Quantifying Financial Stability in Austria – New Tools for Macroprudential Supervision

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This paper's objective is to contribute to the evolving field of macroprudential supervision in Austria in a twofold way: First, we construct an Austrian financial stress index (AFSI) that quantifies the level of stress in the Austrian financial market. Second, drawing on supervisory, market-based and macroeconomic data for the period from 2000 to 2012, we examine various indicators regarding their predictive power for this stress index. These indicators are categorized to cover the following six risk channels that affect financial stability: risk-bearing capacity, mispricing of risk, excessive growth, interconnectedness, concentration, and the macroeconomic environment and its outlook. In our empirical analysis we apply state-of-the-art econometrics including best subset selection, Kalman filters and model averaging. Our results indicate that, as risk channels, excessive growth, interconnectedness and mispricing of risk have the greatest influence on the AFSI. Furthermore, our findings lead to the conclusion that the complexities of risk channel interactions render univariate analysis and/or stand-alone models ineffective for financial stability-oriented policymaking. Instead, an integrated analysis of different indicators turns out to be the more promising approach when trying to identify the buildup of systemic risk.

JEL classification: G01 G28
Keywords: Financial crisis, government policy and regulation

With the global financial crisis, macroprudential supervisors have intensified their efforts to identify systemic vulnerabilities and to predict financial instability. Detecting early warning signs in the financial system, such as price bubbles or a high degree of interdependency, is essential to avoid further crises and the resulting huge welfare losses. The excessive rise of property prices (to the extent of property price bubbles) in the United States and beyond as well as certain risks amplified by market participants' increasing interconnectedness show that early warning signals had already been present before the current crisis emerged. In the wake of the current crisis, the number of contributions to the literature on systemic risk has recently increased significantly, covering topics from predicting systemic risk events (e.g. Lo Duca and Peltonen, 2011; Arsov et al., 2013; Blancher et al., 2013) to policy instruments mitigating the buildup of financial instability (e.g. Lim et al., 2011; CGFS, 2012).

This paper contributes to the growing body of literature in an empirical manner. First, we support macroprudential supervision in Austria by constructing a composite financial stress index that quantifies the current strength of Austrian financial stability – the Austrian financial stress index (AFSI). Second, we develop a model to predict financial distress by examining several indicators with respect to their early warning capability, as measured by their power to forecast the AFSI. In this way, this paper helps identify future financial stability risks and, in doing so, contributes to fulfilling the forthcoming responsibilities of macroprudential supervision.[2]

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[2] *The Capital Requirements Directive IV (CRD IV) and the Capital Requirements Regulation (CRR) define a new role for macroprudential supervision. This paper aims at contributing to the analytical framework of future macroprudential policy.*

Refereed by:
Petr Jakubík, EIOPA

Holló et al. (2012) and Jakubík and Slačík (2013) provide recent examples of how to construct composite financial stress indices by using various subindices. For early warning models, the empirical literature follows multiple approaches. We classify these as follows: (1) the signal extraction approach, (2) the probabilistic approach and (3) the index-based approach.

The signal extraction approach (1) was made popular by Kaminsky and Reinhart (1999), who follow this approach to analyze twin crises – the links between banking and currency crises. They define a banking crisis by the emergence of bank runs that lead to the closure, merging or takeover by the public sector of one or more financial institutions. If there are no bank runs, a banking crisis is defined by the closure, merging or takeover of, or large-scale government assistance to, important financial institutions. The authors analyze a sample of 20 countries, which includes 26 banking crises and 76 currency crises according to their definition. Their model sets threshold values for various indicators covering developments of the financial, real and public sectors as well as foreign trading. Borio and Drehmann (2009) also apply the signal extraction method when they assess the risk of banking crises. Similar to Kaminsky and Reinhart (1999), they define a crisis by government interventions (capital injections, wholesale guarantees, recapitalization program) or the failure of large banks. They test the credit-to-GDP gap, property price gap and equity price gap as early warning indicators and find the credit-to-GDP gap to be the most useful indicator of systemic risk. Alessi and Detken (2009) apply the signal extraction approach to identify asset price boom-bust cycles.

The probabilistic approach (2) is based on a multivariate logit model. Demirgüç-Kunt and Detragiache (1998) estimate the probability of a banking crisis for 65 countries over the period from 1980 to 1994. Their definition of a banking crisis is in a way similar to that of Kaminsky and Reinhart (1999), as they set their crisis dummy to zero if there is no crisis and to a value of one during a crisis.[3] They conclude that a weak macroeconomic environment (particularly with low growth and high inflation) contributes significantly to producing a systemic banking crisis. Lund-Jensen (2012) developed this approach further by designing a dynamic model that monitors systemic risk on the basis of real-time data.

In contrast to the signal extraction and the probabilistic approach, 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 (28 emerging market economies and advanced economies) to predict systemic events as quantified by their financial stress index (FSI). Jakubík and Slačík (2013) choose a similar approach for nine CESEE countries.

In this paper, we follow the third approach as the former two rely on the ex-post classification of crisis periods, which limits their predictive power. Our empirical analysis is based on a

[3] *For the purpose of this study, a banking crisis is deemed to be evident when one of the following predefined conditions holds: nonperforming assets exceed 10% of total assets in the banking system; the costs of rescue operations are higher than 2% of GDP; banks are nationalized on a large scale because of banking sector problems; extensive bank runs occur or emergency measures have to be taken.*

continuous composite financial stress index for Austria (AFSI, see section 2), which allows for measuring the impact of the global financial crisis on the Austrian financial system. Potential early warning indicators are assigned to one of six risk channels (see section 3.1).

For identifying early warning indicators with high predictive power, we choose a new approach that is different to those used in the papers mentioned above (see section 3.3). First, we apply a best subset selection mechanism to find the best indicators for each given model size. Second, to address the variance-versus-bias tradeoff, we run a Kalman filter-based expected maximization algorithm to find the minimum model size. Third, in order to reduce model uncertainty, we use model-averaging techniques for the selected models in the previous two steps. In addition, this last step reflects our opinion that focusing on one single best model in macroprudential policy could result in misleading risk assessment.

In section 4, we present our results including a two-year out-of-sample forecasting exercise and policy implications derived from the empirical findings. Finally, section 5 concludes.

1 The Austrian Financial Stress Index (AFSI)

Quantifying financial stability to measure financial soundness plays an increasingly important role in macroprudential supervision. Since the IMF published its first list of core indicators (IMF Financial Soundness Indicators – FSIs) in 2001, other leading supranational authorities have followed suit. Most recently, in the euro area, Holló et al. (2012) constructed the Composite Indicator of Systemic Stress (CISS), an index that focuses on specific characteristics of the euro area financial system.

1.1 AFSI Construction

In general, contemporaneous financial soundness indices allow for gauging the current strength of the financial system. In order to obtain an index that can be used for real-time monitoring, market-based indicators are required 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-based indicators have their drawbacks as they not only reflect the current market situation but market sentiment as well. However, as expectations materialize, e.g. through prices, market data do indeed mirror the buildup of longer-term structural imbalances (and their quick unraveling).

