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Financial instability and economic activity*

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Abstract

We estimate new indices measuring financial and economic (in)stability in Austria and in the euro area. Instead of estimating the level of (in)stability in a financial or economic system we measure the degree of predictability of (in)stability, where our methodological approach is based on the uncertainty index of Jurado, Ludvigson and Ng (2015). We perform an impulse response analysis in a vector error correction framework, where we focus on the impact of uncertainty shocks on industrial production, employment and the stock market. We find that financial uncertainty shows a strong significantly negative impact on the stock market, for both Austria and the euro area, while economic uncertainty shows a strong significantly negative impact on the economic variables for the euro area. We also perform a forecasting analysis, where we assess the merits of uncertainty indicators for forecasting industrial production, employment and the stock market, using different forecast performance measures. The results suggest that financial uncertainty improves the forecasts of the stock market while economic uncertainty improves the forecasts of macroeconomic variables. We also use aggregate banking data to construct an augmented financial uncertainty index and examine whether models including this augmented financial uncertainty index outperform models including the original financial uncertainty index in terms of forecasting.

Keywords: financial (in)stability, uncertainty, financial crisis, forecasting, stochastic volatility, factor models

JEL codes: C53, G01, G20, E44

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1 Introduction

In the aftermath of the 2008 financial crisis and the Great Recession, the interest of economists and policymakers has been markedly focused on the analysis of tools and techniques to assess the strengths and vulnerabilities of financial systems and, in particular, on measuring financial uncertainty and its effect on the economy. Also before the crisis, however, episodes of financial instability had highlighted the importance of continuous monitoring of financial systems in order to prevent crises. The International Monetary Fund, for example, had identified a broad set of prudential and macroeconomic variables that are relevant for assessing financial soundness (see International Monetary Fund, 2002), which was later reduced to a subset including both aggregate bank balance sheet and income statement information and aggregate indicators of financial fragility of nonfinancial firms and nonbank financial markets. These indicators are referred to as financial soundness indicators and have, more recently, been examined with respect to their ability to predict financial sector distress (see Pietrzak, 2021). The European Central Bank (ECB) has introduced a family of composite indicators of systemic stress (CISS) which are based on five categories – the financial intermediaries sector, money markets, equity markets, bond markets and foreign exchange markets – and which are supposed to measure a country's financial stability.[1]

Other indicators which are (closely) related to the indicators of financial stability are so-called uncertainty indices. Because uncertainty is unobserved, a number of proxies have been proposed in the literature. Traditional methods include, for example, the disagreement among professional forecasters, see Zarnowitz and Lambros (1987) and Bomberger (1996). Another measure of financial uncertainty, which has become very popular, is the realized and implied stock market volatility, see Bloom (2009). A big advantage of this measure is that realized volatility, based on observed stock market returns, is readily available for almost all countries. More recently, alternative measures using a more formal econometric framework have been introduced. Jurado, Ludvigson and Ng (2015) suggest that uncertainty relates to whether the economy is more or less predictable, i.e., less or

[1]The ECB's indicators use different weighting schemes to aggregate individual variables or subindices into one index: weights reflecting the time-varying cross-correlation structure (CISS) or equal weights (new CISS), see Holló, Kremer and Lo Duca (2012). The CISS is computed for the euro area as a whole on a weekly basis, the new CISS is computed for the euro area as a whole and for all euro area countries on a daily basis.

more uncertain. The authors propose to use as uncertainty measure the common variation in forecast errors for a broad range of macroeconomic and financial variables. Rossi and Sekhposyan (2015) agree with Jurado, Ludvigson and Ng (2015) that uncertainty relates to whether the economy is more or less forecastable. However, the uncertainty index they propose relies on the unconditional likelihood of the observed outcome, i.e., their proposed index is the percentile in the historical distribution of forecast errors associated with the realized forecast error. They distinguish between upside and downside uncertainty, because these uncertainties may affect the economy in different ways. Carriero, Clark and Marcellino (2018) deal with common variation in the residual volatilities in a large vector autoregression model and estimate measures of uncertainty jointly with assessing its impact on the macroeconomy. Chuliá, Guillén and Uribe (2017) propose an index of time-varying stock market uncertainty. The index is constructed by first removing the common variations in the series, based on identifying expected variation (risk) and unexpected variation (uncertainty). Baker, Bloom and Davis (2016) develop an index of economic policy uncertainty based on the frequency of key uncertainty-related terms that occur in newspaper articles. Böck, Feldkirchner and Raunig (2021) examine the merits of sovereign CDS volatility as an indicator of economic policy uncertainty, which is not available for all countries. Scotti (2016) uses "surprises" from Bloomberg forecasts to construct measures of economic uncertainty. In contrast to most measures of uncertainty, which deal with common shocks, Bijapur (2021) proposes an indicator of firm-level uncertainty, which is composed of idiosyncratic shocks. Bloom (2014) surveys related literature.

Interest in financial and economic uncertainty has been spurred by a growing body of evidence that uncertainty rises sharply in recessions. In most of the literature, measures of uncertainty are estimated in a first step and then used as if they were observable data series in the following econometric analysis of its impact on macroeconomic variables. Most of the above cited studies include at least a small analysis on the effects of uncertainty on the economy. The authors include their preferred uncertainty measure, together with a small set of macroeconomic variables like industrial production, inflation and employment, in a vector autoregression model and examine the responses of the macroeconomic variables to the uncertainty shock. Uncertainty usually rises in economic downturns; but is uncertainty a source of business cycles or is it rather an endogenous response to them, and does the type of uncertainty matter? Ludvigson, Ma, and Ng (2021) find that higher macroeconomic uncertainty in recessions is often an endogenous response to output shocks, while financial uncertainty is a likely source of output fluctuations.

We propose to use financial uncertainty indicators in the spirit of Jurado, Ludvigson and Ng (2015) in order to measure financial (in)stability in Austria and in the euro area. We thus follow the approach to remove the forecastable component of the variation of the variables under consideration and focus on the conditional expectation of the squared forecast errors. The data we use to compute our financial uncertainty index cover the main financial market segments: money market, equity market, (sovereign) bond market, and foreign exchange market. These data are available at a daily frequency and we transform them to monthly data (using monthly averages), because we propose to estimate financial uncertainty at a monthly frequency. While financial uncertainty is the main focus of this paper we also compute economic uncertainty, for Austria and for the euro area, and examine the resulting differences. The different spikes in uncertainty confirm that the 2008 financial crisis relates to financial uncertainty while the Covid-19 crisis pertains to economic uncertainty. In addition, we compute an augmented financial uncertainty index including aggregate bank balance sheet and income statement information as well as regulatory data describing financial stability. The banking data are taken from the ECB's consolidated banking data base. While market data are available at a high frequency and (almost) in real time, balance sheet, income statement and regulatory data are only available at a lower frequency and with a certain time lag. However, the latter data may reveal a different type of information that could complement the information reflected by market data. Balance sheet and regulatory data, for example, describe much more directly the financial health and soundness of banks than market data. As banking data are only available at a quarterly frequency we use the expectation-maximization algorithm to compute monthly series. We are interested in whether and how the different type of information will change financial uncertainty, and how the subsequent analysis will change if banking data are explicitly taken into account when measuring financial uncertainty.

First we assess the impact of our financial uncertainty on the economy by estimating a vector error correction (VEC) model and analysing the responses of main macroeconomic variables (industrial production, employment) and the stock market to a shock in uncertainty. We consider the ECB's composite indicator of systemic stress (CISS) as an alternative measure of financial instability, and also assess the impact of economic uncertainty on the economy. Furthermore we examine the role of our financial uncertainty index in forecasting. We use different VEC models including or excluding uncertainty indices and assess the respective forecasts. In doing so we employ both traditional loss-based performance measures (root mean squared error and mean absolute error) and more recent profit-based measures (directional accuracy/hit rate and directional value).

The remainder of this paper is organized as follows. Section 2 revises the methodology used to estimate uncertainty. Section 3 describes the data and presents the resulting indices of financial and economic uncertainty, where also the augmented financial uncertainty index is shown, which is based on financial market data and banking data. Section 4 describes the two empirical analyses, the impulse response analysis and the forecasting analysis, and presents the corresponding results. All analyses are performed for Austria and the euro area. Section 5 summarizes and concludes.

2 Methodology

Econometric studies on measuring uncertainty and its effects on the economy started with the seminal paper by Bloom (2009). Other relevant contributions include, among others, Bachmann, Steffen and Sims (2013), Baker, Bloom and Davis (2016), Basu and Bundick (2016), Berger, Grabert and Kempa (2016), Caggiano, Castelnuovo and Groshenny (2014), Chuliá, Guillén and Uribe (2017), Carriero, Clark and Marcellino (2018), Gilchrist, Sim and Zakrajsek (2014), Jurado, Ludvigson and Ng (2015), and Scotti (2016); Bloom (2014) surveys related work.

