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What predicts financial (in)stability? A Bayesian approach

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Non-technical summary

Research Question

The current financial crisis reveals the huge economic and social costs of financial crises. To avoid future crises, it is essential to find reliable and robust early warning indicators. These indicators should help to detect vulnerabilities in the financial system so that appropriate policy measures can be taken. Moreover, in order to gain a better understanding of how important different sources of risk are, measures which quantify financial stability are also valuable. In this paper, we contribute to both topics. First, on the basis of Austrian data, we develop a stress indicator for the financial system. Second, we derive early warning indicators for the Austrian stress index.

Contribution

To determine early warning indicators, we apply a Bayesian approach (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 large number of variables. While most papers consider around 10 – 15 variables, we take into account 30 variables. This is important since results in the literature are often contradictory, which may be due to the fact that not all relevant variables are included . Our method offers the additional advantage that results are very robust since they reflect a large number of models.

Results

We find that excessive credit growth and high returns of bank stocks are the best early warning indicators. Unstable funding of banks (measured by the loan to deposit ratio) also has a high predictive power. However, macroeconomic indicators – except for the EU-27 GDP growth – are less relevant.

Nichttechnische Zusammenfassung

Fragestellung

Wie die aktuelle Finanzkrise zeigt, sind die ökonomischen und sozialen Kosten von Finanzkrisen gewaltig. Zur Vermeidung zukünftiger Krisen ist es daher unbedingt notwendig, zuverlässige und robuste Frühwarnindikatoren zu finden. Diese sollen es ermöglichen, Schwächen im Finanzsystem zu entdecken, um dann geeignete Gegenmaßnahmen ergreifen zu können. Darüber hinaus sind auch Maße, die Finanzstabilität quantifizieren, hilfreich. Derartige Maße verbessern das Verständnis, wie wichtig verschiedene Risikoquellen sind. In diesem Papier tragen wir zu beiden Themen bei. Auf der Grundlage österreichischer Daten entwickeln wir einen Stressindikator für das dortige Finanzsystem. Zudem bestimmen wir geeignete Frühwarnindikatoren für den österreichischen Stressindex.

Beitrag

Zur Bestimmung der Frühwarnindikatoren verwenden wir einen bayesianischen Ansatz (*Bayesian model averaging*). Wir ermitteln die 1.000 wahrscheinlichsten Modelle und suchen die Indikatoren, die am häufigsten in diesen Modellen enthalten sind. Dieser bayesianische Ansatz bietet den Vorteil, dass wir eine große Anzahl an Indikatoren untersuchen können. Während die meisten Papiere ca. 10 – 15 Indikatoren berücksichtigen, analysieren wir 30 Indikatoren. Dies ist deshalb wichtig, weil die Literatur häufig widersprüchliche Ergebnisse findet, die möglicherweise darauf zurückzuführen sind, dass nur ein Teil der relevanten Variablen berücksichtigt wurde. Ein weiterer Vorteil unserer Methode ist, dass sie sehr robust ist, da sie sehr viele Modelle widerspiegelt.

Ergebnisse

Unsere Ergebnisse deuten darauf hin, dass exzessives Wachstum der privaten Verschuldung und eine hohe Rendite von Bankaktien die besten Frühwarnindikatoren sind. Instabile Refinanzierungsverhältnisse der Banken (gemessen über das Verhältnis von Krediten zu Depositen) haben ebenfalls eine hohe Erklärungskraft. Makroökonomische Indikatoren sind hingegen – mit Ausnahme des EU-27 BIP Wachstums – von geringerer Bedeutung.

What predicts Financial (In)Stability? A Bayesian Approach[1]

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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 excessive credit growth and high returns of banks' stocks are the best early warning indicators. Unstable funding (as measured by the loan to deposit ratio) also has a high predictive power.

Keywords: Financial crisis, early warning indicators, government policy and regulation, financial stress index

JEL-Classification: G01 G28

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1 Introduction

The huge costs of financial crises are well-known. Costs result not only from rescue measures, but also in particular from a loss of output. In many cases, total costs amount to 10% of GDP or even more (Laeven and 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 quantifying financial stability and to finding 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.[3]

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 und Detriagache (1998), and Hardy und 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 30 variables. Our method allows us to provide a more balanced view of the predictive power of the various indicators.

We find that total credit growth is the most important early warning indicator for Austria. However, some other measures for excessive credit growth, such as the credit-to-GDP-gap, are insignificant or exhibit a sign that is inconsistent with theory. Total credit is a very broad measure for indebtedness of households and companies, including, for instance, also bonds and trade credit. This broad indicator may therefore better reflect vulnerabilities of the private sector. We find that high returns of the EURO STOXX Banks index also provide a reliable early warning signal. High returns may be accompanied by high risks, making stress in the financial system more likely. Another important early warning indicator is the loan-to-deposit ratio showing that bank funding based on stable deposits contributes to financial stability.

[3] 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 introduce Bayesian model averaging.

Except for the EU-27 GDP growth, we find that macro variables do not have a high predictive power.

We differ in several 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 leads to an improved in-sample fit (reduces the residual variance), but each added variable increases the regression variance that might lead to weak prediction accuracy.

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 more noisy. 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 and 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.

Third, the bulk of the literature investigates domestic developments as explanatory factors for banking crises. Our analysis is based on data for Austria, which provides a good example of an imported crisis. In 2008, the country was in an overall sound shape and prominent early warning indicators from the literature, such as the credit-to-GDP-gap, balance of current accounts and property price development, did not reveal any weaknesses. Nevertheless, the country was severly hit by the financial crisis in 2009. Several large banks had to be rescued by the government and total crisis costs (up to 2011) amounted to nearly 20% of GDP (Laeven and Valencia (2012)). This example illustrates how vulnerable a financial system may be even when standard indicators do not send alarm signals.

Our approach may also be used for macroprudential policy. We identify key risk factors, which helps macroprudential regulators in deciding where to put particular effort. For the design of certain macroprudential instruments, there is a need for indicators which deliver the signal to put the instrument on or off or to calibrate the size of the instrument. For the design of the countercyclical capital buffer, for instance, our analysis indicates that a broad measure of excessive credit growth is superior to narrower ones. Decisions on the size of the buffer should therefore be connected with a broad credit growth indicator.

Our paper is structured as follows. In section 2, we describe the construction of our stress indicator which is used as the left-hand side variable. In Section 3, potential early warning indicators (right-hand side variables) are discussed and the related literature is reviewed. In Section 4, we explain our estimation methods and present our results including a two-year out-of-sample forecasting exercise. We also derive policy implications from the empirical findings. Section 5 briefly outlines the application of our results to macroprudential policy. Finally, Section 6 concludes.

2 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).

2.1 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 and 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 and Liu (2003), who construct a daily stress index for Canada. Due to the current financial crisis, monitoring the stress level in the financial system has become much more important over the last few years. For this reason, a number of papers has emerged on financial stress indices since 2007 (see, for instance, Nelson and Perli (2007) for the US, Hollo, Kremer and Lo Duca (2012) and Islami und Kurz-Kim (2013) for the euro area and Jahn and 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 and Lo Duca (2012), Lo Duca and Peltonen (2011) or Jakubik and Slacik (2013)). Several papers also include information on financial intermediaries, mostly variables derived from a stock market banking sector index (see, for example, Illing and Liu (2003) and Caldarelli, Elekdag and Lall (2011)). Some papers use factor models to derive a composite indicator (see, for instance, Matheson (2012) and 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 and Perli (2007)), monthly (Caldarelli, Elekdag and Lall (2011) or quarterly (e.g. Lo Duca and 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 and 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, Caldarelli, Elekdag and 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 and Lo Duca (2012)).

2.2. 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 and Peltonen (2011) and Hollo, Kremer and 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[4] index, ii) the realized volatility of ATX yoy returns over a horizon of one quarter, and iii), the yoy return of the Datastream Austrian Financials index[5]). Higher equity returns indicate a lower level of tension in the equity market. Hence, the two (normalized) 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-EUREPO spread[6] (spread between uncollateralized and collateralized interbank loans) in the ASFI. The EURIBOR-EUREPO 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).[7] The variable is positively related to the AFSI.

Figure 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[8], the spread of the three-month EURIBOR over the three-month EUREPO and the spread of Austrian ten-year government benchmark bond yields over German ten-year government bond yields.

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

[5] 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.

[6] Given the correlation of 0.99 between the EURIBOR-EUREPO spread and the EURIBOR-OIS spread, including the EURIBOR-OIS spread in the ASFI would add no further information to the AFSI.

[7] We also examined whether we should include the volatility of the EURIBOR-EUREPO spread and the volatility of the Austrian government bond spread. However, the AFSI including these two volatility measures shows a correlation of 0.99 with the AFSI without these measures. Therefore, we do not take account of these volatility subindices.