The above-mentioned properties of market-based indicators can be put to good use for constructing a real-time index. Ideally, such an index should reflect the soundness of the financial system as a whole as potential imbalances in the complex structure of financial systems with interconnected subsegments and agents (e.g. banks, insurance companies, governments, etc.) may influence the real economy, causing welfare losses. Therefore, similarly to Holló et al. (2012), Lo Duca and Peltonen (2011) and Jakubík and Slačík (2013), 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. A higher AFSI signals periods of imbalances in the financial system, peaking during times of acute financial distress.

We test various indices with regard to their suitability as AFSI constituents to see whether they comply with our criteria to best reflect (past) periods of financial distress. At the same time the

AFSI should be as simple as possible, so subindices with little or no additional explanatory power to the financial distress developments were not included. Following our analysis, we divide the equity market into three subindices (ATX[4] return, ATX volatility and Datastream Austrian Financials return[5]). ATX returns are negatively related to the AFSI, i.e. higher equity returns indicate a lower level of tension in the equity market. Equity volatilities, however, tend to rise with investors' uncertainty, hence increasing ATX 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] in the ASFI. As investors demand additional compensation for risky investments, the spread between the collateralized and uncollateralized interbank interest rate tends to increase substantially during periods of stress. Hence, if the EURIBOR-EUREPO spread decreases, the AFSI decreases as well. Finally, as the sovereign bond market represents one 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]

To summarize (see table 1), five components are included in the AFSI: the ATX year-on-year return, the Datastream Austrian Financials year-on-year 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.

Unfortunately, the literature does not agree on one single method how to aggregate the variables of a composite index. Moreover, Illing and Liu (2003) have identified various shortcomings of the different approaches currently in use.

Table 1

AFSI Components

Segments	Equity market	Money market	Sovereign bond market
Weights	1/3	1/3	1/3
Components (equally weighted)	• ATX year-on-year return • Datastream Austrian Financials year-on-year return • Realized ATX volatility	• Three-month EURIBOR-EUREPO spread	• Spread of Austrian ten-year government benchmark bond yields over German ten-year government bond yields

Source: OeNB.

[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] *The AFSI including the volatility of the EURIBOR-EUREPO spread and of the spread between Austrian and German ten-year government benchmark bond yields shows a correlation of 0.99 with the AFSI not including these two volatility measures. Therefore, we do not include these volatility subindices in the AFSI. Furthermore, developments in the Austrian foreign exchange markets are not included in the AFSI, either, because the realized foreign exchange rate volatility based on a basket of the currencies of Austria's nine most important trading partners (excluding the euro area countries) shows high fluctuations over time without clearly indicating tense periods.*

[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.*

One frequently applied option (which is e.g. used for constructing the CISS) is the transformation – based on a cumulative distribution function (CDF) – of variables so that they can be aggregated into one index within which each variable is ranked and divided by the number of observations in the sample.[9] The transformed variables are unit-free and measured on an ordinal scale in a range between 0 and 1, which makes interpretation easier. However, this approach assumes equal distance between any two successively ranked observations. This distorts any subsequent econometric analysis as the distances of observations of the dependent variable are a major driver of estimation results.[10] For a stress index in particular, the difference between peaks and average observations signals the level of tension during a crisis. Furthermore, stress might be overestimated during prolonged periods of financial stability when subsequent low index readings appear more volatile according to the CDF transformation ranking than they actually are. Considering these disadvantages, we are in line with Islami and Kurz-Kim (2013) in choosing an alternative approach. We standardize the subindices in the AFSI by variance-equal weighting: The arithmetic mean is subtracted from each variable before it is divided by its standard deviation.[11] This maps the AFSI to an interval scale, which shows that the distance between two observations – unlike in the case of a CDF transformation – does indeed carry information.

1.2 Financial (In)Stability as Indicated by the AFSI (for Austria) and the CISS (for the Euro Area)

The AFSI and the CISS differ in their construction and scaling, which means that their comparability is limited. Nevertheless, developments of financial stress and stability – as indicated by both indices – are found to be very similar in Austria and the euro area, as chart 1 shows. The AFSI remains below zero – indicating no financial stress in Austria – between 1999 and 2007. Similarly, the CISS signals financial stability in the euro area for the same period. Both indices are at their lowest levels between 2004 and 2005. However, we can observe higher fluctuations for the CISS than for the AFSI. These appear to be a result of the equal distance rank-based CDF method used for CISS construction (see previous section). Financial stress starts to build up in 2007, with CISS readings briefly jumping ahead of the AFSI values until both indices peak in the fourth quarter of 2008. This indicates that in the initial phase of the subprime crisis, financial stability was less impacted in Austria than in the euro area. However, the international market turmoil following the bankruptcy of Lehman Brothers in September 2008 had an immediate impact on both Austria and the euro area. The increase in the stress level following a short recovery indicates the European sovereign debt crises, with both indices peaking again in the fourth quarter of 2011. Surprisingly, the CISS shows significantly less

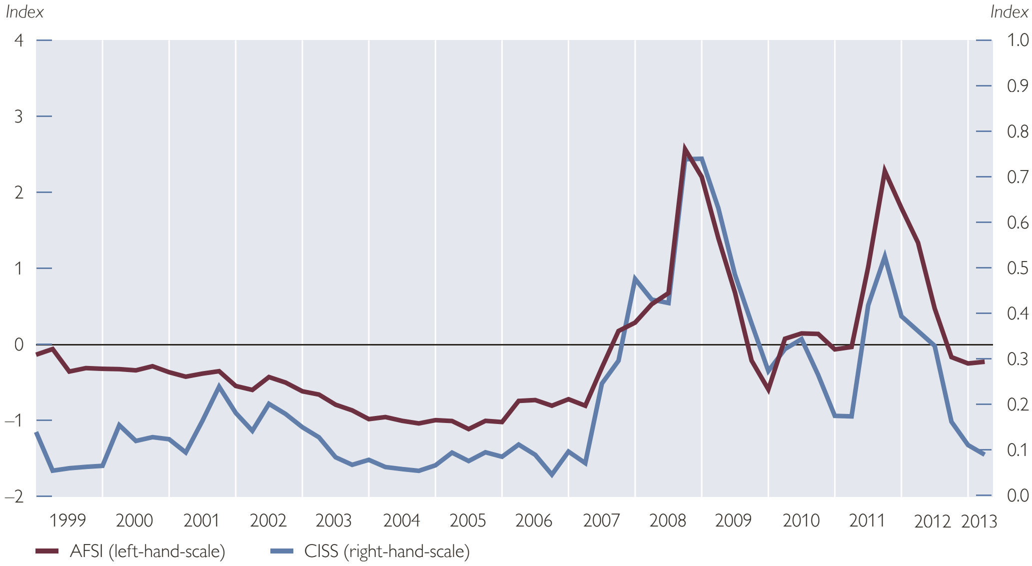
[9] *A variation of the CDF approach is quantile transformation, where each indicator is mapped into quantiles. This approach has advantages when dealing with outliers, but is less suitable in our case for the continuous monitoring of the Austrian data set.*

[10] *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.*

[11] *The trade-off of this approach is that it requires the assumption of normally distributed subindices.*

Chart 1

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



Source: OeNB, ECB.

instability during the sovereign debt crises than in late 2008 and also when compared to the AFSI. We interpret this, again, as a result of the aggregation method.