In order to formally assess uncertainty we follow the approach focusing on unforecastable components of the variation of variables under consideration (see, e.g., Carriero, Clark and Marcellino, 2018; Chuliá, Guillén and Uribe, 2017; and Jurado, Ludvigson and Ng, 2015, later referred to as JLN). Below we briefly sketch the approach used in JLN, where the notion of uncertainty is formalized as follows: Let $y_{jt} \in Y_t \equiv \{y_{1t}, \dots, y_{Nt}\}$ be a variable and let Y_t be the set of variables describing a certain sector, e.g., the financial sector, where we intend to measure uncertainty. Its $h-$period ahead uncertainty, $\mathcal{U}_{jt}(h)$, is the conditional volatility of the purely unforecastable component of the future value of a given variable. Namely,

$$\mathcal{U}_{jt}(h) = \sqrt{\mathbb{E}\left[\left(y_{j,t+h} - \mathbb{E}[y_{j,t+h} | I_t] \right)^2 | I_t \right]} \tag{1}$$

where I_t is information available at t.[2] If the expectation at t of the squared error in forecasting $y_{j,t+h}$ rises then uncertainty in the variable rises. Uncertainty in the whole sector approximated by Y_t is an aggregate of individual uncertainties

$$\mathcal{U}_t^Y(h) = \text{plim}_{N\to\infty} \sum_{j=1}^{N} w_j \mathcal{U}_{jt}(h) \equiv \mathbb{E}\left[\mathcal{U}_{jt}(h)\right] \tag{2}$$

with the aggregation weights w_j and the implicit assumption that the law of large numbers holds. The econometric framework of JLN, which we would like to adopt, is based on the following main steps:

(i) The conditional expectation of the forecast error in (1), and thus $\mathbb{E}[y_{j,t+h}|I_t]$, is approximated by forecasts of diffusion indices (common factors). Common factors are estimated from a large set of predictors, x_{it}, $i = 1, \ldots, N^x$. The information (in more technical terms the σ-field) generated by these predictors is assumed to approximate I_t as closely as possible. In addition we assume that the conditional expectation is linear in x_{it}, $i = 1, \ldots, N^x$. The common factors will be treated as known later on. Forecasts of both real activity and financial returns can be substantially improved by augmenting best-fitting conventional forecasting equations with common factors estimated from large datasets (see Ludvigson and Ng, 2007, 2009; and Stock and Watson, 2006, among others).

$$y_{j,t+1} = \Phi_j^y(L) y_{jt} + \gamma_j^F(L) \hat{\mathbf{F}}_t + \gamma_j^W(L) \mathbf{W}_t + \nu_{j,t+1} \tag{3}$$

where $\Phi_j^y(L)$, $\gamma_j^F(L)$ and $\gamma_j^W(L)$ are finite-order polynomials in the lag operator L,[3] and $\hat{\mathbf{F}}_t$ is the r_F-dimensional vector of consistent estimates of latent common factors of the predictors $\mathbf{X}_t = (x_{1t}, \ldots, x_{N^x t})'$ available for the analysis, which thus have the following factor structure

$$x_{it} = \Lambda_i' \mathbf{F}_t + e_{it} \tag{4}$$

[2] The proper measurement of uncertainty requires removing the forecastable component $\mathbb{E}\left(y_{j,t+h}|I_t\right)$ *before* computing conditional volatility. Otherwise the forecastable variation would be (falsely) classified as uncertain.

[3] Following JLN, we choose polynomials of order four for $\Phi_j^y(L)$ and polynomials of order two for $\gamma_j^F(L)$ and $\gamma_j^W(L)$.

$\mathbf{F}_t$ is the r_F-dimensional vector of latent common factors, Λ_i is the r_F-dimensional vector of factor loadings and e_{it} is the idiosyncratic error. The number of factors, r_F, is much smaller than the number of series N^x. Finally, the r_W-dimensional vector $\mathbf{W}_t$ contains additional predictors such as squares of $\hat{F}_{1t}$ and factors in x_{it}^2 to capture possible nonlinearities and potential effects that conditional volatilities might have on y_{jt}.[4] Time varying volatilities of $y_{j,t+1}$, the factors and additional predictors are allowed. The estimation of the factors uses the method of static principal components. Factors are selected on the basis of potential predictive power, see Bai and Ng (2002, 2006, 2008).

(ii) The conditional expectation of the squared forecast errors in (1) is computed from a parametric stochastic volatility model for the one-step-ahead predictive errors for both y_{jt} and the factors.[5] The conditional volatility for $h > 1$ steps ahead is computed recursively, and through this procedure additional unforecastable variation is created via time varying volatility in the errors of the predictor variables (factors). In more detail, when allowing for the autoregressive dynamics in the factors,[6] (3) can be written in the first order companion form as

$$\begin{bmatrix} \mathcal{Z}_t \\ Y_{jt} \end{bmatrix} = \begin{bmatrix} \Phi^{\mathcal{Z}} & 0 \\ \Lambda_j & \Phi_j^Y \end{bmatrix} \begin{bmatrix} \mathcal{Z}_{t-1} \\ Y_{j,t-1} \end{bmatrix} + \begin{bmatrix} \nu_t^{\mathcal{Z}} \\ \nu_{jt}^Y \end{bmatrix} \tag{5}$$

where $\mathcal{Z}_t = \left(\mathbf{Z}'_t, \ldots, \mathbf{Z}'_{t-q+1}\right)'$, $\mathbf{Z}_t = \left(\hat{\mathbf{F}}'_t, \mathbf{W}'_t\right)'$ and $Y_{jt} = (y_{jt}, \ldots, y_{j,t-q+1})'$. In addition, stationarity of the corresponding time series is assumed. Let $\Omega_{jt}(h) \equiv \mathbb{E}_t\left(\mathcal{Y}_{j,t+h} - \mathbb{E}_t\left(\mathcal{Y}_{j,t+h}\right)\right)\left(\mathcal{Y}_{j,t+h} - \mathbb{E}_t\left(\mathcal{Y}_{j,t+h}\right)\right)'$, with $\mathcal{Y}_{jt} = (\mathcal{Z}'_t, Y'_{jt})'$, be the forecast error variance of $\mathcal{Y}_{jt}$ modeled in (5) which evolves as

$$\Omega_{jt}(1) = \mathbb{E}_t\left(\mathcal{Y}_{j,t+1}\mathcal{Y}'_{j,t+1}\right) \tag{6}$$

and

$$\Omega_{jt}(h) = \Phi_j^{\mathcal{Y}}\left[\Omega_{jt}(h-1)\right]\left(\Phi_j^{\mathcal{Y}}\right)' + \mathbb{E}_t\left(\mathcal{Y}_{j,t+h}\mathcal{Y}'_{j,t+h}\right) \quad \text{for} \quad h > 1 \tag{7}$$

[4]We choose the factor in x_{it}^2 corresponding to the largest eigenvalue.

[5]To estimate stochastic volatility in the forecast errors we use the 'stochvol' R package.

[6]We assume an order of four in the autoregressive dynamics of the factors.

where

$$\Phi_j^{\mathcal{Y}} = \begin{bmatrix} \Phi^{\mathcal{Z}} & 0 \\ \Lambda_j & \Phi_j^Y \end{bmatrix} \tag{8}$$

Thus, the expected forecast uncertainty of $y_{j,t+h}$ is the square root of the corresponding scalar on the diagonal of $\Omega_{jt}(h)$; i.e.,

$$\mathcal{U}_{jt}(h) = \sqrt{e_j' \, \Omega_{jt}(h) e_j} \tag{9}$$

where e_j is the corresponding selection vector. However, if stochastic volatility of y_{jt} and the factors is assumed, e.g., $\nu_{j,t+1} = \sigma_{j,t+1}\varepsilon_{j,t+1}$ with $\varepsilon_{j,t+1} \sim N(0,1)$ and

$$\log\left(\sigma_{j,t+1}^2\right) = \alpha_j + \beta_j \log\left(\sigma_{jt}^2\right) + \tau_j \eta_{j,t+1}, \quad \eta_{j,t+1} \sim N(0,1) \tag{10}$$

then this affects the time variation in uncertainty (7) because, as one can see after some derivations (see JLN), the $h-$step ahead forecast error variance for $Y_{j,t+h}$, $\Omega_{jt}^Y(h)$, is decomposed into: an autoregressive component, a common factor component (affected by stochastic volatility in the innovations of the factors), stochastic volatility in y_{jt} and the covariance between the forecast errors of y_{jt} and its predictors. The stochastic terms in (1) can be calculated using Markov Chain Monte Carlo (MCMC) methods.

(iii) The aggregate uncertainty, $\mathcal{U}_t^Y(h)$, is estimated from individual uncertainty measures $\mathcal{U}_{jt}(h)$. We consider two kinds of weights: equal weights and weights based on the common factors in the individual measures of uncertainty. As the implied uncertainty indices are very similar, we use the simpler version based on equal weights in this paper.

We use slightly modified versions of the codes provided by Jurado, Ludvigson and Ng (2015) to compute our financial and economic uncertainty indices.

3 Data and uncertainty indices

The following subsections describe the data used for estimating the uncertainty indices and present graphs and descriptive statistics of the estimated financial and economic uncertainty indices, for Austria and the euro area.