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

Figure 1: AFSI components

Segments	Components	Relation	Weight
Equity Market	ATX yoy return	-	1/3
	Datastream Austrian Financials yoy return	-	
	Realized ATX volatility	+	
Money Market	3-month EURIBOR-EUREPO spread	+	1/3
Sovereign Bond Market	Spread of Austrian 10-year gov. benchmark bond yields over German 10-year gov. bond yields	+	1/3

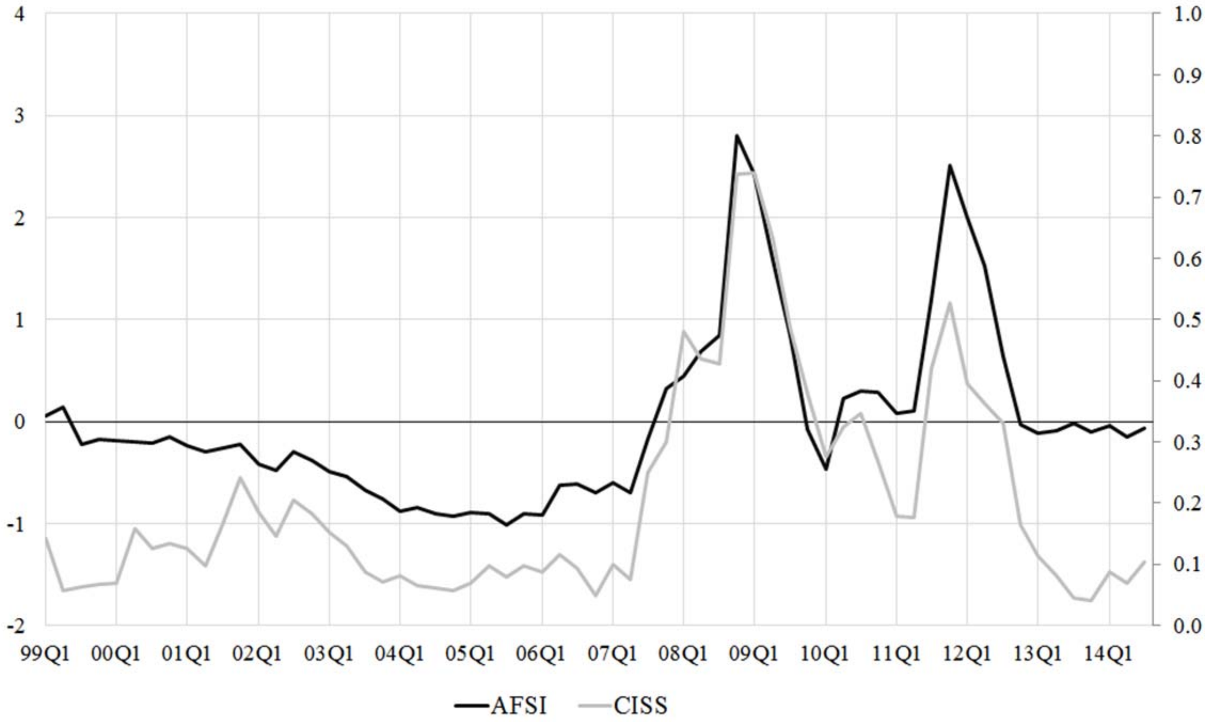
Source: own illustration.

As mentioned earlier, the literature does not agree on one single method of how to aggregate the variables of a composite index (see Illing and 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 implicitely assumes equal distance between any two successively ranked observations. This assumption distorts any subsequent econometric analysis as the distances of observations of the dependent variable are a major driver of estimation results.[9] 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 Caldarelli, Elekdag and Lall (2011) and Islami and Kurz-Kim (2013), we use variance-equal weighting to standardize the subindices in the AFSI, i.e. we substract the arithmetic mean from each variable and divide then the value by its standard deviation.[10] 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.

[9] 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.
[10] The disadvantage of this approach is that it requires the assumption of normally distributed subindices.

Figure 2: Austrian Financial Stress Index (AFSI) and Composite Indicator of Systemic Stress (CISS)



Source: own calculations, ECB.

Figure 2 shows the AFSI development in comparison to the development of the CISS indicator (1999Q1 – 2014Q1). The CISS index is a prominent measure for financial soundness in the euro area (see Hollo, Kremer and Lo Duca (2012)). The CISS comprises 15 individual indicators in five market categories: money market[11], bond market[12], equity market[13], financial intermediaries[14], and foreign exchange market[15]. We use the CISS index for robustness checks in Section 4. 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 – 2007Q3) both indices are below zero – indicating no or moderate financial stress. Financial stress starts to build up

[11] Realised volatility of the 3-month Euribor rate, Interest rate spread between 3-month Euribor and 3-month French T-bills, Monetary Financial Institution's (MFI) emergency lending at Eurosystem central banks

[12] Realised 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

[13] Realised volatility of the Datastram non-financial sector stock market index, CMAX for the Datastream non-financial sector stock market index, Stock-bond correlation

[14] Realised volatility of the idiosyncratic equity return of the Datastream bank sector stock market index, Yield spread between A-rated financial and non-financial, CMAX interacted with the book-price ratio for the financial sector equity market index

[15] Realised volatility of the euro exchange rate vis-à-vis the US dollar, the Japanese Yen and the British Pound

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 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).

3 Predicting Financial (In)stability

As follows, we discuss methodologies in early warning models (Section 3.1). Besides that we give a literature overview of early warning indicators and outline what impact indicators are expected to exert on financial stability (Section 3.2). For the purpose of this study, we group potential early warning indicators into six risk channels. Finally, the data base is described (Section 3.3).

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 and 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 and Drehmann (2009) and Alessi and Detken (2009)) or in discrete choice models. The signal extraction approach evaluates indicators based on their noise to signal ratio.[16] 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 and Detragiache (1998)

[16] The noise to signal ratio combines information on type 1 and type 2 errors and is defined as the fraction of missed crises relative to the fraction of correctly predicted crises.

estimate the probability of a banking crisis for 65 countries using a static logit model. While the earlier literature focused on developing 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 and Peltonen (2011) evaluate the joint role of domestic and global indicators in a panel framework for 28 emerging market economies and advanced economies. Jakubík and Slacík (2013) choose a similar approach for nine CESEE countries.

3.2 Expected impact of early warning indicators

There is a broad range of risks to financial stability. We assign possible risks and correspondent indicators to six 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, (5) concentration risk, and (6) interconnectedness of banks. Our list of indicators is summarized in Table 1.

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 concentration risk and interconnedness.

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 (leverage ratio)[17]. 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.

The second group of indicators is *mispricing of risk* variables, captured by different asset price variables. Collective mispricing of risk 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 and 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 and Peltonen (2013) and Detken et al (2014), while it is not significant in Behn et al (2013). Moreover, Bush et al (2013) shows that low volatility on equity markets is a crisis predictor.

We proxy equity price growth by using the yoy return of the EURO STOXX Banks index. The banks subindex probably better reflects mispricings with respect to banks than a general index. Moreover, we use volatility measures for the European stock market. We measure house price developments relative to growth in household disposable income (difference in yoy growth rates). Moreover, we take account of the corporate bond market by using the spread between European AAA corporate bond yields and high-yield bonds.

Mispricing of risks are 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 real credit growth 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 and Detriagache (1998) and Jorda et al (2011)), although there is evidence that the credit-to-GDP-gap is superior (see Drehmann et al (2011) and 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 the sample. Karim et al

[17] 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.

(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 (e.g. total credit growth, credit-to-GDP gap, customer loan growth). We also 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 exogenous macroeconomic shocks. In the literature the best, most robust 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) and Kauko (2013)). The performance of other macroeconomic variables is mixed. For advanced economies, other macroeconomic variables do not seem to be significant, particularly when information on the risk-bearing capacity and mispricing of risk is included (see Barrell et al (2010) and 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 and Kemme (2011), Bordo and 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, current account-to-GDP ratio, exchange rate volatility, inflation and banks' total assets-to-GDP-ratio. Moreoever, to proxy for macroeconomic developments outside Austria, we take into account EU-27 GDP growth. In addition to variables considered in the literature, we include a sentiment indicator for the Austrian real economy and survey evidence on credit standards.[18]

We also take into account contagion measures. We distinguish between two related, although distinct risk channels: *concentration* (5) and *interconnectedness* (6). Neither channel has been incorporated in other studies yet. Concentration is a measure of the uneven distribution of exposures and typically amplifies the impact of a single (default) event. Prominent examples include sectoral concentration in the banking system (e.g. property-related credit in Ireland or Spain in the buildup of the recent crisis) or dominant single creditors on banks' books (e.g. Saad Groups' multi-billion dollar default in 2009). We focus on the latter and use the ratio of large exposures to total assets (average of all banks).

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

[18] We do not consider interest rates since long- and short-term interest rate proxies (Euribor and ten-year government bond yield) are included in our left-hand-side variable.

are default cascades in banking systems resulting from connections in the interbank market. We use the share of interbank assets as a 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.