2 Early Warning Indicators

2.1 Analytical Framework

In the second part of our analysis we identify macroprudential early warning indicators to detect imbalances in financial stability as quantified by the AFSI. Pressure for the financial system can arise from various sources of systemic risk that disrupt the efficient allocation of capital and eventually impair economic growth and welfare. To begin with, we assign each potential early warning indicator to one of six risk channels, which at the same time constitute the starting point for our quantitative analysis. These risk channels are (1) risk bearing capacity, (2) mispricing of risk, (3) excessive growth (4) concentration, (5) interconnectedness, and (6) the macroeconomic environment.[12]

If financial institutions, corporates and households are financially sound, their risk bearing capacity (1) is higher, so their individual ability to withstand stress will increase. This helps mitigate the propagation of financial instability in the financial system. Companies and households with lower indebtedness, higher earnings and/or higher disposable income are better capable to absorb financial shocks. In case of an economic downturn, borrowers' higher creditworthiness in turn tends to strengthen lenders' balance sheets, i.e. in an economy where financial intermediation

[12] *The IMF (2011) distinguishes between the time dimension and the cross-sectional dimension of systemic risk. In our framework, the cross-sectional dimension is reflected by concentration and interconnectedness while the other channels can be attributed to the time dimension. Associated to the time dimension, the procyclicality mechanism reflects the increasing risk exposures observed during the boom phase and the risk aversion observed during the bust phase of a financial cycle.*

through banks plays such a prominent role, banks come under less pressure.

Collective mispricing of risk (2), often caused by misguided market expectations, may (slowly) lead to the buildup of significant systemic imbalances. The quick correction of the mispricing of risk through large movements in asset prices, with asset price bubbles eventually bursting, can lead to major distortions in the financial system.

Unsustainable or even excessive growth (3) may exacerbate the impact of the former two risk channels, thereby aggravating the risk to financial stability. For example, credit growth that constantly exceeds GDP growth can be classified as an indicator for unsustainable growth. 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.

With regard to contagion, we distinguish between two related, although distinct risk channels: concentration (4) and interconnectedness (5). The former is a measure of the uneven distribution of exposures, which is prone to amplify 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 during the buildup of the recent crisis) and dominant names on banks' books (e.g. Saad Groups' multi-billion dollar default in 2009). Interconnectedness captures the contagion risk based on spillovers caused by interlinkages of stakeholders in the financial system. Via these interlinkages, a (small) shock in one part of the system may be transmitted and another part of the system – with no direct exposure to the initial shock – might come under pressure and thereby threaten wider financial stability. The most prominent example in the literature are the so-called default cascades that can be observed in banking systems as being driven by connections through interbank liabilities.

As macroprudential policy not only focuses on the financial system but also on the interaction of the financial system and the real economy, the macroeconomic environment and its outlook (6) constitute a substantial source of risk. In our case, Austria is not only affected by domestic developments, but as a small open economy it is prone to exogenous macroeconomic shocks. Domestic and foreign GDP growth, international trade dependency and the current low-interest environment are factors that may determine Austria's current and future financial stability.

2.2 Data Base Used for AFSI Estimation

Our data set of indicators considered for the AFSI, which aims to cover the six risk channels described in the previous section, consists of regulatory reporting data, market data (provided by Datastream) 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 consistent four-quarter lag, as this would afford macroprudential authorities at least some time to react[13] to adverse developments in the AFSI by setting policy measures to counter detected systemic imbalances.[14]

For this paper, we base our econometric analysis on an observation hori-

[13] *For structural (macroeconomic as well as supervisory) data, moreover, a publication lag of at least one quarter must be taken into account.*

[14] *In addition, for market-based data we also include six- and eight-quarter lags with the aim of identifying the turning point of market sentiment.*

zon that runs from the first quarter of 2000 to the third quarter of 2012, yielding $T = 51$ time periods[15]. This *long sample* consists of 36 indicators. All indicators are tested for stationarity. Some appear to have a unit root although economic theory would suggests otherwise. Furthermore, for policy reasons (e.g. that allow a clear-cut interpretation of the credit-to-GDP ratio) we do not transform these variables to remove the probably spurious unit root.[16] For the purpose of robustness checks and in order to include further variables that only became available at a later point in time, we constructed an additional *short sample* of 31 additional indicators from the first quarter of 2005 to the third quarter of 2012.[17] 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 might be of interest could be included in our analysis.

In table 2, we list all indicators – according to the above-mentioned risk channel framework – for the *long sample* together with their expected impact on the AFSI and the univariate regression results.[18] The latter should, however, only serve as a rough indication of variables that could be useful as early warning indicators. The dynamics of the AFSI can only be properly approximated with the help of an entire set of indicators, as the omitted-variable bias is substantial in each univariate regression unless the selected indicator is uncorrelated with all other indicators.[19]

Table 2

Indicators Used for AFSI Prediction (Long Sample)

Indicators	Description	Expected sign	Coefficient	Average value over sample period
Risk-bearing capacity				
Return on assets (average)	Ratio of return after taxes to total assets, average	+/–	0.73	0.36
Return on assets (20% percentile)	Ratio of return after taxes to total assets, 20% percentile	+/–	–2.44	0.21
Net interest margin	Ratio of net interst earnings to total assets	+/–	–3.34***	0.99
Interest rate spread	Net total of interest earnings in relation to interest bearing assets (on the one hand) and interest expenses in relation to interest bearing liabilities (on the other)	+/–	–3.46***	1.08
Loan-to-deposit (average)	Loan-to-deposit ratio, average	+	–0.14***	95.32
Loan-to-deposit ratio (80% percentile)	Loan-to-deposit ratio, 80% percentile	+	0.64***	101.45
Loan loss provisions ratio	Ratio of specific loan loss provisions to gross exposure	+	–1.38***	3.04
Bank ratings (average)	Total assets-weighted average bank rating	+	0.49***	7.24

Source: Authors' calculations.