3.1 Data

The financial data we use in order to estimate the financial uncertainty index include monthly observations on interest rates, yields on government bonds, yields on corporate bonds, interest rate swaps, overnight interest rates, spreads between different yields and/or rates, stock indices, bond indices, foreign exchange rates, dividend-price ratios, earnings-price ratios, and volatilities of stock/bond index and foreign exchange returns. We consider different maturities for the rates/yields and use averages of the daily observations to compute monthly values. In total we have 77 financial variables for Austria, and 74 for the euro area.[7] The data set which is used to extract the factors used for forecasting the conditional volatilities for the financial variables, consists of both the financial variables just described and additional macroeconomic variables. The macroeconomic variables include sentiment indicators, data on employment, retail sales, manufacturing, orders, price indices, and survey data for twelve industries related to important economic questions concerning order books, production trend observed in recent months, production expectations, employment expectations, etc.[8] The macroeconomic data set includes 122 time series for Austria and the euro area, respectively.[9] All data range from January 2000 until December 2020, i.e., we have 252 observations per variable. Details on the data used and a list of all variables can be found in Appendix A.1. When we compute the macroeconomic uncertainty indicator we use again the macroeconomic and the financial data to extract the factors, but we forecast conditional volatilities for the macroeconomic variables (not for the financial variables). In doing so we follow Jurado, Ludvigson and Ng (2015) to group some variables

[7] This means that $N = 77$ for Austria, and $N = 74$ for the euro area, when we compute the financial uncertainty index.

[8] In total, the survey data cover seven questions relating to i) production trend observed in recent months, ii) order books, iii) export order books, iv) stocks of finished products, v) production expectations, vi) selling price expectations, vii) employment expectations, and one overall variable, the industrial confidence indicator.

[9] Thus, $N^x = 199$ for Austria, and $N^x = 196$ for the euro area.

which are originally included in the financial variables with the macroeconomic variables. In this case $N = 138$ for Austria, and $N = 135$ for the euro area, respectively. For more details see Appendix A.1.

In addition to market financial data we consider banking data from balance sheets and profit and loss accounts as well as regulatory banking data in order to calculate the financial uncertainty index. These data include various income categories, different equity and debt instruments, various risk exposures, and regulatory capital instruments like the tier 1 ratio and are taken from the consolidated banking data provided by the European Central Bank. In total we have 45 banking variables for Austria and 37 banking variables for the euro area.[10] Banking data are available only at quarterly frequency and we create monthly series by filling the missing data through the Kalman filter and Kalman smoother, see Appendix B. After filling missing observations we have monthly data from December 2008 to December 2020, i.e., 145 observations per variable. This sample period is significantly shorter than the one for the market financial data (January 2000 to December 2020). More details on the banking data and a list of all variables used can be found in Appendix A.2.

3.2 Uncertainty indices

We present graphs of the financial and economic uncertainty indices for Austria and for the euro area in Figure 1. We show three indices in each case, relating to forecast horizons of one, three and twelve months. Some descriptive statistics are given in Table 1. While the level of uncertainty clearly increases with the forecast horizon (on average), the variability of uncertainty decreases, at least with a larger forecast horizon of twelve months.[11] Financial uncertainty in Austria and in the euro area show a very similar development and show spikes around the bursting of the dot-com bubble 2000–2001, the global financial crisis 2007–2008, the European sovereign debt crisis 2010–2011, as well as around the outbreak of the Covid-19 crisis in early 2020. Macroeconomic uncertainty exhibits both a smaller level (on average) and a significantly smaller variability than financial uncertainty. It exhibits two spikes, around the great depression (global financial crisis) 2008–2009 and around the outbreak of the Covid-19 crisis in 2020. Albeit rather similar, the development

[10] In fact we consider all variables which begin in 2007, and not in 2014, and which are stock data, as flow data are not annualized. When flow data are reported in percent of other flow data we can also use them.

[11] Note that the forecast tends to the unconditional mean as the forecast horizon tends to infinity.

of economic uncertainty is a bit more diverse between Austria and the euro area than financial uncertainty. In particular the two spikes are more clearly pronounced in the euro area than in Austria.

The financial uncertainty indices for different forecast horizons, for Austria and the euro area, are highly correlated (around 0.99).[12] Also the economic uncertainty indices are positively correlated, within Austrian and within the euro area, at levels larger than 0.90; however, at a lower degree across the two regions (0.43–0.73). The descriptive statistics suggest that all uncertainty indices exhibit a (strongly) positive skewness. This implies that the distribution is not symmetric and, in particular, that the right tail of the distribution is longer and the mass of the distribution is concentrated on the left. The kurtosis is mostly around three, which is the value for the Gaussian distribution, only for economic uncertainty in the euro area the numbers are well above ten. This suggests that the underlying distribution produces more extreme realizations than the normal distribution. When looking at Figure 1 we observe a sharp increase in economic uncertainty for Austria and the euro area during the Covid-19 crisis, where the effect is even stronger for the euro area. We claim that this is the main driver of excess kurtosis for economic uncertainty in the euro area. To verify this claim, we estimate the kurtosis of the economic uncertainty index for the subsample excluding the Covid-19 crisis (May 2000 to December 2019), and obtain values which are indeed much lower (between 4.5 and 7.6) than for the total sample.

We also compare our financial uncertainty index with other measures of financial uncertainty, namely the stock market volatility (of the ATX and the Euro Stoxx 50) and the ECB's composite indicator of systemic stress (CISS), see Figure 2. We can observe both similarities and differences. While the financial uncertainty index for Austria is positively correlated with the ATX volatility (0.35), there are some peaks which are not correspondingly reflected by both indicators. For example, the increase in financial uncertainty in 2000–2001 is not shown in the ATX volatility at all. This is probably partially due to the small size of the Austrian stock market. In the euro area the correlation between financial uncertainty and the Euro Stoxx 50 volatility is 0.47, but also here the two indices do not always agree on peaks, neither with respect to size nor with respect to exact timing. When we compare our financial uncertainty indices with the CISS, we see that correlations are slightly higher than with respect to the stock market volatility indices, namely 0.50 for Austria, and 0.55 for the euro area. Again, however, the indices do not always agree on

[12] This is true for both within and across the regions.

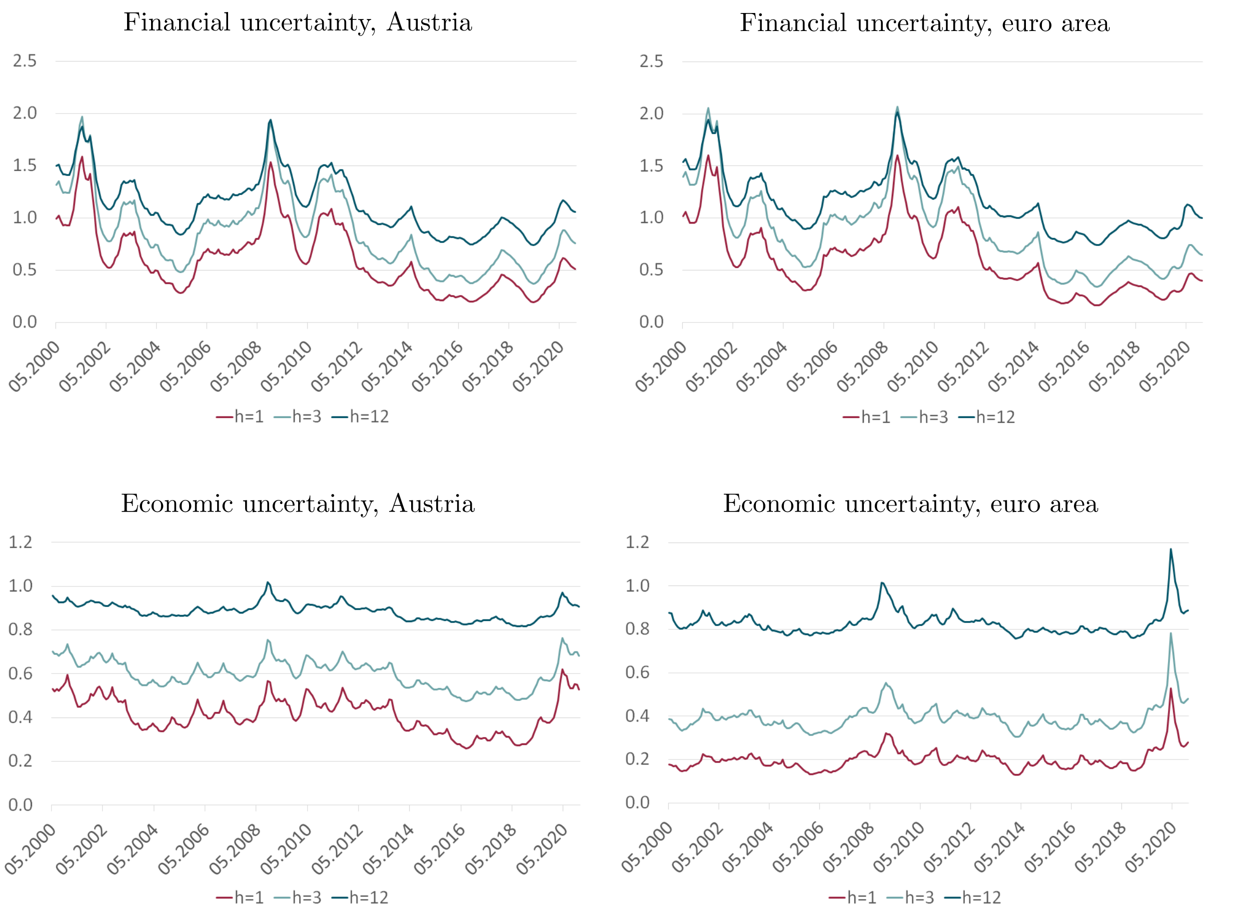

Figure 1: Financial and economic uncertainty indices for Austria (left) and the euro area (right), for forecast horizons of one, three and twelve months.

peaks. In particular the enhanced systemic stress in 2015–2016 visible in the CISS is not reflected in the financial uncertainty index, neither in Austria nor in the euro area.