3.3 Data

Our data set of early warning indicators consists of regulatory reporting data, market data (provided by Datastream and Bloomberg) and macroeconomic data (retrieved from the OeNB's macroeconomic database). 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 2004 to the third quarter of 2013, yielding $T = 39$ time periods. The sample consists of 30 indicators. All indicators are tested for stationarity. Some variables appear to have a unit root although economic theory suggests otherwise. Furthermore, for policy reasons (e.g. a clear-cut interpretation of the credit-to-GDP ratio) we do not transform these variables to remove the probably spurious unit roots.[19]

Due to data restrictions such as changes in the regulatory reporting scheme (Basel II implementation, e.g. capital definitions and legal changes to the consolidation framework) not all predictors that are of potential interest can be included in our analysis. In Table 1, we list all indicators – according to the above-mentioned risk channel framework. Although it is not necessary from a statistical point of view, we demean all possible predictors to ensure that the units of the regression coefficients are the same.

[19] It is a well-known fact in time series literature on stationarity that standard unit root tests have low statistical power in that they cannot distinguish between true unit root processes and near unit root processes (e.g. slowly mean reverting processes). Some of the tested indicators show structural breaks that might induce a positive unit root test. Since we use a linear model in our empirical analysis our forecasting performance is likely to be superior to that of nonlinear time series models. We therefore do not address these breaks directly.

Table 1: Comprehensive List of Variables Used for AFSI Prediction

Indicators	Description	Source
Risk-bearing capacity		
Bank ratings (average)	average rating of 6 Austrian banks (scale 1 to 6 where 1 is the highest grade)	Bloomberg
Bank's return on equity before tax	average return on equity before tax (all Austrian banks)	Supervisory Reporting Data
Loan-to-deposit average	average loan-to-deposit (banks & non-banks) ratio (all Austrian banks)	Supervisory Reporting Data
Net interest margin	Net interest income divided by total assets (all Austrian banks)	Supervisory Reporting Data
Ratio of corporate debt to profit	ratio of Austrian corporate debt (i.e. total loans and bonds) to corporate profit (debt service ratio, corporates)	OeNB's Macroeconomic Data Base
Ratio of household debt to disposable income	ratio of Austrian household debt to household disposable income (debt service ratio, households)	OeNB's Macroeconomic Data Base
Tier 1 Capital Ratio	tier 1 capital ratio (all Austrian banks)	Supervisory Reporting Data
Mispricing of risk		
VSTOXX	volatility index of the EURO STOXX 50	Datastream
EURO STOXX Banks return	yoy returns of EURO STOXX Banks index	Datastream
High yield bond spread	spread between European AAA corporate bonds and high yield corporate bonds (indices provided by Morgan Stanley)	own calculation (Datastream)
Growth gap between disposable income and housing prices	difference between household disposable income growth and residential property price growth (both growth rates yoy)	OeNB's Macroeconomic Data Base
Excessive growth		
Total asset growth	yoy growth rate of total assets (all Austrian banks)	Supervisory Reporting Data
Total credit growth	yoy growth rate of Austrian total credit (including all sources of credit)	BIS
Total credit-to-GDP ratio	total credit of Austrian banks divided by GDP	BIS, OeNB's Macroeconomic Data Base
Total credit-to-GDP gap	difference between credit-to-GDP ratio and its long term trend (two sided Hodrick-Prescott filtered credit-to-GDP gap with lamba equal to 400,000)	own calculation (BIS, OeNB's Macroeconomic Data Base)
Customer loans growth	yoy growth rate of customer loans (all Austrian banks)	Supervisory Reporting Data
Off-balance sheet growth	yoy growth rate of off-balance sheet exposures (all Austrian banks)	Supervisory Reporting Data
Macroeconomic environment		
Exchange rate volatility	weighted average of exchange rate volatility of those nine currencies where Austria has the most trade in	OeNB's Macroeconomic Data Base
Inflation Austria	Austrian GDP deflator	OeNB's Macroeconomic Data Base
GDP Austria	Austrian real GDP growth (seasonal and working day adjusted)	OeNB's Macroeconomic Data Base
GDP EU-27	EU-27 real GDP growth (seasonal and working day adjusted)	OeNB's Macroeconomic Data Base
Banks' total assets-to-GDP ratio	Austrian banks' total assets divided by GDP	Supervisory Reporting Data &
Current account-to-GDP ratio	Austrian current account net balance divided by GDP	OeNB's Macroeconomic Data Base
Average of sentiment indicators (Fed. of A. Industries & A. Economic Chambers)	average of two sendiment indicators (Austrian Federal Economic Chamber and Federation of Austrian Industries)	The Austrian Federal Economic Chamber, Federation of Austrian Industries
Credit standards for loans to enterprises	development of Austrian banks' credit standards for loans to enterprises during the past 3 months (Diffusion index)	ECB Bank Lending Survey
Interconnectedness		
Interbank asset share	share of interbank assets on total assets (all Austrian banks)	Supervisory Reporting Data
Concentration risk		
Ratio of large exposures to total assets	share of large exposures on total assets (all Austrian banks)	OeNB's central credit registry, Supervisory Reporting Data

Supervisory Data are unconsolidated.

4 Estimation and Results

4.1 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.[20]

$$y_t = \beta_0 + \sum_{j \in K} x_{j,t}\beta_j + \epsilon_t \qquad (1)$$

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 macroeconomic 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 high variance-versus-low bias tradeoff in a nonheuristic way, we partly depart from these approaches and consider a fully probabilistic approach, namely the Bayesian model averaging approach (BMA).[21] We search the most important predictors by applying the methods developed in Feldkircher and 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.

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

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 posterior model probabilities asymptotically either behave like the Bayesian information criterion (with $g = N$) or the risk inflation criterion ($g = K^2$) by Foster and George (1994).[22]

Concerning the prior model size we consider all possible models equally probable which a priori favors model with more predictors. The prior model size is therefore K/2.[23]

[20] As a robustness check, we provide estimations with a lagged dependent variable which is treated as a fixed regressor.
[21] Pathbreaking contributions to the BMA framework can be found in Raftery (1995) and Hoeting et al. (1999).
[22] In the Appendix we show results with several other priors for g.

4.2 Estimation Results

In this section we summarize the results of our chosen model framework. In Table 2 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 posterior mean (Post Mean) of a variable is the average value of a variable's coefficient across the considered models. The posterior standard deviation (Post SD) is the average standard deviation of a variable's coefficient in the considered models. 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. Variables showing an unexpected/counterintuitive coefficient sign are marked with an asterisk (*), those with an unclear coefficient sign with a tilde ~.

Total credit growth, as a measure for *excessive credit growth*, turns out to be the most important early warning indicator in our framework. The variable is selected in all models. In line with our expectations the variable shows a positive sign in each specification. Other measures for excessive growth of assets, such as total asset growth, off-balance sheet growth or the credit-to-GDP-gap are less selected (inclusion probability between 5% and 46%). Surprisingly, customer loan growth is found to be negatively related to the AFSI. While total credit reflects all types of companies' and households' debt (including e.g. bonds, trade credits and other nonbank debt), customer loans are defined more narrowly and include only bank loans. We conclude that financing sources other than bank credit are of great relevance for financial stability in Austria. Moreover, the credit-to-GDP-gap, the main BCBS indicator for the countercyclical capital buffer, also displays a negative sign, probably reflecting common problems in the construction of the indicator (see, for instance, evidence for the CESEE countries in Gersl and Seidler (2010)). It is selected in 18%.

[23] In the Appendix we also provide results with different model size priors.

Table 2: AFSI Estimation Results

Variable	Risk channel	PIP	Post Mean	Post SD	Conditional Positive Sign	unexpected or unclear sign
Total credit growth	Excessive growth	1.00	26.77	6.21	1.00	
Loan-to-deposit average	Risk-bearing capacity	0.96	32.29	9.76	1.00	
Euro Stoxx banks return, lag 8	Mispricing of risk	0.95	1.28	0.46	1.00	
Ratio of household debt to disposable income	Risk-bearing capacity	0.52	-5.70	6.36	0.00	*
Customer loans growth	Excessive growth	0.46	-6.61	8.27	0.00	*
GDP EU-27	Macro environment	0.41	-8.69	12.43	0.01	
Bank ratings (average)	Risk-bearing capacity	0.34	0.13	0.22	0.95	
Total credit-to-GDP ratio	Excessive growth	0.33	0.04	0.06	1.00	
Ratio of large exposures to total assets	Concentration risk	0.22	-1.60	3.94	0.01	*
Total credit-to-GDP gap	Excessive growth	0.18	-1.15	2.90	0.01	*
Growth gap between disposable income and housing prices	Macro environment	0.17	-0.53	1.39	0.00	*
GDP Austria	Macro environment	0.17	-0.78	10.94	0.30	
Current account-to-GDP ratio	Macro environment	0.13	0.02	0.08	0.95	
Ratio of corporate debt to profit	Risk-bearing capacity	0.13	0.15	0.64	0.78	*
Banks' total assets-to-GDP ratio	Excessive growth	0.13	0.11	0.64	0.60	
VSTOXX, lag 8	Mispricing of risk	0.12	0.21	0.73	0.99	
Total assets growth	Excessive growth	0.12	-0.49	1.90	0.09	*
Euro Stoxx banks return	Mispricing of risk	0.10	-0.01	0.03	0.18	
High yield bond spread	Mispricing of risk	0.10	-0.06	0.26	0.15	
Credit standards for loans to enterprises	Macro environment	0.10	-0.08	0.32	0.07	
Exchange rate volatility	Macro environment	0.09	-4.06	20.90	0.12	
VSTOXX	Mispricing of risk	0.09	-0.09	0.67	0.17	
Tier 1 Capital Ratio	Risk-bearing capacity	0.07	0.49	4.11	0.64	
Interbank asset share	Interconnectedness	0.07	-0.47	2.73	0.09	
Bank's return on equity before tax	Risk-bearing capacity	0.07	-0.29	1.62	0.06	
Average of sentiment indicators (Fed. of A. Industries & A. Economic Chambers)	Macro environment	0.06	0.00	0.00	0.58	~
Net interest margin	Risk-bearing capacity	0.06	-2.02	57.70	0.38	~
Inflation Austria	Macro environment	0.05	0.06	3.61	0.43	
Off-balance sheet growth	Excessive growth	0.05	0.02	0.60	0.67	