*Note: *, ** and *** denote significance at the 1%, 5% and 10% level, respectively.*

[15] *At the close of empirical data collection for this paper, not all structural data had been available for the fourth quarter of 2012 yet.*

[16] *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. However, as we use a linear model that is well known to exhibit a forecasting performance that is superior to that of nonlinear time series models, especially for a large data set, these breaks are not addressed directly.*

[17] *For an exhaustive list of all analyzed indicators and their availability, see annex.*

[18] *Concentration risk indicators were only included in the short sample.*

[19] *Lo Duca and Peltonen (2011) also find that considering indicators jointly in a multivariate framework outperforms considering stand-alone indicators.*

Table 2 continued

Indicators Used for AFSI Prediction (Long Sample)

Indicators	Description	Expected sign	Coefficient	Average value over sample period
Mispricing of risk				
Spread of high-yield bonds (lag 4)	Spread between AAA bond yields on the one hand and CCC and lower bond yields on the other (lag 4)	–	0.00	694.68
Spread of high-yield bonds (lag 6)	Spread between AAA bond yields on the one hand and CCC and lower bond yields on the other (lag 6)	–	0.00	679.50
Spread of high-yield bonds (lag 8)	Spread between AAA bond yields on the one hand and CCC and lower bond yields on the other (lag 8)	–	0.00	649.01
EONIA (lag 4)	EONIA overnight interest rate	–	–0.04	2.29
EURO STOXX 50 return (lag 4)	EURO STOXX 50 year-on-year return (lag 4)	+	0.00	–4.00
EURO STOXX 50 return (lag 6)	EURO STOXX 50 year-on-year return (lag 6)	+	0.00	–3.57
EURO STOXX 50 return (lag 8)	EURO STOXX 50 year-on-year return (lag 8)	+	0.00	–2.49
EURO STOXX Banks return (lag 4)	EURO STOXX Banks year-on-year return (lag 4)	+	–0.00*	–4.96
EURO STOXX Banks return (lag 6)	EURO STOXX Banks year-on-year return (lag 6)	+	0.00	–5.44
EURO STOXX Banks return (lag 8)	EURO STOXX Banks year-on-year return (lag 8)	+	0.00	–4.72
VIX (lag 4)	Volatility of the Standard & Poor's 500 (lag 4)	–	0.00	21.94
VIX (lag 6)	Volatility of the Standard & Poor's 500 (lag 6)	–	0.00	21.81
VIX (lag 8)	Volatility of the Standard & Poor's 500 (lag 8)	–	–0.01	21.58
VSTOXX (lag 4)	Volatility of the EURO STOXX 50 (lag 4)	–	0.00	26.35
VSTOXX (lag 6)	Volatility of the EURO STOXX 50 (lag 6)	–	0.00	26.47
VSTOXX (lag 8)	Volatility of the EURO STOXX 50 (lag 8)	–	–0.02	26.19
Excessive growth				
Total credit growth	Total credit volume provided by all sectors to private sector year-on-year growth	+	0.08**	5.10
Total credit-to-GDP ratio	Ratio of total credit volume to GDP	+	0.04***	147.79
Total credit-to-GDP gap	Deviation of credit-to-GDP ratios from long-term trend	+	0.01	0.11
Customer loan growth	Private sector bank loans, year-on-year growth	+	0.01	4.38
Real estate loan growth	Real estate loans, year-on-year growth	+	0.00	1.04
Subsidized housing loan growth	Subsidized housing loans, year-on-year growth	+	–0.01	3.96
Real estate and subsidized housing loan growth	Sum of real estate loans' and subsidized housing loans' year-on-year growth	+	0.00	6.29
Total asset growth	Total assets, year-on-year growth	+	0.00	5.31
Off-balance sheet growth	Off-balance sheet positions, year-on-year growth	+	1.67	0.06
Interconnectedness				
Interbank assets, growth	Interbank assets, year-on-year growth	–	0.00	5.82
Interbank assets, share in total assets	Ratio of interbank assets to total assets	–	0.16**	29.93
Interbank liabilities, growth	Interbank liabilities, year-on-year growth	–	0.00	3.98
Interbank liabilities, share in total assets	Ratio of interbank liabilities to total assets	–	–0.13**	30.03
Macroeconomic environment				
GDP Austria	Austrian GDP, year-on-year growth	–	0.07	1.63
GDP EU-27	EU-27 GDP, year-on-year growth	–	0.00	1.33
GDP Germany	German GDP, year-on-year growth	–	0.12**	1.17
Inflation Austria	Consumer Price Index for Austria (2005=100)	+	0.36***	2.08
Banks' total assets-to-GDP ratio	Ratio of banks' total assets to GDP	+	0.86***	3.21
Current account-to-GDP ratio	Ratio of current account balance to GDP	–	0.17***	2.41
Exchange rate volatility	Exchange rate volatility based on a basket of the currencies of Austria's nine most important trading partners outside the euro area (based on import volumes)	+/–	43.40	0.00

Source: Authors' calculations.

*Note: *, ** and *** denote significance at the 1%, 5% and 10% level, respectively.*

2.3 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 linear regression model in which all explanatory variables are observable:

$$y_{i,t} = \beta_{0,i} + \sum_{j=1}^{k} x_{j,t}\beta_{j,i} + \epsilon_{i,t} \qquad (1)$$

where y_i is the AFSI calculated by method *i, 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 in the introduction, the theoretical and empirical literature on how to select the most important predictors (x_j) is inconclusive. In previous work on this topic, predictors have been selected by mere qualitative reasoning. Lo Duca and Peltonen (2011) e.g. select predictors based on impact channels[20] while Jakubík and Slačík (2013) select predictors with a view to covering five risk channels.[21] To deal with the high variance-versus-low bias tradeoff in a nonheuristic way, we partly depart from these qualitative approaches and consider a data-driven subset selection mechanism.[22]

Among the different forms of subset selection, we opt for best subset selection, which for each $k \in \{0,1,2,..,p\}$ selects the subset of size *k* that gives the smallest residual sum of squares.[23] However, the best subset selection algorithm only chooses the *n*-best models for a given model size *k* (i.e. the number of selected predictors).[24] Therefore, we need an additional criterion to address the variance-versus-bias tradeoff. Following the procedure developed by Kerbl and Sigmund (2011), we test the influence of an unobserved component on the AFSI in a state space framework to measure the hypothetical bias of any omitted variables. We add an unobserved risk factor to the framework of equation (1) and refer to this new equation as the measurement equation (2). We explicitly model the unobserved risk factor as an autoregressive state process that evolves through time, thereby mimicking the behavior of many observable predictors, especially growth rates, and refer to this specification as the state equation (3).

$$\begin{aligned} y_{i,t} &= X_{i,t}\Gamma_i + z_{i,t}\lambda_i + v_{i,t} \\ v_{i,t} &\sim N\,(0,ri) \end{aligned} \qquad (2)$$

$$\begin{aligned} z_{i,t} &= \phi_i z_{i,t-1} + W_{i,t} \\ W_{i,t} &\sim N(0,q_i) \end{aligned} \qquad (3)$$

In addition to the previous notation, $\lambda_i, \Gamma_i, \phi_i, q_i$ and r_i are parameters to be estimated, $z_{i,t}$ is the unobserved factor, and $v_{i,t}$ and $w_{i,t}$ are error terms. Capital letters denote matrices (or vectors) and small letters denote scalars. Moreover, we assume that $Cov(v_{i,t};w_{i,t}) = 0$ and that there are no cross-correlations in the state and measurement equations between the sectors *i*, $Cov(w_{j,t};w_{i,t}) = 0$ and $Cov(v_{i,t};\ v_{i,t}) = 0$ for any $i \neq j$.