3.3 Financial uncertainty indices with banking data

Figure 3 shows graphs of financial uncertainty indices with and without banking data, for Austria and for the euro area. We present the indices for forecast horizons of one, three and twelve months. Some descriptive statistics and correlations are given in Table 2. For a forecast horizon of one month the two financial uncertainty indices are rather similar, for both Austria and the euro area. For a forecast horizon of three months financial uncertainty considering banking data is clearly larger than financial uncertainty without banking data

Table 1: Summary statistics for uncertainty indices.
The table reports the mean, standard deviation (Std), skewness (Skew), kurtosis (Kurt), minimum (Min), and maximum (Max) for financial (fin) and economic (eco) uncertainty indices, for Austria and the euro area, for forecast horizons of one, three and twelve months, over the sample period May 2000 to December 2020.

	Austria						Euro area					
	fin, 1	fin, 3	fin, 12	eco, 1	eco, 3	eco, 12	fin, 1	fin, 3	fin, 12	eco, 1	eco, 3	eco, 12
Descriptive statistics												
Mean	0.602	0.859	1.129	0.414	0.600	0.887	0.607	0.898	1.168	0.200	0.393	0.828
Std	0.315	0.366	0.273	0.081	0.066	0.038	0.335	0.403	0.291	0.049	0.060	0.055
Skew	0.920	0.844	0.715	0.097	0.047	0.274	0.880	0.799	0.689	2.559	2.439	2.485
Kurt	3.384	3.208	2.925	2.215	2.220	2.910	3.245	3.068	2.898	14.465	13.314	12.420
Min	0.195	0.371	0.740	0.260	0.474	0.817	0.162	0.341	0.740	0.129	0.304	0.759
Max	1.589	1.969	1.939	0.622	0.762	1.020	1.604	2.070	2.017	0.530	0.784	1.171
Correlation matrix												
Austria												
fin, 1	1											
fin, 3	1.000	1										
fin, 12	0.997	0.998	1									
eco, 1	0.622	0.629	0.647	1								
eco, 3	0.666	0.672	0.692	0.996	1							
eco, 12	0.771	0.777	0.800	0.919	0.951	1						
Euro area												
fin, 1	0.992	0.992	0.990	0.598	0.644	0.760	1					
fin, 3	0.992	0.992	0.991	0.607	0.653	0.767	1.000	1				
fin, 12	0.991	0.992	0.993	0.633	0.680	0.791	0.997	0.998	1			
eco, 1	0.177	0.179	0.195	0.429	0.441	0.457	0.122	0.126	0.162	1		
eco, 3	0.268	0.269	0.287	0.491	0.510	0.543	0.214	0.218	0.254	0.993	1	
eco, 12	0.485	0.487	0.508	0.637	0.667	0.731	0.437	0.441	0.478	0.902	0.945	1

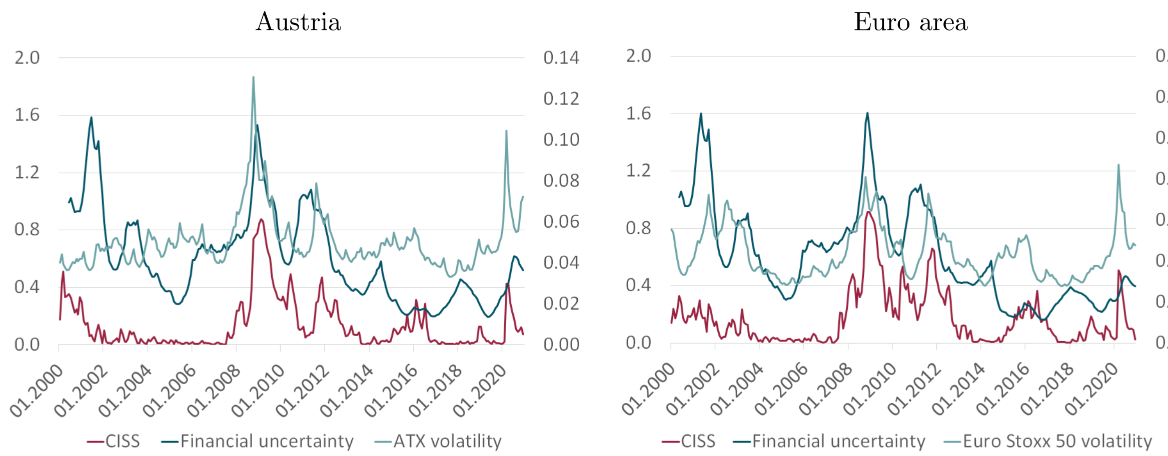

Figure 2: Financial indices for Austria and the euro area.
The right axis applies to the ATX and Euro Stoxx 50 volatilities. The financial uncertainty indices relate to $h = 1$.
Austria: Correl(financial uncertainty, CISS) = 0.50, Correl(financial uncertainty, ATX volatility) = 0.35, Correl(CISS, ATX volatility) = 0.64. Euro area: Correl(financial uncertainty, CISS) = 0.55, Correl(financial uncertainty, Euro Stoxx 50 volatility) = 0.47, Correl(CISS, Euro Stoxx 50 volatility) = 0.65.

for Austria, and mostly larger for the euro area. If uncertainty relates to forecasting twelve months ahead then taking account of banking data somehow takes out certain peaks for both Austria and the euro area. While in Austria, however, financial uncertainty including banking data is significantly higher than uncertainty without banking data, in the euro area financial uncertainty with banking data is significantly lower up to the year 2017 than financial uncertainty without banking data, and rather similar afterwards.

Financial uncertainty with and without banking data are highly correlated (for any forecast horizons) in Austria (larger than 0.96), and the corresponding correlation coefficients are slightly smaller, albeit still large (about 0.87), in the euro area. Even if the correlation over the total period considered (April 2009 to December 2020) is high, the financial uncertainty indices sometimes disagree quite strongly on the exact timing and degree of financial uncertainty, both in Austria and the euro area. So it may make sense to consider banking data, even if this requires additional technical work related to the transformation of quarterly to monthly frequency and banking data are only available with a much larger time lag than market data. The difference between the two indices may reflect the different types of information revealed by banking and market data. Balance sheet, profit & loss and regulatory data, for example, describe much more directly the financial health and soundness of banks than market data, which might be relevant in certain times.

4 Empirical analysis

The data sample covers monthly observations for the period ranging from May 2000 through December 2020. We do not start earlier because our uncertainty indices can only be created from May 2000 onwards due to data availability of the predictors and the autoregressive structure of (3), where the maximum finite order polynomial is four. We perform an impulse response analysis to quantify the dynamic responses of macroeconomic variables (industrial production, employment) and stock market indices (ATX and Euro Stoxx 50) to uncertainty shocks (of both financial and economic nature) as well as to shocks of an alternative financial stability indicator, namely the ECB's composite indicator of systemic stress (CISS). We use the Cholesky decomposition to identify the structural shocks, for both Austria and the euro area, in the vector error correction (VEC) framework

$$\Delta \mathbf{y}_t \quad = \quad \boldsymbol{\delta}\mathbf{D}_t + \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{y}_{t-1} + \sum_{j=1}^{q} \boldsymbol{\Gamma}_j \Delta \mathbf{y}_{t-j} + \mathbf{u}_t \tag{11}$$

where $(\mathbf{y}_t)$ is an $n-$dimensional stochastic process, t denotes the time dimension and $\mathbf{D}_t \in \mathbb{R}^p$ collects the deterministic terms (such as a constant) and strictly exogenous variables. The corresponding parameters are $\boldsymbol{\delta} \in \mathbb{R}^{n \times p}$, i.e., p denotes the number of these variables. For Austria we consider the following variables as deterministic or exogenous: intercept, lagged growth rates of the short-term interest rate for the euro area and of industrial production for the euro area,[13] i.e., $p = 3$, while for the euro area we consider only an intercept, i.e., $p = 1$. The matrix $\boldsymbol{\alpha}$ is of dimension $n \times r$, while the matrix of cointegrating vectors $\boldsymbol{\beta}$ is an $n \times r$ matrix, where n is the number of endogenous variables and r is the number of cointegrating relationships. For matrix $\boldsymbol{\beta}$ we apply the usual normalization such that $\boldsymbol{\beta}_{1:r,1:r}$ is the r-dimensional identity matrix. The "short run dynamics" are described by the $n \times n$ matrices $\boldsymbol{\Gamma}_j$, $j = 1, \ldots, q$. Finally, $\mathbf{u}_t$ is a white noise process with mean zero and covariance matrix $\boldsymbol{\Sigma}$.

[13] As Austria is a small open economy, we assume that it is influenced by the economy of the euro area. For the case of industrial production this is supported by the Granger causality test.

Table 2: Summary statistics for financial uncertainty indices.
The table reports the mean, standard deviation (Std), skewness (Skew), kurtosis (Kurt), minimum (Min), and maximum (Max) for financial uncertainty indices with (ban) and without (no) banking data, for Austria and the euro area, for forecast horizons of one, three and twelve months, over the sample period April 2009 to December 2020.