The table includes summary statistics over the 1,000 best models. It shows the posterior inclusion probability (PIP), i.e. the probability that the variable is selected, the posterior mean (Post Mean) and the posterior standard deviation (Post SD), i.e. the average coefficient and the average standard deviation of the coefficient over the considered models. 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. Variables showing an unexpected/ counterintuitive coefficient sign are marked with an asterisk (*), those with an unclear coefficient sign with a tilde ~. All variables are lagged by 4 quarters unless otherwise stated.

Some indicators on *mispricing of risk* are also important. The EURO STOXX Banks return index, lagged by eight quarters, is included in nearly all models. The same return index, lagged by four quarters, is selected in 9% of the models. The sign of the relation between the AFSI and the return index changes with the length of the lag: While the AFSI and the EURO STOXX Banks returns, lagged by eight quarters, are positively related, the AFSI and the return index, lagged by four quarters, are negatively associated. This in line with the pattern described in Drehmann et al (2011). Boom phases are positively correlated with high risks which seem to increase probability of crises two years later. However, from a short term perspective, a higher profitability improves banks' capitalization and helps them to withstand crises.

We also included a volatility measure, lagged by four and eight quarters: volatility of the EURO STOXX 50 index (VSTOXX). Again, the coefficient turns negative for shorter lags, indicating that the time dimension has to be carefully taken into account when using market based indicators for an early warning framework.

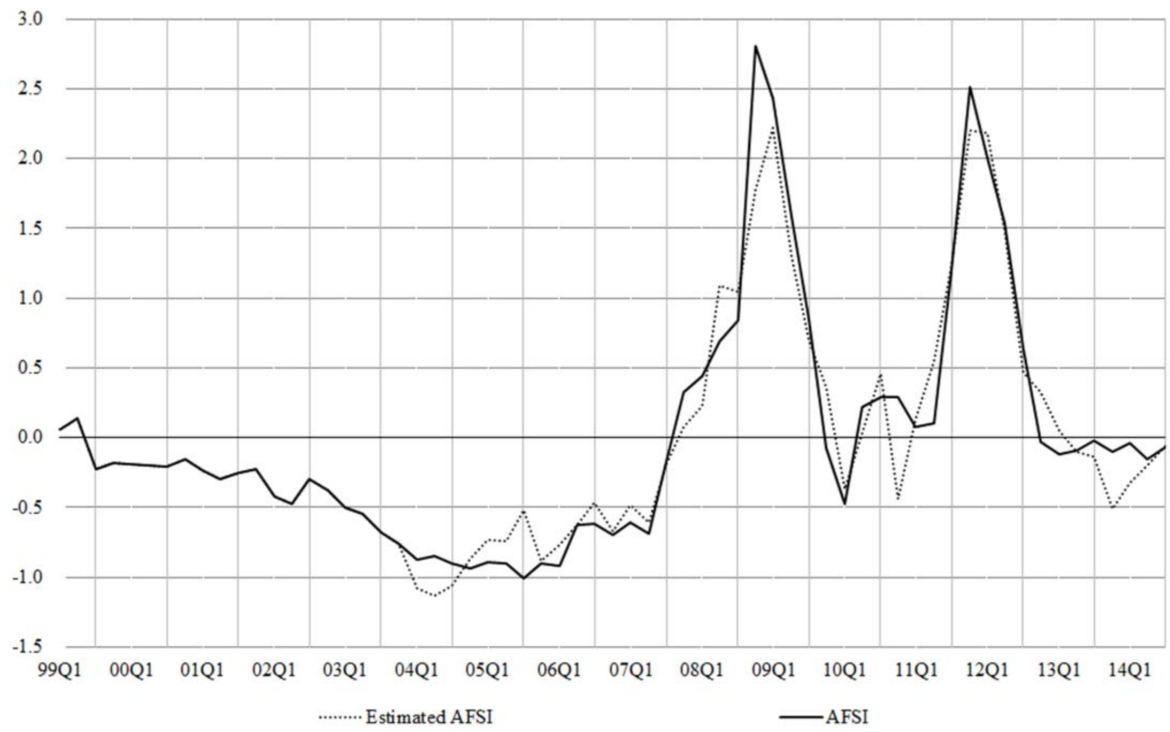
With respect to the *risk-bearing capacity* of banks, households and companies, the ratio of the loan to deposit rate turns out to be a very important predictor for financial stress. The variable is selected in nearly all models. We find a positive sign indicating that bank funding based on stable deposits contributes to financial stability. This result is in line with widespread evidence from the recent financial crisis of how important funding issues are. Other indicators are of lesser importance when explaining the AFSI. Average banks' ratings are selected in 34% of the considered models. Surprisingly, the ratio of household debt to disposable income variable is found to be negatively related to the AFSI. Overall 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. Moreover, the Tier 1 capital ratio also shows a counterintuitive (positive) sign, however the high post SD make the coefficients more or less insignificant. The positive sign may result from the fact that the banks especially hit by the crisis increased their capitalization more than average banks.

Regarding *interconnectedness*, interbank asset share carries a negative sign in explaining the AFSI. We interpret the negative sign as a confirmation of the – at least historically valid – thesis that a high share of interbank assets indicates positive market sentiment, i.e. a well-functioning (short-term) interbank market. However, strong interlinkages obviously posed a challenge to financial stability-oriented policymakers, as the high degree of interconnectedness in the banking system reinforced the financial shock waves following the bankruptcy of Lehman Brothers. *Concentration* risk (as measured by the ratio of large exposures to total assets) is not a relevant predictor for financial stress.

Finally, the variables covering the Austrian *macroeconomic environment* also appear to be less relevant as early warning indicators for Austrian financial stability than the variables assigned to the other risk channels. Among macroeconomic variables, the EU-27 GDP growth is one of the most important predictors (included in 34% of the models with a negative sign). This reflects the status of Austria as a small open market economy where financial stability is more driven by international financial developments than by the domestic macroeconomic environment. The lower importance of macro variables is also in line with evidence for advanced economies (see Section 3.2).

Figure 3 compares the estimated AFSI (with estimating starting in 2004Q1) and the realized AFSI. Overall the estimation fits well. However, the two spikes and the developments in 2010 are not captured to the full extent.

Figure 3: Estimated AFSI versus Realized AFSI



Source: own calculation

We use the 1,000 best models of the BMA procedure for assessing the six predefined systemic risk channels in order to limit model uncertainty. Our paper shows that, due to the complex nature of the interaction between the individual risk factors, it is necessary to look at a set of indicators simultaneously in order to account for the various risk drivers behind financial instability. Despite a high predictive power, we are acutely aware that some indicators which performed well during stressful periods for the Austrian financial system in 2008 and 2011 might not necessarily be equally important in predicting a future increase in the stress level. On the other hand, indicators covering real estate prices in Austria have not contributed to economically meaningful results so far. However, monitoring real estate developments will likely gain importance in the future. Hence, more broadly speaking, we have to understand that even the best models cannot exonerate us from subjective judgment in the interpretation of results.

The relative importance of international market variables reflects the status of Austria as a small open economy, which adds an additional layer of complexity to macroprudential analysis in Austria. As domestic exposure represents the largest part of Austrian banking assets, this paper's focus on domestic financial stability is well justified. Nevertheless, the Austrian financial system is significantly influenced by external sources. Global and European market developments, the economic situation of Austria's main trading partners and the high degree of Austrian financial intermediaries' exposure to the CESEE region affect financial stability in Austria. Local developments in other countries that could have a major impact on Austrian financial stability are beyond the scope of our current framework. As a consequence, macroprudential supervision should ensure that non-domestic indicators are monitored constantly in order to capture relevant external developments at an early stage.

4.3 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 and prior model sizes from the literature. Third, we augment our set of explanatory variables by adding lagged dependent variables.

For explaining the CISS index, we use the same set of variables as above although they are Austrian specific (see Table 3). The results for the CISS prediction are similar to our AFSI results in Table 2 except for concentration risk being now relevant for the CISS prediction. Similar to AFSI models the loan-to-deposit ratio and excessive credit growth are important early warning indicators.