[20] *Lo Duca and Peltonen (2011) cover domestic and global factors as well as interactions between them.*

[21] *Jakubík and Slačík (2013) cover sovereign risk, the banking sector, contagion risk, the real sector and macroeconomic indicators.*

[22] *Although more shopisticated selection mechanisms are available, we choose subset selection for interpretation purposes.*

[23] *We use the leaps and bound procedure by Furnival and Wilson (1974), which is implemented in the R-package "leaps."*

[24] *For a given model size, we searched for the six combinations of variables with the best fit (measured by R^2) out of all possible combinations.*

We estimate the equation systems (2) and (3) via an expectation maximization (EM) algorithm.[25] Based on an initial set of parameters (λ_i,Γ_i,ϕ_i,q_i and r_i), the unobserved component is extracted via the Kalman filter in the expectation step. Given the unobserved component z_i, the likelihood of equation (2) is maximized with respect to the parameter set. We repeat these steps until convergence occurs.[26, 27]

To judge whether a latent factor is statistically significant within each estimated model, we follow Koopman et al. (2009) and conduct a likelihood ratio (LR) test defined by

$$2\left(l_u - l_r\right) \overset{a}{\sim} X_m^2$$

where l_u represents the likelihood of the unrestricted model with the latent factor and l_r the likelihood of the restricted models without this factor. m is the number of restrictions implemented. The only imposed restriction is λ_i=0 (see equation 2).

If the latent factor is statistically not significant in any model with model size k^l, none of the models with $k < k^l$ is used for further analysis such as model averaging and forecasting. k^l is therefore the lower bound on model size in the variance-versus-bias tradeoff. The upper bound k^u will be determined by the mean squared error in a hypothetical out-of-sample forecasting exercise.

3 Estimation Results

In a first step we generate output for selected models based on the best subset selection mechanism. Once these models are selected, we determine the lower (k^l) and upper bound (k^u) of model size k to identify the models which we use for model averaging. We run a Kalman filter EM algorithm estimation procedure to find the minimum model size following the methodology described in section 3. We find that with six or more predictors, the additional latent factor does not significantly contribute to the model fit. Therefore, we fix the k^l at six.

As a next step, we re-estimate the selected models for the period from the first quarter of 2000 to the third quarter of 2010 (instead of the third quarter of 2012), calculate an out-of-sample forecast and compare the mean squared forecasting error of all models. We find that the average mean squared forecasting error is the lowest for model sizes from six to ten. Therefore, $k^u = 10$. Hence, we use the best subset of models size k, where $k = 6, \dots ,10$.

Chart 2 presents the frequency with which these models contain a certain explanatory variable, i.e. an early warning indicator. The default lag for each indicator is four quarters (see section 3.2) if not explicitly indicated otherwise. Moreover, the blue bars represent the fraction in which this variable has a positive sign; the purple bars indicate a negative sign. Again, we classify the indicators with respect to our risk channel framework (see section 3.1).

Among the risk-bearing capacity indicators, average bank ratings and the loan loss provision ratio (LLPR) are selected in more than 30% of the best subsets. Bank ratings have the expected positive sign, confirming that a wors-

[25] *See McLachlan and Thriyambakam (1996) for details.*

[26] *See Shumway and Stoffer (2006) and Holmes (2010) for details.*

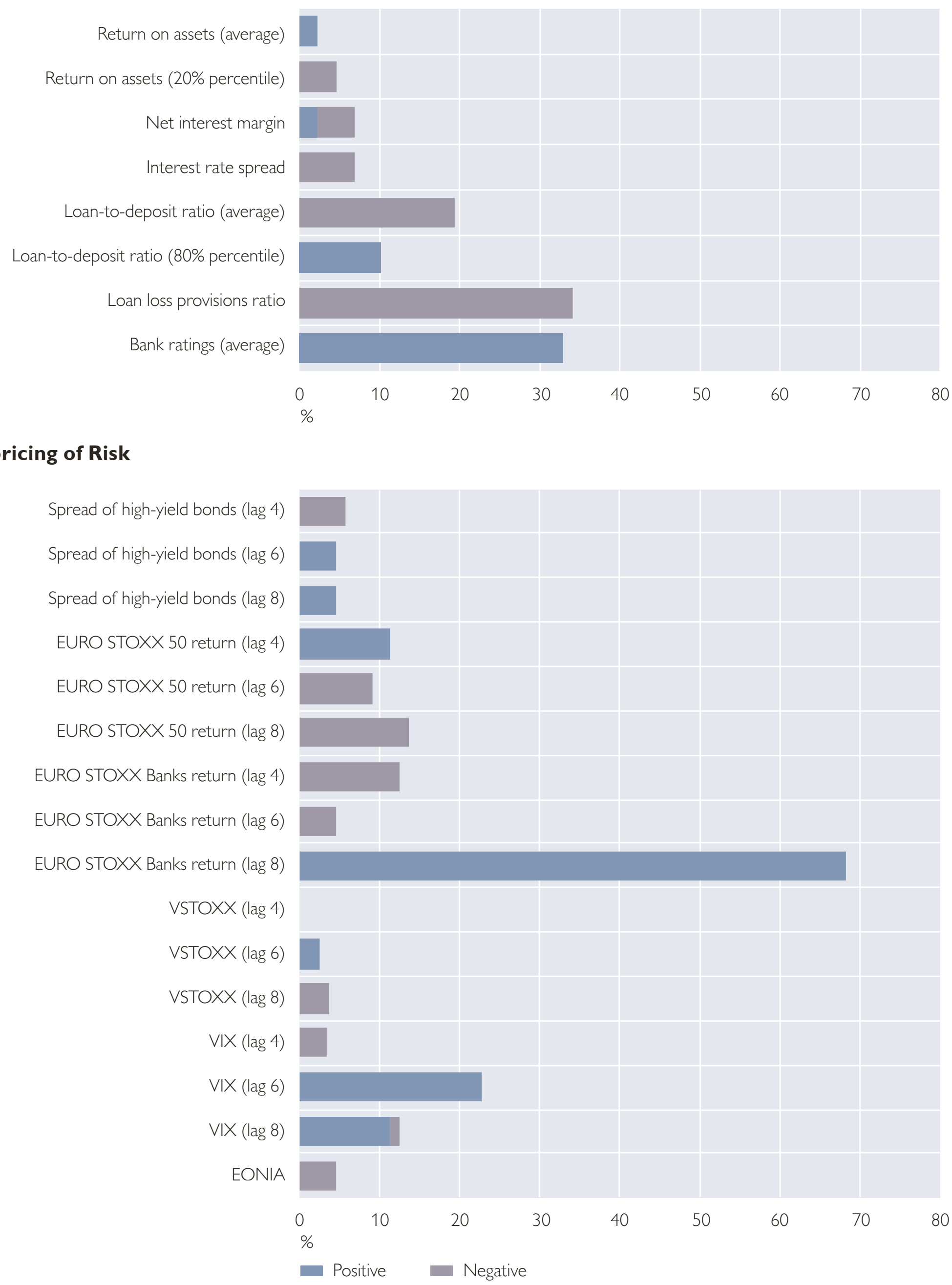
[27] *As the state space representation of a given dynamic system might not be uniquely defined by a given parameter set without restricting some of these parameters (see Hamilton, 1994; Carro et al., 2010), we fix the metric of the unobserved variable by restricting $qi = 1$ without loss of generality.*