	Austria						Euro area					
	no, 1	no, 3	no, 12	ban, 1	ban, 3	ban, 12	no, 1	no, 3	no, 12	ban, 1	ban, 3	ban, 12
Descriptive statistics												
Mean	0.412	0.510	1.098	0.384	1.096	1.922	0.442	0.562	1.215	0.395	0.672	0.917
Std	0.286	0.235	0.434	0.228	0.229	0.141	0.216	0.156	0.363	0.186	0.204	0.097
Skew	4.012	3.860	3.985	4.129	4.178	4.090	3.641	3.569	3.700	4.287	4.242	4.107
Kurt	0.054	-0.207	0.002	0.285	0.421	0.190	-0.187	-0.287	-0.094	1.023	0.840	0.377
Min	0.081	0.213	0.585	0.150	0.866	1.775	0.153	0.345	0.736	0.195	0.449	0.805
Max	1.208	1.127	2.294	1.092	1.820	2.351	1.029	0.969	2.217	1.082	1.407	1.240
Correlation matrix												
Austria												
no, 1	1											
no, 3	0.999	1										
no, 12	1.000	0.999	1									
ban, 1	0.966	0.962	0.967	1								
ban, 3	0.966	0.961	0.967	1.000	1							
ban, 12	0.967	0.963	0.968	1.000	1.000	1						
Euro area												
no, 1	0.961	0.963	0.960	0.906	0.906	0.907	1					
no, 3	0.963	0.968	0.964	0.915	0.914	0.916	0.994	1				
no, 12	0.965	0.967	0.965	0.914	0.914	0.914	1.000	0.996	1			
ban, 1	0.939	0.930	0.937	0.960	0.961	0.958	0.871	0.868	0.877	1		
ban, 3	0.944	0.936	0.943	0.965	0.966	0.964	0.874	0.877	0.881	0.999	1	
ban, 12	0.948	0.941	0.948	0.970	0.970	0.969	0.874	0.880	0.881	0.995	0.998	1

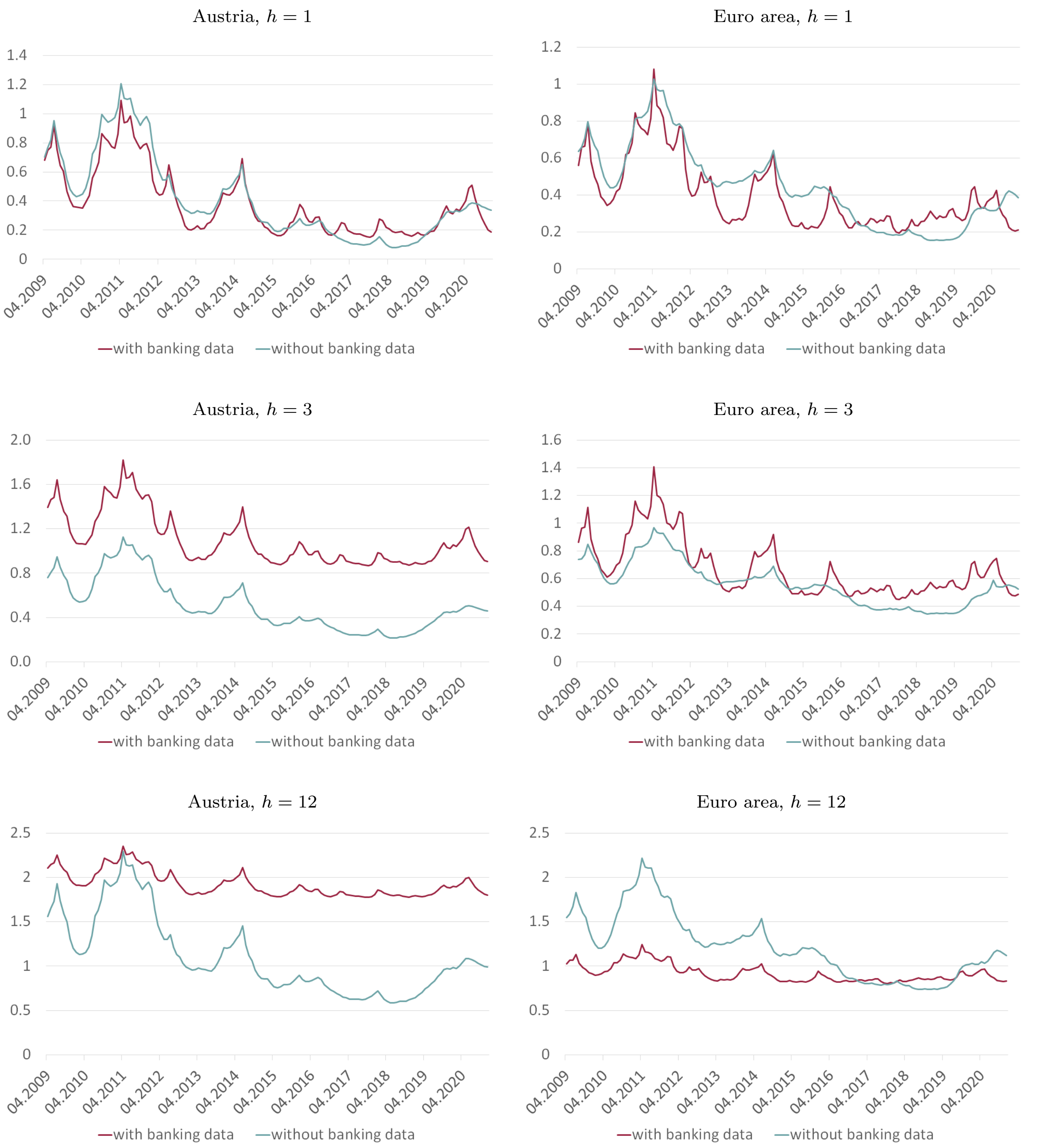

Figure 3: Financial uncertainty indices for Austria (left) and the euro area (right) with and without banking data.

Our VEC model for Austria contains the following endogenous variables: the uncertainty index (financial uncertainty index, economic uncertainty index or CISS), x_t^{AT}, the industrial production index for Austria, ip_t^{AT}, employment for Austria, $empl_t^{AT}$, the consumer price index for Austria, cpi_t^{AT}, and the stock index for Austria (ATX), atx_t, i.e., $n = 5$ and $\mathbf{y}_t = \left(x_t^{AT}, ip_t^{AT}, empl_t^{AT}, cpi_t^{AT}, atx_t\right)'$. The endogenous variables for the euro area are: the uncertainty index (financial uncertainty index, economic uncertainty index or CISS), x_t^{EA}, the industrial production index for the euro area, ip_t^{EA}, employment for the euro area, $empl_t^{EA}$, the consumer price index for the euro area, cpi_t^{EA}, the stock index for the euro area (Euro Stoxx 50), $stoxx_t$, and short-term interest rates for the euro area, ir_t i.e., $n = 6$ and $\mathbf{y}_t = \left(x_t^{EA}, ip_t^{EA}, empl_t^{EA}, cpi_t^{EA}, stoxx_t, ir_t\right)'$. All variables, except for the interest rates and uncertainty index, enter in log-levels.

The number of lags is chosen based on the Schwarz information criterion.[14] The application of the error correction model (11) is supported as follows: For the time series considered, except for the uncertainty indices, the null hypothesis of a unit root cannot be rejected at the 5% significance level, using augmented Dickey-Fuller tests.

To deal with a stationary variable in a VEC model we follow Lütkepohl (2005)[page 250]. That is, the first coordinate of $\mathbf{y}_t$ is the $I(0)$ random variable and the first cointegrating vector has one as the first component and zeros elsewhere (in our application as the stationary variable, the uncertainty index x_t, is the first element of $\mathbf{y}_t$).

We have performed Johansen cointegration tests among all integrated endogenous variables[15]and obtained evidence of an additional cointegrating vector, for both Austria and the euro area. Thus, we have two cointegrating vectors, i.e., $\widehat{r} = 2$.

4.1 Impulse response analysis

To identify the impact of an uncertainty shock on macroeconomic variables and the stock market we employ the impulse response analysis based on the Cholesky decomposition. We present results of estimated impulse responses of logged values of industrial production, employment and the stock market to one standard deviation increases ("shocks") in the financial uncertainty index and the economic uncertainty index over the next 60 months

[14]Namely, $\widehat{q} = 2$ for Austria and $\widehat{q} = 1$ for euro area.

[15]Both trace and maximum eigenvalue tests indicated the same result, namely the rank of cointegrating space being one. In case of Austria in addition to an intercept we have included among the exogenous variables also growth rates of industrial production of the euro area and of the short-term interest rates.

in Figure 4 for Austria, and in Figure 5 for the euro area.[16] In addition, we look at the impact of a one standard deviation increase of the CISS upon the above mentioned variables (industrial production, employment and the stock market) in order to compare these results with the ones driven by the financial uncertainty shock (see again Figures 4 and 5).

Austria

Figure 4, left panel, plots the estimated impact of a one standard deviation increase in financial uncertainty on the Austrian logged industrial production, employment and the stock market (ATX). Since the variables are measured on a logarithmic scale, the numbers on the vertical axis are logarithmic growth rates (where due to the relatively small values logarithmic growth rates are almost equal to growth rates). That is, for a one standard deviation shock in the Austrian financial uncertainty index we predict an instantaneous decline of industrial production of approximately 0.2%. For industrial production we expect a long lasting decline of approximately 0.8%. For employment the short-run effect is of minor importance, while in the long run the shock decreases employment by approximately 0.1%. Given the corresponding 95% confidence intervals, we observe that this effect is not significant at the 5% level. For the stock market we observe a long lasting and significant effect of approximately -7%.