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 and Potter (2004) (i.e. $g = \log(T)$)

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

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

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

Table 3: CISS Estimation Results

Variable	Risk channel	PIP	Post Mean	Post SD	Conditional Positive Sign	unexpected or unclear sign
Loan-to-deposit average	Risk-bearing capacity	0.98	7.60	1.66	1.00	
Ratio of large exposures to total assets	Concentration risk	0.97	-2.89	1.06	0.00	*
Total credit growth	Excessive growth	0.96	3.25	1.13	1.00	
Euro Stoxx banks return	Mispricing of risk	0.90	-0.24	0.12	0.00	
Ratio of household debt to disposable income	Risk-bearing capacity	0.38	-0.75	1.18	0.00	*
GDP EU-27	Macro environment	0.31	-1.17	2.14	0.01	
Banks' total assets-to-GDP ratio	Excessive growth	0.30	0.10	0.21	0.97	
Inflation Austria	Macro environment	0.27	1.42	2.72	1.00	
VSTOXX, lag 8	Mispricing of risk	0.23	0.10	0.21	0.98	
Growth gap between disposable income and housing prices	Macro environment	0.22	-0.14	0.31	0.00	*
Euro Stoxx banks return, lag 8	Mispricing of risk	0.20	0.03	0.06	1.00	
GDP Austria	Macro environment	0.16	0.32	1.66	0.70	
High yield bond spread	Mispricing of risk	0.16	0.00	0.01	0.12	
VSTOXX	Mispricing of risk	0.14	-0.04	0.16	0.10	
Bank's return on equity before tax	Risk-bearing capacity	0.13	-0.18	0.56	0.01	
Total credit-to-GDP gap	Excessive growth	0.13	-0.12	0.52	0.05	*
Net interest margin	Risk-bearing capacity	0.12	-2.85	17.89	0.22	~
Interbank asset share	Interconnectedness	0.10	-0.17	0.90	0.30	
Tier 1 Capital Ratio	Risk-bearing capacity	0.10	0.28	1.12	0.96	
Ratio of corporate debt to profit	Risk-bearing capacity	0.10	0.03	0.16	0.83	*
Total credit-to-GDP ratio	Excessive growth	0.09	0.00	0.01	0.90	
Customer loans growth	Excessive growth	0.09	-0.12	0.66	0.20	*
Total assets growth	Excessive growth	0.09	-0.04	0.27	0.30	*
Average of sentiment indicators (Fed. of A. Industries & A. Economic Chambers)	Macro environment	0.08	0.00	0.00	0.79	~
Bank ratings (average)	Risk-bearing capacity	0.08	0.00	0.04	0.52	
Off-balance sheet growth	Excessive growth	0.08	0.04	0.23	0.87	
Credit standards for loans to enterprises	Macro environment	0.06	-0.01	0.06	0.09	
Exchange rate volatility	Macro environment	0.06	-0.14	2.86	0.34	
Current account-to-GDP ratio	Macro environment	0.05	0.00	0.01	0.73	

The table includes summary statistics over the 1,000 best models. It shows the posterior inclusion probability (PIP), i.e. the probability that the variable is selected, the posterior mean (Post Mean) and the posterior standard deviation (Post SD), i.e. the average coefficient and the average standard deviation of the coefficient over the considered models. 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. Variables showing an unexpected/counterintuitive coefficient sign are marked with an asterisk (*), those with an unclear coefficient sign with a tilde ~. All variables are lagged by 4 quarters unless otherwise stated.

Table 4: AFSI Estimation Results: Posterior Inclusion Probability (PIP) with different g-Priors

	PIP BRIC Customk	PIP EBL Customk	PIP HQ Customk	PIP KoopPotter Customk	PIP RIC Customk	PIP UIP Customk
Total credit growth	1.00	1.00	1.00	0.91	1.00	1.00
Loan-to-deposit average	0.96	0.82	0.81	0.78	0.96	0.81
Euro Stoxx banks return, lag 8	0.95	0.95	0.97	0.73	0.95	0.96
Ratio of household debt to disposable income	0.52	0.52	0.50	0.50	0.52	0.51
Customer loans growth	0.46	0.56	0.58	0.49	0.46	0.58
GDP EU-27	0.41	0.51	0.51	0.46	0.41	0.50
Bank ratings (average)	0.34	0.30	0.28	0.38	0.34	0.28
Total credit-to-GDP ratio	0.33	0.50	0.51	0.43	0.33	0.50
Ratio of large exposures to total assets	0.22	0.62	0.63	0.50	0.22	0.64
Total credit-to-GDP gap	0.18	0.34	0.34	0.38	0.18	0.34
Growth gap between disposable income and housing prices	0.17	0.53	0.54	0.46	0.17	0.54
GDP Austria	0.17	0.34	0.31	0.41	0.16	0.32
Current account-to-GDP ratio	0.13	0.27	0.24	0.41	0.13	0.25
Ratio of corporate debt to profit	0.13	0.28	0.25	0.38	0.12	0.26
Banks' total assets-to-GDP ratio	0.13	0.45	0.44	0.46	0.13	0.45
VSTOXX, lag 8	0.12	0.40	0.38	0.40	0.12	0.39
Total assets growth	0.12	0.43	0.42	0.45	0.12	0.43
High yield bond spread	0.10	0.26	0.23	0.38	0.10	0.24
Euro Stoxx banks return	0.10	0.28	0.23	0.43	0.10	0.25
Credit standards for loans to enterprises	0.10	0.38	0.38	0.38	0.10	0.38
Exchange rate volatility	0.09	0.24	0.22	0.36	0.09	0.23
VSTOXX	0.09	0.24	0.21	0.38	0.09	0.22
Tier 1 Capital Ratio	0.07	0.26	0.24	0.38	0.07	0.25
Interbank asset share	0.07	0.31	0.29	0.38	0.06	0.30
Bank's return on equity before tax	0.07	0.21	0.17	0.36	0.07	0.19
Average of sentiment indicators (Fed. of A. Industries & A. Economic Chambers)	0.06	0.24	0.20	0.38	0.06	0.22
Net interest margin	0.06	0.25	0.22	0.39	0.06	0.24
Inflation Austria	0.05	0.23	0.20	0.36	0.06	0.21
Off-balance sheet growth	0.05	0.21	0.17	0.37	0.05	0.19

The table shows PIP values derived for different g-priors. Column PIP BRIC Customk contains the PIP of table 2 to simplify comparisons. PIP EBL Customk shows the results of the empirical Bayes criterion. PIP HQ Customk refers to the Hannan Quinn g-prios. The PIP KoopPotter Customk column reports the PIP for the g-prior by Koop and Potter. The PIP RIC Customk refers to the risk inflation criterion of George and Foster. Finally the UIP PIP shows the PIP for the unit information g-prior. For each variable (each row) the mean and the standard deviation over all PIPs (derived for the different g-priors) are calculated (not shown). PIPs outside the interval mean +/- one standard deviation are highlighted with a lighter shade.

Table 5: AFSI Estimation Results: Average Coefficients (Post Mean) with different g-Priors

	PIP BRIC Customk	PIP EBL Customk	PIP HQ Customk	PIP KoopPotter Customk	PIP RIC Customk	PIP UIP Customk
Total credit growth	26.77	27.13	27.88	18.98	26.80	27.63
Loan-to-deposit average	32.29	24.10	24.04	19.21	32.31	23.90
Euro Stoxx banks return, lag 8	1.28	1.29	1.34	0.82	1.28	1.32
Ratio of household debt to disposable income	-5.70	-5.05	-5.04	-4.05	-5.70	-5.11
Customer loans growth	-6.61	-8.41	-9.02	-5.22	-6.67	-8.85
GDP EU-27	-8.69	-10.62	-10.65	-7.64	-8.59	-10.56
Bank ratings (average)	0.13	0.04	0.04	0.03	0.14	0.04
Total credit-to-GDP ratio	0.04	0.05	0.06	0.03	0.04	0.05
Ratio of large exposures to total assets	-1.60	-7.42	-7.69	-4.51	-1.60	-7.75
Total credit-to-GDP gap	-1.15	-1.87	-2.02	-1.08	-1.12	-1.96
Growth gap between disposable income and housing prices	-0.53	-1.98	-2.09	-1.30	-0.53	-2.08
GDP Austria	-0.78	-1.64	-2.21	0.30	-0.87	-1.99
Current account-to-GDP ratio	0.02	0.03	0.03	0.04	0.02	0.03
Ratio of corporate debt to profit	0.15	0.32	0.32	0.22	0.13	0.34
Banks' total assets-to-GDP ratio	0.11	0.78	0.84	0.45	0.11	0.84
VSTOXX, lag 8	0.21	0.76	0.77	0.48	0.20	0.77
Total assets growth	-0.49	-2.31	-2.44	-1.83	-0.47	-2.42
High yield bond spread	-0.01	-0.00	-0.00	-0.00	-0.01	-0.00
Euro Stoxx banks return	-0.06	-0.12	-0.10	-0.22	-0.06	-0.11
Credit standards for loans to enterprises	-0.08	-0.36	-0.39	-0.23	-0.08	-0.39
Exchange rate volatility	-4.06	6.53	7.33	-0.50	-4.14	7.05
VSTOXX	-0.09	-0.14	-0.11	-0.30	-0.10	-0.13
Tier 1 Capital Ratio	0.49	2.86	2.88	3.04	0.48	2.91
Interbank asset share	-0.47	-3.22	-3.17	-2.57	-0.44	-3.24
Bank's return on equity before tax	-0.29	-0.64	-0.52	-0.81	-0.29	-0.55
Average of sentiment indicators (Fed. of A. Industries & A. Economic Chambers)	0.00	-0.00	-0.00	0.00	0.00	-0.00
Net interest margin	-2.02	14.26	16.86	-25.08	-2.08	17.90
Inflation Austria	0.06	1.21	1.37	0.69	0.09	1.29
Off-balance sheet growth	0.02	0.09	0.06	0.46	0.01	0.08

