
Interest rate corporates	0.08	0.04	0.02	0.98
Total credit growth	0.08	0.03	0.02	0.88
Customer loans growth	0.06	–0.01	0.00	0.04
VIX, lag 8	0.04	0.01	0.00	1.00
Tier 1 ratio	0.04	0.01	0.00	1.00
Net interest margin	0.04	0.02	0.02	0.86
Household debt-to-income ratio	0.03	0.00	0.00	0.04
Current account-to-GDP ratio	0.03	0.00	0.00	0.52
VIX	0.03	0.00	0.00	0.98

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Variable	*PIP*	*Cond. Post Mean*	*Cond. Post SD*	*Cond. Positive Sign*
GDP Austria	0.03	0.00	0.00	0.65
MSCI Eastern Europe return	0.02	0.00	0.00	0.13
AFSI, lag 4	0.02	0.00	0.00	0.24
Total assets-to-GDP ratio	0.02	0.00	0.00	0.30
Business climate	0.02	0.00	0.00	0.80
Exchange rate volatility	0.01	0.00	0.00	0.98
High yield bond spread	0.01	0.00	0.00	0.48
Banking sector competition	0.01	0.00	0.00	0.05
Off-balance sheet growth	0.01	0.00	0.00	0.41

The table includes summary statistics for estimating the AFSI under the restriction that the lagged AFSI is included as explanatory variable. The estimations are carried out using the benchmark prior suggested by *Fernandez* et al. (2001) (g = BRIC). Prior expected model size is equal to 6 variables. Summary statistics is provided for the 1,000 best models. It shows the posterior inclusion probability (PIP), i.e. the probability that the variable is selected. The table also contains the conditional posterior mean (Cond. Post Mean) and the conditional posterior standard deviation (Cond. Post SD), i.e. the average coefficient and the average standard deviation of the coefficient of a variable conditional on inclusion in the model. The column cond. positive sign gives the share of positive coefficients of a variable in the considered 1,000 best models. Values close to 1 or 0 indicate a consistent sign across our regressions. All variables are lagged by 4 quarters unless otherwise stated.

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