The estimated effects of an increase in economic uncertainty are provided in Figure 4, middle panel. We observe a decline of industrial production of approximately 0.5%, a decrease in employment of approximately 0.2%, and a reduction of the ATX of approximately 3%. However, given the 95% confidence bounds the effects of a raise in economic uncertainty on industrial production, employment and the stock market are – with the exception of some smaller effects in the short run – not significant at the 5% level. The right panel of Figure 4 shows the impulse response functions obtained from a one standard deviation increase in the CISS, where only a significant decrease in the stock market index is predicted, all the other effects are not significant. The ATX is expected to decline by 3% in the long run, which is a smaller response than the one caused by the financial uncertainty index (-7%).

[16]Note that estimates of the impulse response function are in black and the 95% confidence intervals are in red.

Euro area

Figure 5, left panel, presents the expected impacts of a one standard deviation increase of financial uncertainty in the euro area. For industrial production and for employment the effects are not significant at the 5% level, while for the Euro Stoxx 50 the effect is significant and in the long run the aggregate stock market index decreases by approximately 4%. By contrast, an increase in economic uncertainty has an insignificant impact on the stock market as can be observed in Figure 5, middle panel, while the impact on euro area employment and industrial production is significant at the 5% level. In the long run we observe a decrease in industrial production of approximately 0.8% and a reduction in employment of approximately 0.4%. Finally, the right panel of Figure 5 presents the effects of a one standard deviation increase of the CISS in the euro area. The impact on industrial production is not significant, while for employment we observe a significant effect. In the long run we see a reduction in employment of approximately 0.3%. For the stock market index the upper 95% confidence bound is slightly above zero for longer forecasting horizons. Hence, for the stock market the expected impact of an increase in the CISS is close to being significant at the 5% level. Here, a decline of approximately 1.5% is expected in the long run for the Euro Stoxx 50, which is below the decline of the Euro Stoxx 50 triggered by the financial uncertainty shock (4%).

The summary of our findings from the impulse response analysis is as follows. For the euro area economic uncertainty (significantly) affects more the economic variables (industrial production and employment) than the stock market while financial uncertainty shows a significant impact on the stock market for both markets. In addition, financial uncertainty has a stronger impact on the stock market (in the long run) than the CISS, for both Austria and the euro area, and to some extent also on industrial production. Finally, financial uncertainty also has a stronger impact on the ATX and the Euro Stoxx 50 than economic uncertainty.

4.2 Forecasting analysis

To analyze the potential effect or value added of our uncertainty indices on forecasts of the variables which are examined in the above impulse response analysis (namely industrial production, employment and the stock market), we compare the forecast performance of these variables when the uncertainty index is included in the VEC model and when it is

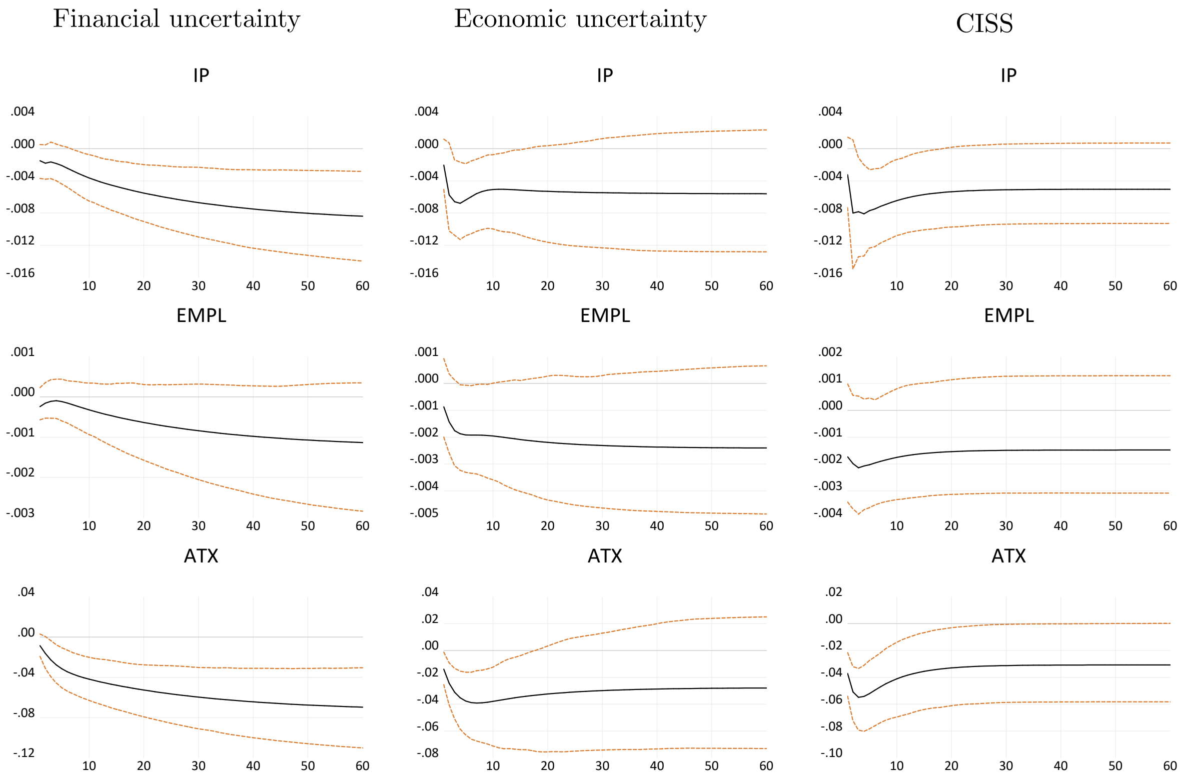

Figure 4: Impulse responses of industrial production (IP), employment (EMPL) and the ATX to a one standard deviation shock of financial uncertainty (left), of economic uncertainty (middle), and of CISS (right), for Austria and $h = 1$, with a 95% confidence interval.

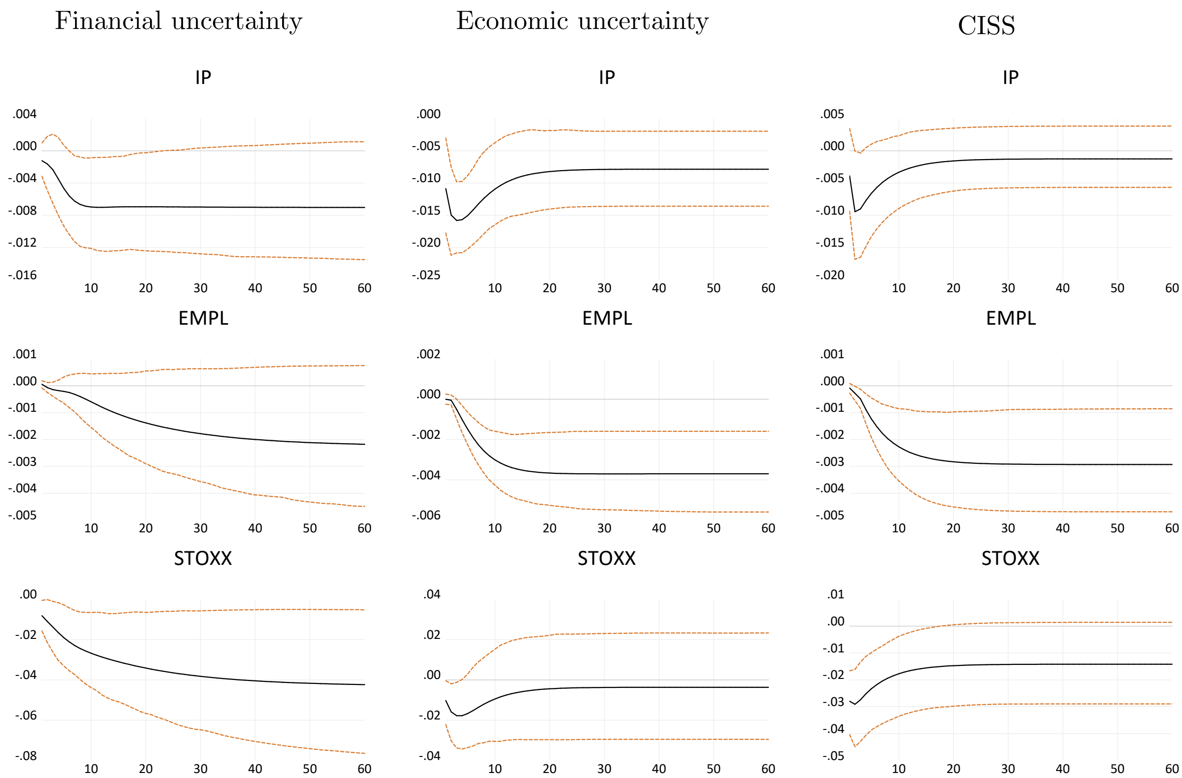

Figure 5: Impulse responses of industrial production (IP), employment (EMPL) and the Euro Stoxx 50 (STOXX) to a one standard deviation shock of financial uncertainty (left), of economic uncertainty (middle), and of CISS (right), for the euro area and $h = 1$, with a 95% confidence interval.