The table shows the corresponding average coefficients for Table 4, derived for different g-priors. Column PIP BRIC Customk contains the post mean value of table 2 to simplify comparisons. PIP EBL Customk shows the results of the empirical Bayes criterion. PIP HQ Customk refers to the Hannan Quinn g-prios. The PIP KoopPotter Customk column reports the post mean value for the g-prior by Koop and Potter. The PIP RIC Customk refers to the risk inflation criterion of George and Foster. Finally the UIP PIP shows the post mean value for the unit information g-prior. For each variable (each row) the mean and the standard deviation over all coefficients (derived for the different g-priors) are calculated (not shown). Coefficients outside the interval mean +/- one standard deviation are highlighted with a lighter shade.

Tables 4 and 5 show results for AFSI prediction. With respect to posterior inclusion probabilities (PIP) in Table 4, all g-priors deliver similar results to our previous output, except the KoopPotter Model assigns higher posterior inclusion probabilities to more variables. Tables 7 and 8 in the appendix provide results for CISS prediction. The same conclusions as for the AFSI can be drawn. Overall, our results are therefore relatively robust with respect to different g-priors.

In our next robustness check we investigate whether our results are influenced by prior model size. In Section 4.2, we assumed that all models are equally probable which corresponds to a uniform model size prior. We examine two alternative model size priors: i) a random model size prior which assumes all possible model sizes are a-priori equally likely and ii), a more informative model size prior as proposed by Sala-i-Martin et al. (2004). They specify a prior mean model size $\bar{k}$, with each variable having a prior probability $\bar{k}$/K of being included, independent of the inclusion of any other variable. We specify three different $\bar{k}$ with 7,10 and 15. Tables 6 (see below) and 9 (appendix) show results for AFSI and CISS, respectively. For both indices, it can be observed that models with a small number of predictors are preferred. Only three to four variables are selected with a high PIP. In most cases, PIP values for the important predictors do not change much. When using a random model size prior PIP values generally tend to decrease. Overall, it can thus be concluded that our results are robust with respect to the choice of the prior model size.

Finally, we check the robustness of our regressions by adding the lagged dependent variable to the set of predictors. We use the fourth lag (see Table 10). In comparison to our previous results (see Table 2), output does not change substantially. The lagged AFSI is selected only in 15% of all models and its coefficient is close to zero. This result shows that the AFSI is a useful contemporaneous stress index that is only explained to a small extent by its own past. For most other predictors the posterior means of the coefficients are similar to above.

In Table 11, we repeat this robustness check for the CISS index. The PIP of the lagged dependent variable is now considerably higher than that of the lagged AFSI in Table 10. This result is not surprising since the other predictors are Austrian specific and the CISS can thus be better explained by its own past. Again, in comparison to the output in Table 3, the posterior inclusion probabilities do not alter much.

Table 6: AFSI Estimation Results: Posterior Inclusion Probability (PIP) with alternative Model Size Priors

	PIP BRIC Customk	PIP BRIC Random	PIP BRIC Fixed 7	PIP BRIC Fixed 10	PIP BRIC Fixed 15
Total credit growth	1.00	1.00	1.00	1.00	1.00
Loan-to-deposit average	0.96	1.00	1.00	0.99	0.95
Euro Stoxx banks return, lag 8	0.95	0.39	0.75	0.89	0.95
Ratio of household debt to disposable income	0.52	0.18	0.43	0.53	0.51
Customer loans growth	0.46	0.10	0.22	0.33	0.48
GDP EU-27	0.41	0.06	0.15	0.27	0.44
Bank ratings (average)	0.34	0.15	0.34	0.39	0.33
Total credit-to-GDP ratio	0.33	0.06	0.12	0.20	0.34
Ratio of large exposures to total assets	0.22	0.02	0.05	0.10	0.24
Total credit-to-GDP gap	0.18	0.02	0.04	0.08	0.19
Growth gap between disposable income and housing prices	0.17	0.02	0.04	0.07	0.20
GDP Austria	0.17	0.03	0.06	0.10	0.17
Current account-to-GDP ratio	0.13	0.02	0.05	0.08	0.14
Ratio of corporate debt to profit	0.13	0.03	0.07	0.10	0.13
Banks' total assets-to-GDP ratio	0.13	0.01	0.03	0.05	0.14
VSTOXX, lag 8	0.12	0.01	0.03	0.05	0.13
Total assets growth	0.12	0.02	0.03	0.05	0.13
High yield bond spread	0.10	0.02	0.04	0.06	0.10
Euro Stoxx banks return	0.10	0.04	0.07	0.08	0.10
Credit standards for loans to enterprises	0.10	0.01	0.02	0.03	0.11
Exchange rate volatility	0.09	0.03	0.05	0.07	0.09
VSTOXX	0.09	0.02	0.05	0.06	0.09
Tier 1 Capital Ratio	0.07	0.02	0.03	0.05	0.08
Interbank asset share	0.07	0.01	0.02	0.03	0.07
Bank's return on equity before tax	0.07	0.02	0.03	0.05	0.07
Average of sentiment indicators (Fed. of A. Industries & A. Economic Chambers)	0.06	0.01	0.02	0.03	0.07
Net interest margin	0.06	0.01	0.02	0.03	0.07
Inflation Austria	0.05	0.01	0.02	0.03	0.06
Off-balance sheet growth	0.05	0.01	0.02	0.03	0.05

The table shows PIP values for different model size priors. Column PIP BRIC Customk contains the PIP of table 2 to simplify comparisons. PIP BRIC Random shows PIP values derived under the assumption that all model sizes are a-priori equally likely. In the columns PIP BRIC Fixed 7, 10 and 15 a prior mean model size of 7,10 and 15 variables is assumed, respectively. For each variable (each row) the mean and the standard deviation over all PIPs (derived for alternative model size priors) are calculated (not shown). PIPs outside the interval mean +/- one standard deviation are highlighted with a lighter shade.

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 lagged dependent variables. Moreover, this robustness is not caused by the AFSI construction since CISS estimation also delivers robust results.

5 Application for Macroprudential Policy

Macroprudential policy is a relatively new area, especially in Europe. The Basel III Capital Accord, implemented in the EU by CRD IV and CRR, lays the foundations for several macroprudential instruments. CRD IV and CRR state for which type of risks instruments are provided. For instance, the countercyclical capital buffer should deal with risks related to excessive credit growth. Since CRD IV and CRR are rather general, national macroprudential supervisors are now in the process of developing instruments that are tailored specifically to the needs of their country. The implementation of the new regulation also includes finding the best indicators for the decision to use instruments and to determine the size of the instrument.

Our approach may be helpful in this context. 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. Updating stress events is therefore easier. Moreover, our approach also delivers early warning indicators for stress at lower levels which may not lead to financial crises but still cause considerable welfare losses.

Second, our approach delivers a ranking of risk factors and helps to identify the relevant areas in which macroprudential instruments are needed. Our results suggest that excessive credit growth and unstable funding of banks are key risk drivers for the Austrian financial system. This underlines the importance of the countercyclical capital buffer (which addresses vulnerabilities from excessive credit growth) and the net stable funding ratio (which is in the process of being formulated). Another example are measures according to section 458 of the CRR. This section allows a broad range of macroprudential measures at the national level which go beyond mandatory pillar 1 requirements for Basel III implementation in the EU. Stricter regulations may be applied to interbank exposures, real estate loans and large loans. Our approach helps macroprudential supervisors to decide whether and which measures should be taken pursuant to section 458 of the CRR.

Third, our approach may also be used in the design of macroprudential instruments. In order to implement macroprudential instruments, indicators are needed that deliver the signal to put the instrument on or off and to calibrate the size of the instrument. For instance, for the design of the countercyclical capital buffer our analysis shows that a broad measure of excessive credit growth is superior to more narrow ones. Therefore, decisions on the size of the buffer should be based on a broad credit growth indicator. Moreover, in the medium term, our approach can also be extended to analyze appropriate indicators for other instuments as well.

For instance, we can investigate the predictive power of various indicators for the net-stable-funding ratio.