Chart 2

Relative Frequency of Selected Indicators

Risk-Bearing Capacity

Mispricing of Risk



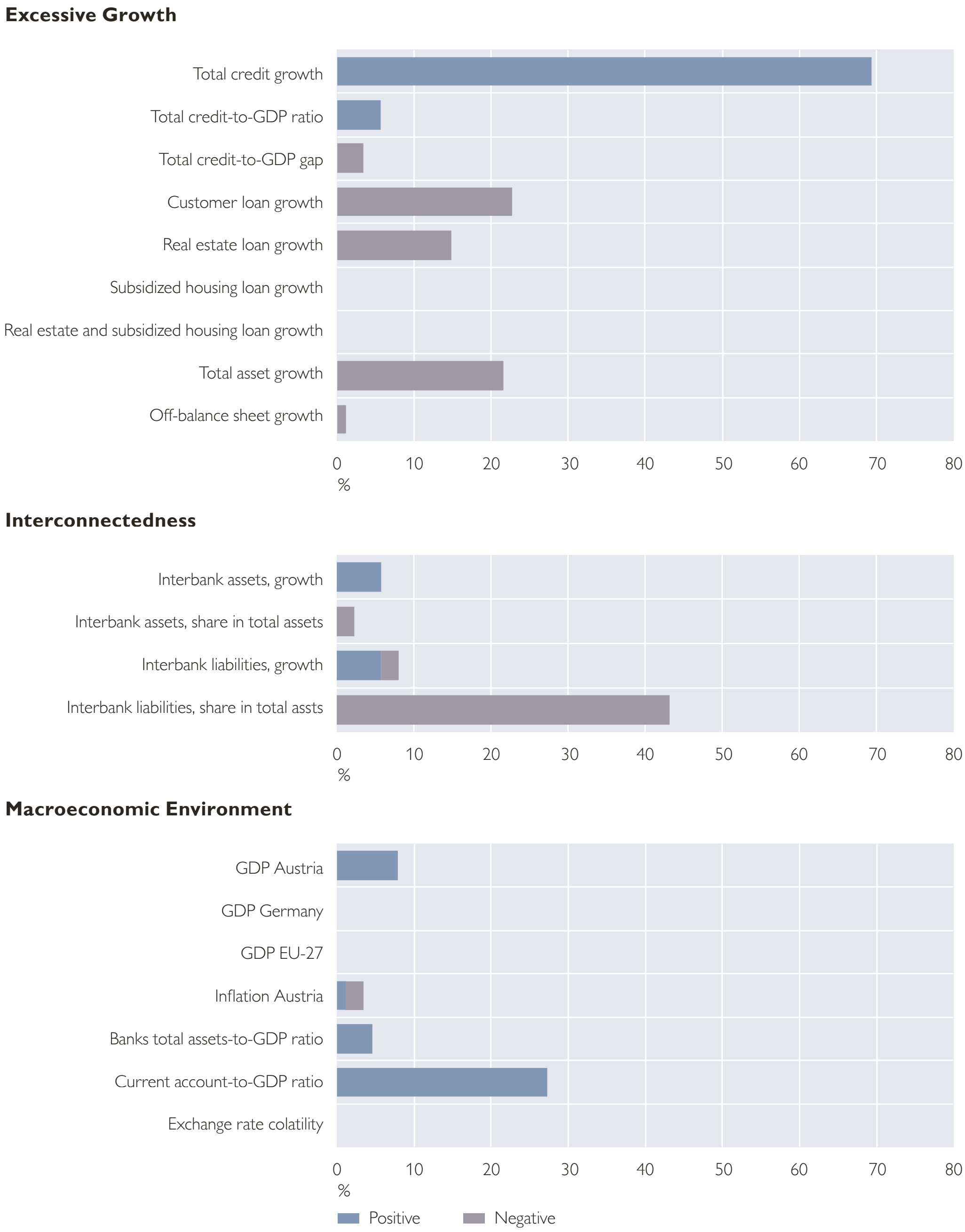
Source: OeNB.

Note: Blue bars show the fractions assigned to positive coefficients for the particular macroeconomic indicators. If an indicator was not selected, no bar is shown. All indicators are lagged by four quarters unless otherwise indicated.

ening of bank ratings increases the AFSI, which indicates a deterioration of financial stability in Austria. However, the LLPR consistently carries a negative sign. We interpret this in two ways: 1) the provisioning cycle lags the (market-based) AFSI; 2) a clean-up of banks' portfolios and hence a higher

Chart 2 continued

Relative Frequency of Selected Indicators



Source: OeNB.

Note: Blue bars show the fractions assigned to positive coefficients for the particular macroeconomic indicators. If an indicator was not selected, no bar is shown. All indicators are lagged by four quarters unless otherwise indicated.

LLPR might actually indicate improving financial stability. Moreover, the negative sign of the average loan-to-deposit (LTD) ratio might at first glance appear counterintuitive. However, the positive sign of the 80th-percentile LTD (meaning that 20% of the Austrian banks have a higher LTD) puts the combined result into perspective. We conclude that on average Austrian banks draw on sound, deposit-based refinancing while a deterioration of the LTD at the less stable refinanced banks has the expected negative influence on financial stability in Austria. Furthermore, results based on the short sample seem to indicate that the total level of corporate indebtedness contributes positively to the AFSI.

Concerning indicators of mispricing of risk, the EURO STOXX Banks return index has the highest selection rate in our best subsets. The sign of the relation between the AFSI and the EURO STOXX Banks return index tends to depend on the length of the lag. The consistently negative impact on Austrian financial stability associated with high levels of EURO STOXX Banks returns with a lag of eight quarters could be associated with boom phases that have negative consequences eight quarters later. Returns based on shorter lags are less often selected in our models, but show the expected negative coefficient, which indicates that recently realized returns reduce stress levels. Together with the results on the broader EURO STOXX 50 return index, which is not as important for explaining the AFSI as the more specific EURO STOXX Banks return index, there might be evidence that the business cycle and the financial cycle are not completely synchronized. The volatility of the Standard & Poor's 500 index (VIX), which has a relatively higher selection rate compared to the volatility of the EURO STOXX 50 index (VSTOXX), seems to be a better indicator for the 2007/08 crisis, which had its origins in the U.S. subprime market.

Among the indicators of excessive growth, total credit growth[28] turns out to be an important early warning indicator. The variable with the expected positive sign is included in approximately 70% of all models. 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 relevance for financial stability in Austria.