omitted. In addition, we consider the forecast performance of a VEC model when the uncertainty index is replaced by the CISS and we examine the forecast performance of two benchmark models, the random walk (RW) and the univariate autoregressive model of order one, DAR(1).[17] We consider rolling-window estimation for our analysis, i.e., we keep the size of the estimation sample constant and equal to ten years, and move forward the sample by one month, while re-estimating the model parameters. The out-of-sample period, in which we evaluate the forecast performance, ranges from January 2010 to December 2020. The "best" models are chosen based on the individual forecast performance of the VEC models for all lags (up to twelve) and two restricted cointegrating vectors as described above and one cointegrating vector for the case when no uncertainty index is present in the model. In order to evaluate different forecasts we do not only employ traditional loss measures, like root mean squared error (RMSE) and mean absolute error (MAE), but also profit-based measures like directional accuracy (DA) and directional value (DV). The directional accuracy, or hit rate, is a binary variable measuring whether the direction of a variable change was correctly forecasted. The directional value additionally incorporates the economic value of directional forecasts by assigning to each correctly predicted change its magnitude. The loss-based and profit-based performance measures are formally defined as follows,

$$\begin{aligned}
AE_{t+h,h} &= \left|\hat{z}_{t+h|t} - z_{t+h}\right| \\
SE_{t+h,h} &= \left(\hat{z}_{t+h|t} - z_{t+h}\right)^2 \\
DA_{t+h,h} &= \mathbb{I}\left(\mathrm{sgn}(z_{t+h} - z_t) = \mathrm{sgn}(\hat{z}_{t+h|t} - z_t)\right) \\
DV_{t+h,h} &= |z_{t+h} - z_t|\ DA_{t+h,h}
\end{aligned}$$

where z_t is the variable we want to forecast, namely $z_t \in \left\{ip_t^{AT}, ip_t^{EA}, empl_t^{AT}, empl_t^{EA}, atx_t, stoxx_t\right\}$ at time t, $\hat{z}_{t+h|t}$ is the forecast of the variable for time $t+h$ conditional on the information available at time t, i.e., h is the forecast horizon, and $\mathbb{I}(\cdot)$ is the indicator function. The aggregate performance measures for each model are calculated over the out-of-sample period

[17] As all forecasted variables are integrated, we apply the AR(1) model on log-differences of the underlying variable.

for a given forecast horizon as follows,

$$
\begin{aligned}
RMSE_h &= \sqrt{\sum_{j=0}^{T_2-T_1} \frac{SE_{T_1+j,h}}{T_2 - T_1 + 1}} \\
MAE_h &= \sum_{j=0}^{T_2-T_1} \frac{AE_{T_1+j,h}}{T_2 - T_1 + 1} \\
DA_h &= 100 \sum_{j=0}^{T_2-T_1} \frac{DA_{T_1+j,h}}{T_2 - T_1 + 1} \\
DV_h &= 100 \, \frac{\sum_{j=0}^{T_2-T_1} DV_{T_1+j,h}}{\sum_{j=0}^{T_2-T_1} |z_{T_1+j} - z_{T_1+j-h}|} \\
&= 100 \, \frac{\sum_{j=0}^{T_2-T_1} |\hat{z}_{T_1+j|T_1+j-h} - z_{T_1+j-h}| DA_{T_1+j,h}}{\sum_{j=0}^{T_2-T_1} |z_{T_1+j} - z_{T_1+j-h}|}
\end{aligned}
$$

where T_1 = January 2010 and T_2 = December 2020. Results are presented in Tables 3 to 5 for forecast horizons of one, three and twelve months, where we compare the performance of the "best" VEC models (with respect to the lag length) for the cases with: (i) no uncertainty index and no CISS,[18] (ii) financial uncertainty index, (iii) economic uncertainty index, (iv) CISS, and for two benchmark models, (v) autoregressive model of order one in differences, DAR(1), and (vi) random walk (RW).

Table 3 presents the forecast performance for industrial production for both Austria and the euro area. Regarding the loss measures (RMSE and MAE) the best performance is achieved by the random walk model (except for the case of Austria and a forecast horizon of three months, when the lowest loss measures are achieved by the VEC model when no uncertainty index is included). With respect to the profit-based measures and a forecast horizon of one month, the best models for Austria are achieved when the financial uncertainty index is included, and for the euro area when the economic uncertainty index is included. For a forecast horizon of three months the model with no uncertainty index is the best with respect to the directional value for Austria, and with respect to the hit rate for the euro area. On the other hand, the model with economic uncertainty yields the largest directional value for the euro area, and for Austria the largest hit rate is achieved by the

[18] For ease of notation we say "no uncertainty index" when we mean: no financial uncertainty, no economic uncertainty, and no CISS.

random walk model. Finally, for a forecast horizon of twelve months the random walk and the autoregressive model of order one give the largest directional accuracy and directional value for Austria, while for the euro area the model with no uncertainty provides the largest hit rate and the model with economic uncertainty provides the largest directional value. Note that for the euro area the model with economic uncertainty yields the largest directional value for all forecast horizons ($h = 1$, 3, 12).

Regarding the forecast performance for employment (see Table 4) one can observe that the model with economic uncertainty implies the the smallest RMSE and MAE for the euro area (except for the case of a forecast horizon of twelve months and MAE when the best model is the model with financial uncertainty). For Austria the best model with respect to forecast accuracy is the one where the CISS is included, followed by DAR(1)[19] and the random walk model.[20] Regarding the profit-based measures, the largest performance is implied by the model with the CISS for Austria and a forecast horizon of one month, and also for the euro area in most cases; more precisely, for DV and $h = 1$, for both DA and DV for $h = 3$, and for DA and $h = 12$. Note that the model with no uncertainty is the best one only for Austria for profit-based measures and a forecast horizon of twelve months, and coincides with the profit-based performance of the model with economic uncertainty. In addition, the model with financial uncertainty is the best one for the euro area with respect to the hit rate and $h = 1$, and for Austria with respect to the directional value and $h = 3$. The model with economic uncertainty gives the largest DV for the euro area and $h = 12$.

Table 5 presents the forecast performance for the stock market indices for Austria (ATX) and the euro area (Euro Stoxx 50). Most of the time the benchmark models provide the best forecasting accuracy (smallest RMSE and MAE). Regarding the performance with respect to the profit-based measures, the model with no uncertainty is the best only in case of Austria and $h = 1$. The model with financial uncertainty yields the best profit-based performance for the euro area for $h = 3$ (hit rate), while for $h = 12$ the best performance is implied by the model with economic uncertainty. The model with the CISS performs the best for Austria and $h = 3$.

All in all, we can observe the following systematic pattern in the euro area (for all forecast horizons, $h = 1$, 3, 12): (i) the model with economic uncertainty dominates the best models for industrial production with respect to the directional value, (ii) the model with

[19]For the cases when MAE and $h = 1$, and RMSE and $h = 3$.

[20]For the case when RMSE and $h = 1$.

economic uncertainty dominates the best models for employment with respect to forecast accuracy (RMSE and MAE), (iii) the model with financial uncertainty (and economic uncertainty for $h = 12$) dominates the best models for the Euro Stoxx 50. The results are less clear for Austria.

In order to find out whether some forecasts are significantly better than others (with respect to a certain performance measure, i.e., RMSE, MAE, DA or DV), we perform the Diebold-Mariano test of equal forecast accuracy (see Diebold and Mariano, 1995). We are particularly interested in whether models including uncertainty indices (both financial and economic) achieve significantly better forecasts than models without uncertainty indices. Our results suggest that this is not the case.

4.3 The effect of banking data

We perform the forecasting analysis (for industrial production, employment and the stock market) also for the case when the financial uncertainty indicator is calculated based on a financial data set that includes banking data in addition to the previously considered financial data. Doing so, however, we obtain the financial uncertainty index only from April 2009 until December 2020, as the banking data are available only from December 2008 onwards. Thus, the out-of-sample period in this case will range from January 2015 to December 2020. The purpose of this analysis is to assess the effect (in terms of the forecasting performance) of the additional banking data. That is, we compare the forecasting performance of models that include financial uncertainty with banking data with the forecasting performance of models that include financial uncertainty without banking data. To have a fair comparison, we redo the forecasting analyis for the case when the financial uncertainty without banking data is included in the VEC model for this shorter period.

Table 6 presents the forecast performance for industrial production for Austria and the euro area. As in the case of the longer (original) time period the best model with respect to the loss-based measures (RMSE and MAE) is again the random walk in all cases (but one). Regarding the profit-based measures, for Austria the best performance is achieved by models with the financial uncertainty index without banking data[21] while for the euro area the best performance is achieved by models with the financial uncertainty index with

[21] This is true for all cases under examination except for one, namely for a forecast horizon of one month and DV, when the best model is the one with the financial uncertainty index with banking data.

Table 3: Forecasting industrial production for Austria and the euro area.
We consider best vector error correction models including either no uncertainty index, the financial uncertainty index, the macroeconomic uncertainty index or the CISS as well as two benchmark models, the random walk (RW) and the autoregressive model of order one in differences (DAR(1)). The time period used is May 2000 to December 2020, the out-of-sample period is January 2010 to December 2020.