6 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 identify developments in the Austrian financial system as measured by the AFSI. We find that excessive credit growth and high returns of bank stocks are the best early warning indicators. Unstable funding of banks (measured by the loan to deposit ratio) also has high predictive power. However, macroeconomic indicators – except for the EU-27 GDP growth – are less relevant.

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 missspecification since they reflect a large number of models.

Our approach may also be used for macroprudential supervision. We identify key risk factors which help regulators to decide where to put particular effort. Moreover, 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. Decisions on the size of the buffer should therefore be connected with a broad indicator.

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Table 7: CISS Estimation Results: Posterior Inclusion Probability (PIP) with different g-Priors

	PIP BRIC Customk	PIP EBL Customk	PIP HQ Customk	PIP KoopPotter Customk	PIP RIC Customk	PIP UIP Customk
Total credit growth	0.96	0.87	0.87	0.71	0.95	0.88
Loan-to-deposit average	0.98	0.89	0.88	0.85	0.98	0.89
Euro Stoxx banks return, lag 8	0.20	0.46	0.43	0.47	0.20	0.45
Ratio of household debt to disposable income	0.38	0.60	0.60	0.51	0.38	0.60
Customer loans growth	0.09	0.34	0.33	0.40	0.10	0.33
GDP EU-27	0.31	0.41	0.39	0.45	0.30	0.40
Bank ratings (average)	0.08	0.33	0.32	0.40	0.08	0.32
Total credit-to-GDP ratio	0.09	0.32	0.30	0.40	0.09	0.29
Ratio of large exposures to total assets	0.97	0.97	0.99	0.76	0.97	0.98
Total credit-to-GDP gap	0.13	0.34	0.33	0.40	0.13	0.32
Growth gap between disposable income and housing prices	0.22	0.56	0.58	0.48	0.22	0.57
GDP Austria	0.16	0.33	0.31	0.40	0.16	0.32
Current account-to-GDP ratio	0.05	0.20	0.16	0.39	0.05	0.18
Ratio of corporate debt to profit	0.10	0.37	0.37	0.41	0.10	0.37
Banks' total assets-to-GDP ratio	0.30	0.60	0.62	0.49	0.30	0.61
VSTOXX, lag 8	0.23	0.34	0.32	0.39	0.23	0.33
Total assets growth	0.09	0.32	0.30	0.41	0.09	0.31
High yield bond spread	0.16	0.31	0.30	0.38	0.15	0.30
Euro Stoxx banks return	0.90	0.76	0.80	0.60	0.90	0.78
Credit standards for loans to enterprises	0.06	0.32	0.31	0.38	0.07	0.31
Exchange rate volatility	0.06	0.24	0.21	0.36	0.05	0.22
VSTOXX	0.14	0.25	0.21	0.37	0.14	0.23
Tier 1 Capital Ratio	0.10	0.28	0.26	0.38	0.10	0.27
Interbank asset share	0.10	0.37	0.38	0.37	0.11	0.37
Bank's return on equity before tax	0.13	0.26	0.23	0.38	0.13	0.24
Average of sentiment indicators (Fed. of A. Industries & A. Economic Chambers)	0.08	0.27	0.24	0.40	0.08	0.25
Net interest margin	0.12	0.26	0.22	0.41	0.12	0.24
Inflation Austria	0.27	0.47	0.45	0.45	0.27	0.47
Off-balance sheet growth	0.08	0.27	0.23	0.40	0.07	0.24

The table shows PIP values derived for different g-priors. Column PIP BRIC Customk contains the PIP of table 3 to simplify comparisons. PIP EBL Customk shows the results of the empirical Bayes criterion. PIP HQ Customk refers to the Hannan Quinn g-prios. The PIP KoopPotter Customk column reports the PIP for the g-prior by Koop and Potter. The PIP RIC Customk refers to the risk inflation criterion of George and Foster. Finally the UIP PIP shows the PIP for the unit information g-prior. For each variable (each row) the mean and the standard deviation over all PIPs (derived for the different g-priors) are calculated (not shown). PIPs outside the interval mean +/- one standard deviation are highlighted with a lighter shade.

Table 8: CISS Estimation Results: Average Coefficients (Post Mean) with different g-Priors

	PIP BRIC Customk	PIP EBL Customk	PIP HQ Customk	PIP KoopPotter Customk	PIP RIC Customk	PIP UIP Customk
Total credit growth	3.25	2.93	2.92	2.00	3.24	2.97
Loan-to-deposit average	7.60	5.69	5.66	4.76	7.59	5.73
Euro Stoxx banks return, lag 8	0.03	0.06	0.06	0.06	0.03	0.06
Ratio of household debt to disposable income	-0.75	-1.30	-1.34	-0.86	-0.76	-1.33
Customer loans growth	-0.12	-0.70	-0.83	-0.18	-0.14	-0.74
GDP EU-27	-1.17	-1.45	-1.36	-1.21	-1.15	-1.41
Bank ratings (average)	-0.00	-0.04	-0.05	-0.02	-0.00	-0.04
Total credit-to-GDP ratio	0.00	0.00	0.00	0.00	0.00	0.00
Ratio of large exposures to total assets	-2.89	-3.83	-4.01	-2.26	-2.90	-3.93
Total credit-to-GDP gap	-0.12	-0.16	-0.08	-0.28	-0.11	-0.15
Growth gap between disposable income and housing prices	-0.14	-0.45	-0.49	-0.28	-0.14	-0.46
GDP Austria	0.32	0.05	0.12	-0.08	0.32	0.08
Current account-to-GDP ratio	0.00	0.00	0.00	0.01	0.00	0.00
Ratio of corporate debt to profit	0.03	0.19	0.22	0.08	0.04	0.20
Banks' total assets-to-GDP ratio	0.10	0.30	0.34	0.13	0.10	0.32
VSTOXX, lag 8	0.10	0.11	0.11	0.06	0.10	0.11
Total assets growth	-0.04	-0.25	-0.24	-0.22	-0.04	-0.25
High yield bond spread	-0.00	-0.00	-0.01	0.00	-0.00	-0.00
Euro Stoxx banks return	-0.24	-0.19	-0.20	-0.12	-0.24	-0.19
Credit standards for loans to enterprises	-0.01	-0.07	-0.08	-0.04	-0.01	-0.07
Exchange rate volatility	-0.14	1.65	1.68	0.36	-0.12	1.66
VSTOXX	-0.04	-0.01	-0.01	-0.00	-0.04	-0.01
Tier 1 Capital Ratio	0.28	0.78	0.74	0.77	0.29	0.74
Interbank asset share	-0.17	-0.99	-1.18	-0.37	-0.20	-1.06
Bank's return on equity before tax	-0.18	-0.22	-0.20	-0.25	-0.17	-0.21
Average of sentiment indicators (Fed. of A. Industries & A. Economic Chambers)	0.00	0.00	0.00	0.00	0.00	0.00
Net interest margin	-2.85	3.19	3.42	-7.33	-2.85	3.88
Inflation Austria	1.42	2.27	2.23	1.62	1.42	2.31
Off-balance sheet growth	0.04	0.13	0.11	0.17	0.04	0.12

The table shows the corresponding average coefficients for Table 6, derived for different g-priors. Column PIP BRIC Customk contains the post mean value of table 3 to simplify comparisons. PIP EBL Customk shows the results of the empirical Bayes criterion. PIP HQ Customk refers to the Hannan Quinn g-prios. The PIP KoopPotter Customk column reports the post mean value for the g-prior by Koop and Potter. The PIP RIC Customk refers to the risk inflation criterion of George and Foster. Finally the UIP PIP shows the post mean value for the unit information g-prior. For each variable (each row) the mean and the standard deviation over all coefficients (derived for the different g-priors) are calculated (not shown). Coefficients outside the interval mean +/- one standard deviation are highlighted with a lighter shade.