Turning now to the indicators of interconnectedness, the multivariate regressions show that the most important indicator is the share of interbank liabilities. It carries the expected negative sign in explaining the AFSI. We see this as a confirmation of the – at least historically valid – thesis that a high share of interbank liabilities 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.[29] Finally, and also somewhat surprisingly, the variables covering macroeconomic environment appear to be less important as early warning indicators for Austrian financial stability than the variables assigned to the other risk channels. These results are, however, in line with our findings on the mis-

[28] *As Drehman (2013) argues, including all types of credit to the nonfinancial sector when quantifying indebtedness has an additional explanatory value for crisis prediction.*

[29] *This corroborates the rationale for liquidity regulation (see Schmitz and Ittner, 2007); if market failure can indeed cause such significant externalities, regulation policy needs to change the mode of financial intermediaries' refinancing even if such a change incurs additional costs in benign times. In our models, this circumstance might impact estimation results, as the role of the short-term interbank market as a source of refinancing might change.*

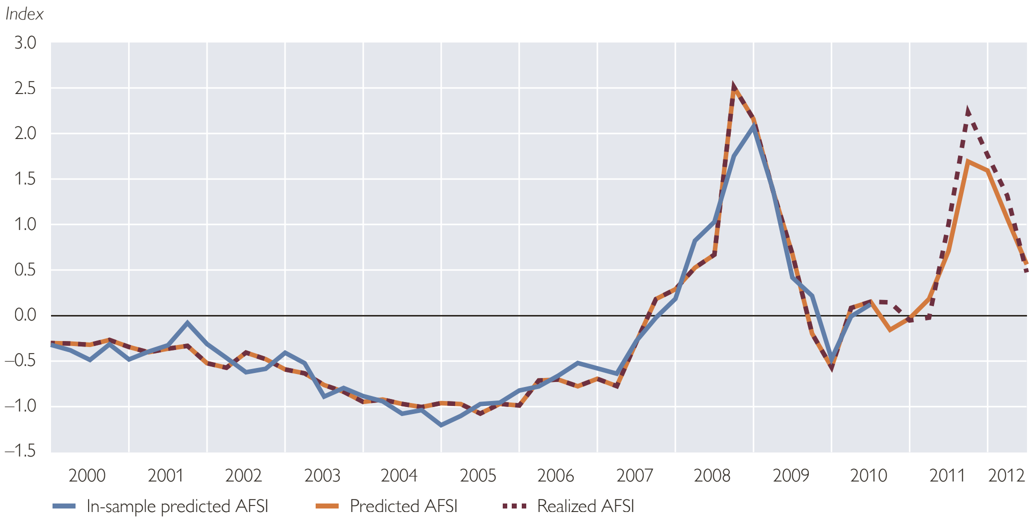
pricing of risk, namely that the business and financial cycles appear not to be synchronized, with the former lagging behind the latter.

In addition to the early warning indicators depicted in chart 2, we applied the same econometric analysis on an extended data set for a *short sample* (first quarter of 2005 to third quarter of 2012). Overall, the estimation output yields similar results for the overlapping indicators, which in turn serve as a valuable robustness check for our main results. The large exposure ratio[30] has the expected positive sign, indicating that higher concentration risk drives up the stress level as measured by a rise in the AFSI. Another indicator that is selected in a quarter of all models for the *short sample* is the impact of banks' liquidity position on credit standards. It is defined in the interval [–1,1] and measures to what degree banks' lending policy is affected by liquidity shortage. A negative value of this variable means that banks' lending is highly restricted. We find a negative coefficient, which means that liquidity constraints induce stress in the Austrian financial system.

Returning to our two-year out-of-sample forecast for the period from the fourth quarter of 2010 to the third quarter of 2012 (see chart 3), we use a model-averaging procedure for assessing the six predefined systemic risk channels in order to limit model uncertainty. The results indicate that excessive growth, interconnectedness and mispricing of risk are the most important channels through which risks to financial stability are transmitted in Austria. 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 to account for the various risk drivers behind financial instability. Despite an impressive out-of-sample forecasting performance, we

Chart 3

Predicted (In- and Out-of-Sample) AFSI versus Realized AFSI



Source: OeNB.

[30] *The large exposure ratio is defined as the share of large exposure (i.e. an exposure exceeding EUR 500,000 and/ or of more than 10% of the eligible capital) to total assets.*

are acutely aware that some indicators that 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. More broadly speaking, we have to understand that even the best models cannot exonerate us from subjective judgment in the interpretation of results and, consequently, in the formulation of macroprudential policy. For instance, the indicators covering property-related credit growth in Austria did not contribute to significant forecasting results of changes in stress levels as measured by the AFSI. However, due to the recent sharp rise of real estate prices after a decade of mere stagnation, it can be argued that monitoring real estate market developments will likely gain importance in the future, although the related indicators are currently not selected in our models.

Similarly, 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 nondomestic indicators are monitored constantly in order to capture relevant external developments at an early stage.

4 Conclusion

This paper has two objectives: First, we develop the Austrian Financial Stress Index (AFSI) as a continuous measure of the current financial stability situation in Austria. We believe the AFSI will add significant value to monitoring and benchmarking during day-to-day macroprudential supervision. 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. Assigning each early warning indicator to one of six predefined risk channels has produced plausible results. These results also imply that these indicators should not be analyzed on a stand-alone basis, but based on an integrated analytical framework. Our proposal serves as a quantitative starting point for constant monitoring during macroprudential supervision as envisaged in the upcoming implementation of macroprudential tools via Basel III (Capital Requirements Directive IV (CRD IV) and Capital Requirements Regulation (CRR)). We believe that this empirical approach will contribute positively to macroprudential policymaking and thereby strengthen the resilience of the financial system.

However, our early warning framework would benefit from additional input. Several indicators (e.g. capitalization of financial intermediaries or network contagion indicators) are not available in longer time series. Our analysis focuses predominately on banks, since they play a crucial role as financial intermediaries in the Austrian economy because they often act as the single providers of credit to the corporate sector. Nevertheless, we should not underestimate the importance other financial intermediaries have for financial stability in Austria. Moreover, as Austria is a small open economy with a large banking system that has significant cross-border assets, its financial stability is obviously also influenced by external sources. In a further step, our analyses would benefit from further external indicators and possibly the creation of a cross-country panel. But no matter how sophisticated our models become, it is most unlikely that financial stability and systemic risk can ever be irrevocably quantified.