Table 9: CISS Estimation Results: Posterior Inclusion Probability (PIP) with alternative Model Size Priors

	PIP BRIC Customk	PIP BRIC Random	PIP BRIC Fixed 7	PIP BRIC Fixed 10	PIP BRIC Fixed 15
Loan-to-deposit average	0.98	1.00	1.00	1.00	0.98
Ratio of large exposures to total assets	0.97	0.97	0.97	0.97	0.98
Total credit growth	0.96	0.96	0.96	0.96	0.96
Euro Stoxx banks return	0.90	0.96	0.96	0.94	0.90
Ratio of household debt to disposable income	0.38	0.07	0.09	0.18	0.40
GDP EU-27	0.31	0.06	0.08	0.17	0.32
Banks' total assets-to-GDP ratio	0.30	0.04	0.05	0.12	0.32
Inflation Austria	0.27	0.09	0.11	0.18	0.28
VSTOXX, lag 8	0.23	0.06	0.08	0.14	0.24
Growth gap between disposable income and housing prices	0.22	0.05	0.06	0.11	0.23
Euro Stoxx banks return, lag 8	0.20	0.04	0.05	0.09	0.21
GDP Austria	0.16	0.02	0.03	0.06	0.16
High yield bond spread	0.16	0.02	0.03	0.08	0.17
VSTOXX	0.14	0.04	0.06	0.10	0.14
Bank's return on equity before tax	0.13	0.04	0.05	0.09	0.13
Total credit-to-GDP gap	0.13	0.03	0.04	0.07	0.14
Net interest margin	0.12	0.03	0.04	0.08	0.12
Interbank asset share	0.10	0.02	0.02	0.04	0.12
Tier 1 Capital Ratio	0.10	0.02	0.03	0.05	0.11
Ratio of corporate debt to profit	0.10	0.02	0.02	0.04	0.11
Total credit-to-GDP ratio	0.09	0.01	0.02	0.04	0.10
Customer loans growth	0.09	0.01	0.02	0.04	0.10
Total assets growth	0.09	0.02	0.02	0.04	0.09
Average of sentiment indicators (Fed. of A. Industries & A. Economic Chambers)	0.08	0.01	0.02	0.04	0.09
Bank ratings (average)	0.08	0.01	0.02	0.03	0.09
Off-balance sheet growth	0.08	0.01	0.02	0.03	0.08
Credit standards for loans to enterprises	0.06	0.01	0.01	0.03	0.07
Exchange rate volatility	0.06	0.01	0.02	0.03	0.06
Current account-to-GDP ratio	0.05	0.02	0.02	0.03	0.06

The table shows PIP values for different model size priors. Column PIP BRIC Customk contains the PIP of table 3 to simplify comparisons. PIP BRIC Random shows PIP values derived under the assumption that all model sizes are a-priori equally likely. In the columns PIP BRIC Fixed 7, 10 and 15 a prior mean model size of 7,10 and 15 variables is assumed, respectively. For each variable (each row) the mean and the standard deviation over all PIPs (derived for alternative model size priors) are calculated (not shown). PIPs outside the interval mean +/- one standard deviation are highlighted with a lighter shade.

Table 10: AFSI Estimation Results with Lagged Dependent Variable (Lag 4)

Variable	Risk channel	PIP	Post Mean	Post SD	Cond.Pos. Sign	
Total credit growth	Excessive growth	1.00	26.57	6.12	1.00	
Loan-to-deposit average	Risk-bearing capacity	0.97	32.74	9.08	1.00	
Euro Stoxx banks return, lag 8	Mispricing of risk	0.92	1.23	0.50	1.00	
Ratio of household debt to disposable income	Risk-bearing capacity	0.53	-6.01	6.46	0.00	*
Customer loans growth	Excessive growth	0.42	-5.91	8.02	0.01	*
GDP EU-27	Macroeconomic environment	0.40	-8.16	12.08	0.01	
Bank ratings (average)	Risk-bearing capacity	0.37	0.15	0.24	0.97	
Total credit-to-GDP ratio	Excessive growth	0.30	0.03	0.06	1.00	
Ratio of large exposures to total assets	Concentration risk	0.19	-1.38	3.63	0.02	*
Total credit-to-GDP gap	Excessive growth	0.17	-1.07	2.81	0.01	*
Growth gap between disposable income and housing prices	Macroeconomic environment	0.16	-0.48	1.31	0.00	*
GDP Austria	Macroeconomic environment	0.16	-0.75	10.39	0.29	
AFSI, Lag 4	Lagged Dependent Variable	0.15	-0.04	0.14	0.04	
Euro Stoxx banks return	Mispricing of risk	0.14	-0.13	0.43	0.09	
Ratio of corporate debt to profit	Risk-bearing capacity	0.12	0.13	0.62	0.77	*
Banks' total assets-to-GDP ratio	Excessive growth	0.12	0.11	0.64	0.63	
Current account-to-GDP ratio	Macroeconomic environment	0.12	0.02	0.07	0.94	
VSTOXX, lag 8	Mispricing of risk	0.11	0.19	0.68	0.98	
Total assets growth	Excessive growth	0.11	-0.42	1.73	0.11	*
Credit standards for loans to enterprises	Macroeconomic environment	0.09	-0.08	0.31	0.06	
High yield bond spread	Mispricing of risk	0.09	0.00	0.03	0.21	
Exchange rate volatility	Macroeconomic environment	0.09	-4.31	21.36	0.11	
VSTOXX	Mispricing of risk	0.09	-0.10	0.67	0.17	
Interbank asset share	Interconnectedness	0.07	-0.69	3.71	0.08	
Tier 1 Capital Ratio	Risk-bearing capacity	0.07	0.51	4.07	0.65	
Average of sentiment indicators (Fed. of A. Industries & A. Economic Chambers)	Macroeconomic environment	0.07	0.00	0.00	0.63	~
Bank's return on equity before tax	Risk-bearing capacity	0.07	-0.30	1.64	0.05	
Net interest margin	Risk-bearing capacity	0.06	-2.97	59.82	0.35	~
Inflation Austria	Macroeconomic environment	0.05	0.08	3.37	0.46	
Off-balance sheet growth	Excessive growth	0.05	0.01	0.61	0.65	

The table includes summary statistics for estimating the AFSI under the restriction that the lagged AFSI is included as explanatory variable. 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 posterior mean (Post Mean) and the posterior standard deviation (Post SD), i.e. the average coefficient and the average standard deviation of the coefficient over the considered models. The column conditional positive sign (Cond. Pos. 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. Variables showing an unexpected/counterintuitive coefficient sign are marked with an asterisk (*), those with an unclear coefficient sign with a tilde ~. All variables are lagged by 4 quarters unless otherwise stated.

Table 11: CISS Estimation Results with Lagged Dependent Variable (Lag 4)

Variable	Risk channel	PIP	Post Mean	Post SD	Cond.Pos. Sign	
Loan-to-deposit average	Risk-bearing capacity	0.99	7.62	1.53	1.00	
Ratio of large exposures to total assets	Concentration risk	0.97	-2.76	1.01	0.00	*
Total credit growth	Excessive growth	0.95	3.18	1.14	1.00	
Euro Stoxx banks return	Mispricing of risk	0.82	-0.22	0.13	0.00	
Ratio of household debt to disposable income	Risk-bearing capacity	0.41	-0.78	1.15	0.00	*
GDP EU-27	Macroeconomic environment	0.28	-1.07	2.11	0.01	
Euro Stoxx banks return, lag 8	Mispricing of risk	0.27	0.05	0.09	1.00	
Banks' total assets-to-GDP ratio	Excessive growth	0.25	0.07	0.17	0.96	
Inflation Austria	Macroeconomic environment	0.25	1.28	2.62	0.99	
Growth gap between disposable income and housing prices	Macroeconomic environment	0.22	-0.14	0.31	0.00	*
VSTOXX, lag 8	Mispricing of risk	0.22	0.09	0.21	0.98	
CISS, Lag 4	Lagged Dependent Variable	0.17	0.07	0.21	0.94	
GDP Austria	Macroeconomic environment	0.15	0.39	1.85	0.73	
High yield bond spread	Mispricing of risk	0.15	0.00	0.01	0.11	
VSTOXX	Mispricing of risk	0.14	-0.05	0.17	0.08	
Total credit-to-GDP gap	Excessive growth	0.14	-0.16	0.50	0.01	*
Bank's return on equity before tax	Risk-bearing capacity	0.12	-0.16	0.54	0.01	
Total credit-to-GDP ratio	Excessive growth	0.11	0.00	0.01	0.96	
Net interest margin	Risk-bearing capacity	0.11	-2.56	17.15	0.23	~
Tier 1 Capital Ratio	Risk-bearing capacity	0.11	0.32	1.20	0.96	
Ratio of corporate debt to profit	Risk-bearing capacity	0.10	0.03	0.13	0.85	*
Customer loans growth	Excessive growth	0.09	-0.11	0.56	0.18	*
Interbank asset share	Interconnectedness	0.09	-0.12	0.74	0.34	
Total assets growth	Excessive growth	0.08	-0.03	0.22	0.31	*
Average of sentiment indicators (Fed. of A. Industries & A. Economic Chambers)	Macroeconomic environment	0.08	0.00	0.00	0.78	~
Bank ratings (average)	Risk-bearing capacity	0.07	0.00	0.02	0.60	
Off-balance sheet growth	Excessive growth	0.07	0.03	0.20	0.82	
Current account-to-GDP ratio	Macroeconomic environment	0.06	0.00	0.01	0.77	
Exchange rate volatility	Macroeconomic environment	0.05	-0.19	2.82	0.29	
Credit standards for loans to enterprises	Macroeconomic environment	0.05	0.00	0.04	0.12	

The table includes summary statistics for estimating the CISS under the restriction that the lagged CISS is included as explanatory variable. 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 posterior mean (Post Mean) and the posterior standard deviation (Post SD), i.e. the average coefficient and the average standard deviation of the coefficient over the considered models. The column conditional positive sign (Cond. Pos. 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. Variables showing an unexpected/counterintuitive coefficient sign are marked with an asterisk (*), those with an unclear coefficient sign with a tilde ~. All variables are lagged by 4 quarters unless otherwise stated.