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Annex

Table A1

Comprehensive List of Variables Used for ASFI Prediction (Including Data Availability Periods)

Indicators	Data availability periods		Sample
	From	To	
Risk-bearing capacity			
Bank ratings (average)	Q3 95	Q4 12	L
Return on assets (20% percentile)	Q1 99	Q4 12	L
Return on assets (average)	Q1 99	Q4 12	L
Return on assets (80% percentile)	Q1 99	Q4 12	L
Loan-to-deposit ratio (average)	Q1 99	Q4 12	L
Loan-to-deposit ratio (20% percentile)	Q1 99	Q4 12	L
Loan-to-deposit ratio (80% percentile)	Q1 99	Q4 12	L
Interest rate spread	Q1 95	Q4 12	L
Net interest margin	Q1 95	Q4 12	L
Loan loss provisions ratio	Q4 95	Q4 12	L
Ratio of corporate debt to profit	Q1 03	Q4 12	S
Ratio of household debt to disposable income	Q1 03	Q4 12	S
Interest margin for corporate loans	Q1 03	Q4 12	S
Interest margin for loans to households	Q1 03	Q4 12	S
Interest margin (average)	Q1 03	Q4 12	S
Core tier 1 ratio, credit risk, consolidated	Q4 04	Q4 12	
Tier 1 ratio, credit risk, consolidated	Q4 04	Q4 12	
Tier 1 ratio, consolidated	Q4 04	Q4 12	
Core tier 1 ratio, consolidated	Q1 08	Q4 12	
Tier 1 ratio, consolidated (20% percentile)	Q4 04	Q4 12	
Tier 1 ratio, consolidated (average)	Q4 04	Q4 12	
Leverage ratio, consolidated (20% percentile)	Q4 04	Q4 12	
Leverage ratio, consolidated (average)	Q4 04	Q4 12	
Leverage, consolidated (80% percentile)	Q4 04	Q4 12	
Ratio of risk-weighted assets to total assets, consolidated (20% percentile)	Q4 04	Q4 12	
Ratio of risk-weighted assets to total assets, consolidated (average)	Q4 04	Q4 12	
Return on assets, consolidated (20% percentile)	Q1 05	Q4 12	
Return on assets, consolidated (average)	Q1 05	Q4 12	
Return on assets, consolidated (80% percentile)	Q1 05	Q4 12	
Return on equity, consolidated (20% percentile)	Q1 05	Q4 12	
Return on equity, consolidated (average)	Q1 05	Q4 12	
Return on equity, consolidated (80% percentile)	Q1 05	Q4 12	
Loan-to-deposit ratio, consolidated (20% percentile)	Q1 05	Q4 12	
Loan-to-deposit ratio, consolidated (average)	Q1 05	Q4 12	
Loan-to-deposit ratio, consolidated (80% percentile)	Q1 05	Q4 12	
Nonperforming loans	Q1 08	Q1 12	
Mispricing of risk			
Spread of high-yield bonds	Q1 98	Q4 12	L
EONIA	Q1 99	Q4 12	L
VSTOXX (volatility of the EURO STOXX 50)	Q1 99	Q4 12	L
VIX (volatility of the Standard & Poor's 500)	Q1 95	Q4 12	L
EURO STOXX 50 return	Q1 95	Q4 12	L
EURO STOXX Banks return	Q1 95	Q4 12	L
Residential property prices, growth rate	Q1 01	Q4 12	S
Ratio of residential property prices to disposable income	Q1 00	Q4 12	S
Gap between house price growth and disposable income growth	Q1 01	Q4 12	S
EURO STOXX 50, price book ratio	Q2 01	Q4 12	
EURO STOXX Banks, price book ratio	Q2 99	Q4 12	

Source: OeNB.

Note: L = long sample, S = short sample; if no sample is indicated, the respective data series were not included in the model selection for reasons of data availability or owing to economic insignificance.

Table A1 continued

Comprehensive List of Variables Used for ASFI Prediction (Including Data Availability Periods)

Indicators	Data availability periods		Sample
	From	To	
Excessive growth			
Total asset growth	Q1 96	Q4 12	L
Real estate loan growth	Q4 96	Q3 12	L
Subsidized housing loan growth	Q4 96	Q3 12	L
Real estate and subsidized housing loan growth	Q4 96	Q3 12	L
Total credit growth	Q1 95	Q3 12	L
Total credit-to-GDP ratio	Q1 95	Q3 12	L
Total credit-to-GDP gap	Q1 99	Q3 12	L
Customer loan growth	Q4 96	Q4 12	L
Off-balance sheet growth	Q1 96	Q4 12	L
Private sector loan growth	Q3 00	Q4 12	S
Total assets growth, top 6 banks	Q1 05	Q4 12	
Share of other financial intermediaries in financial assets of MFIs	Q1 06	Q4 12	
Interconnectedness			
Interbank assets, growth	Q4 96	Q4 12	L
Interbank assets, share in total assets	Q4 95	Q4 12	L
Interbank liabilities, growth	Q4 96	Q4 12	L
Interbank liabilities, share in total assets	Q4 95	Q4 12	L
Concentration risk			
Ratio of large exposures to total assets	Q2 01	Q4 12	S
Macroeconomic environment			
Exchange rate volatility	Q1 99	Q4 12	L
Inflation Austria	Q1 95	Q4 12	L
GDP EU-27	Q1 95	Q4 12	L
GDP Germany	Q1 95	Q4 12	L
GDP Austria	Q1 95	Q4 12	L
Banks' total assets-to-GDP ratio	Q1 95	Q4 12	L
Current account-to-GDP ratio	Q1 95	Q4 12	L
Historical quarterly GDP forecasts (OeNB)	Q2 99	Q4 12	S
Sentiment indicator (Federation of Austrian Industries)	Q1 00	Q4 12	S
Sentiment indicator (Austrian Economic Chambers)	Q4 02	Q4 12	S
Average of sentiment indicators (Federation of Austrian Industries and Austrian Economic Chambers)	Q3 02	Q4 12	S
Ratio of household debt to GDP	Q1 03	Q4 12	S
Ratio of corporate debt to GDP	Q1 03	Q4 12	S
Ratio of public debt to GDP, EU-27	Q4 00	Q3 12	S
Ratio of public debt to GDP, Austria	Q1 00	Q4 12	S
Credit standards for loans to enterprises	Q4 02	Q4 12	S
Credit standards for long-term loans to enterprises	Q4 02	Q4 12	S
Impact of equity costs on credit standards	Q4 02	Q4 12	S
Impact of money market on credit standards	Q4 02	Q4 12	S
Impact of liquidity position on credit standards	Q4 02	Q4 12	S
Impact of refinancing costs on credit standards	Q4 02	Q4 12	S
Development of loan volume	Q4 02	Q4 12	S
Development of collateral requirements	Q4 02	Q4 12	S
Development of covenants	Q4 02	Q4 12	S
Development of maturities	Q4 02	Q4 12	S
Expected development of credit standards	Q4 02	Q4 12	S
Expected development of credit standards for long-term loans	Q4 02	Q4 12	S
Insolvencies, production sector	Q1 95	Q4 12	
Insolvencies, services	Q1 95	Q4 12	
Insolvencies, construction	Q1 95	Q4 12	
Insolvencies, trade	Q1 95	Q4 12	
Insolvencies, transportation	Q1 95	Q4 12	
Insolvencies, tourism	Q1 95	Q4 12	
Insolvencies, total	Q1 95	Q4 12	

Source: OeNB.

Note: L = long sample, S = short sample; if no sample is indicated, the respective data series were not included in the model selection for reasons of data availability or owing to economic insignificance.