	Industrial production, AT				Industrial production, EA			
	RMSE	MAE	DA	DV	RMSE	MAE	DA	DV
	$h = 1$							
No uncertainty	2.80	1.47	55.00	57.45	3.09	1.19	54.17	51.82
Financial unc.	2.88	1.59	**55.83**	**66.25**	3.15	1.21	53.33	49.02
Economic unc.	2.74	1.52	54.17	58.04	3.04	1.20	**55.00**	**64.75**
CISS	2.81	1.54	54.17	57.27	3.22	1.24	55.00	52.34
DAR(1)	2.76	1.47	51.67	46.93	3.29	1.25	38.33	21.94
RW	**2.44**	**1.41**	49.17	50.24	**2.48**	**1.10**	40.00	35.25
	$h = 3$							
No uncertainty	**4.04**	**2.10**	60.00	**69.67**	4.93	1.80	**57.50**	55.36
Financial unc.	4.24	2.37	57.50	68.23	5.07	1.88	55.00	57.65
Economic unc.	4.47	2.29	58.33	64.39	5.87	2.13	53.33	**58.38**
CISS	4.20	2.23	58.33	55.50	5.01	1.99	55.00	56.24
DAR(1)	4.54	2.23	59.17	58.41	5.94	1.99	35.83	35.92
RW	4.17	2.15	**60.83**	61.17	**4.21**	**1.71**	33.33	14.62
	$h = 12$							
No uncertainty	4.99	3.53	70.83	72.26	5.14	3.01	**65.00**	57.31
Financial unc.	5.49	4.19	66.67	69.48	5.13	3.07	60.83	61.67
Economic unc.	5.21	3.54	69.17	66.76	5.40	3.34	58.33	**72.70**
CISS	5.08	3.46	71.67	70.65	5.30	3.37	62.50	55.53
DAR(1)	5.15	3.49	**75.00**	**75.11**	5.09	3.03	22.50	8.76
RW	**4.90**	**3.42**	**75.00**	**75.11**	**4.69**	**2.67**	20.00	5.58

Bold figures indicate the best performance.

Table 4: Forecasting employment for Austria and the euro area.
We consider best vector error correction models including either no uncertainty index, the financial uncertainty index, the macroeconomic uncertainty index or the CISS as well as two benchmark models, the random walk (RW) and the autoregressive model of order one in differences (DAR(1)). The time period used is May 2000 to December 2020, the out-of-sample period is January 2010 to December 2020.

	Employment, AT				Employment, EA			
	RMSE	MAE	DA	DV	RMSE	MAE	DA	DV
				$h = 1$				
No uncertainty	25.62	10.86	69.17	79.83	0.38	0.16	83.33	89.42
Financial unc.	25.85	11.09	65.83	74.32	0.38	0.17	**88.33**	89.33
Economic unc.	26.62	10.98	66.67	67.93	**0.35**	**0.15**	85.00	91.08
CISS	25.08	10.72	**71.67**	**81.07**	0.37	0.17	84.17	**94.02**
DAR(1)	24.07	**10.35**	60.83	54.92	0.49	0.19	80.83	91.10
RW	**22.76**	10.46	66.67	61.79	0.42	0.18	73.33	67.51
				$h = 3$				
No uncertainty	38.29	16.56	81.67	73.03	0.75	0.33	93.33	92.56
Financial unc.	37.58	16.26	81.67	**76.43**	0.80	0.30	91.67	91.22
Economic unc.	44.54	17.88	82.50	72.61	**0.70**	**0.30**	88.33	89.69
CISS	36.66	**15.73**	83.33	74.79	0.74	0.29	**94.17**	**93.25**
DAR(1)	**36.59**	16.01	**85.00**	70.98	1.21	0.51	77.50	79.23
RW	37.60	20.28	**85.00**	70.98	0.87	0.54	74.17	67.49
				$h = 12$				
No uncertainty	53.82	30.81	**91.67**	**83.75**	1.49	0.93	82.50	81.89
Financial unc.	55.13	34.86	90.83	83.18	1.53	**0.83**	83.33	82.37
Economic unc.	54.11	32.19	**91.67**	**83.75**	**1.39**	0.92	80.00	**85.57**
CISS	**53.07**	**30.28**	90.83	83.06	1.56	0.98	**84.17**	83.60
DAR(1)	55.08	35.52	**91.67**	**83.75**	1.83	1.54	71.67	75.86
RW	61.46	52.85	**91.67**	**83.75**	1.87	1.58	53.33	49.12

Bold figures indicate the best performance.

Table 5: Forecasting ATX and Euro Stoxx 50.
We consider best vector error correction models including either no uncertainty index, the financial uncertainty index, the macroeconomic uncertainty index or the CISS as well as two benchmark models, the random walk (RW) and the autoregressive model of order one in differences (DAR(1)). The time period used is May 2000 to December 2020, the out-of-sample period is January 2010 to December 2020.

	ATX				Euro Stoxx 50			
	RMSE	MAE	DA	DV	RMSE	MAE	DA	DV
				$h=1$				
No uncertainty	148.66	100.80	**66.67**	**71.02**	147.13	104.67	61.67	59.23
Financial unc.	151.23	102.25	63.33	65.59	148.95	102.66	61.67	**62.65**
Economic unc.	162.48	113.12	55.00	59.45	154.36	108.65	60.83	60.36
CISS	148.22	102.09	60.83	65.66	147.96	103.08	**62.50**	60.31
DAR(1)	141.50	**95.28**	55.83	65.02	143.21	**99.24**	51.67	54.83
RW	**141.46**	95.72	42.50	34.28	**143.21**	100.25	52.50	52.04
				$h=3$				
No uncertainty	348.87	228.51	61.67	63.67	266.83	197.27	57.50	56.96
Financial unc.	361.82	243.75	60.00	59.43	294.12	202.92	**63.33**	**61.19**
Economic unc.	376.59	253.38	63.33	63.78	286.54	211.01	54.17	57.09
CISS	338.22	225.00	**65.83**	**66.68**	262.92	193.40	57.15	60.00
DAR(1)	277.31	207.78	47.50	48.29	262.10	192.01	52.50	48.08
RW	**268.80**	**198.03**	40.00	30.88	**257.07**	**189.51**	55.83	53.73
				$h=12$				
No uncertainty	618.26	456.74	51.67	45.91	415.46	355.91	65.00	67.14
Financial unc.	648.13	524.68	**59.17**	**53.13**	454.86	367.01	69.17	73.00
Economic unc.	719.24	566.01	41.67	36.10	419.86	344.46	**74.17**	**74.58**
CISS	601.50	458.15	50.83	52.23	399.17	**338.76**	69.17	72.36
DAR(1)	576.68	454.06	39.17	25.32	413.34	357.74	53.33	52.23
RW	**500.77**	**414.61**	44.17	28.39	**399.16**	344.80	30.83	33.22

Bold figures indicate the best performance.

banking data.[22] Note that for the euro area and with respect to the directional value the best performance for all horizons is achieved by the model considering the financial uncertainty index with banking data. In addition, with respect to loss-based measures (RMSE, MAE) the model with the financial uncertainty index with banking data outperforms the one without banking data for $h = 3$, 12 (for the euro area).

Regarding the forecast performance for employment, see Table 7, the model with the financial uncertainty index without banking data (in the majority of cases) marginally outperforms the model with the financial uncertainty index with banking data, for both Austria and the euro area. However, for a forecast horizon of twelve months and profit-based measures there is no difference between considering banking data or not, for both Austria and the euro area. Overall, in all cases (but one) the benchmark models (DAR(1) and RW) perform the best for Austria, while for the euro area the VEC models with the financial uncertainty index without banking data perform the best (except for one case).

Finally, Table 8 presents the forecast performance of the stock market indices for Austria (ATX) and the euro area (Euro Stoxx 50). Benchmark models perform the best for loss-based measures (except for one case[23]). The best forecast performance with respect to profit-based measures is mixed. For Austria, the benchmark models imply the largest DA and DV for forecast horizons of one and twelve months, while for the euro area the best performance achieved by a benchmark model occurs for a horizon of three months. Note, however, that models with banking data imply the largest DV for Austria when $h = 3$ and for the euro area when $h = 1$. When comparing the forecast performance of VEC models with and without banking data we observe that for Austria there is not a clear pattern; however, considering only loss-based measures, the VEC model with banking data outperforms the one without banking data for longer forecast horizons ($h = 3$, 12). For the euro area and loss-based measures, the VEC model with banking data outperforms the one without banking data for shorter forecast horizons ($h = 1$, 3); also for the directional value the VEC model with banking dasta outperforms the one without banking data for $h = 1$.

Again, we are interested in whether there is a significant difference between competing forecast models with or without banking data. As before, however, we cannot reject the null hypothesis of equal forecast accuracy at the 5% significance level (with respect to a

[22]This is true for all cases but one, namely for a forecast horizon of three months and DA, when the best model is the one with the financial uncertainty index without banking data.

[23]Namely for the euro area and $h = 12$, when the VEC model with the financial uncertainty index without banking data has the lowest MAE.

Table 6: Forecasting industrial production for Austria and the euro area.
We consider best vector error correction models including either the financial uncertainty index without banking data or the financial uncertainty index with banking data as well as two benchmark models, the random walk (RW) and the autoregressive model of order one in differences (DAR(1)). The time period used is April 2009 to December 2020, the out-of-sample period is January 2015 to December 2020.

	Industrial production, AT				Industrial production, EA			
	RMSE	MAE	DA	DV	RMSE	MAE	DA	DV
				$h = 1$				
no banking data	3.36	*1.91*	**56.67**	69.20	*4.88*	*2.15*	50.00	59.70
with banking data	*3.31*	1.96	55.00	**72.55**	5.30	2.35	**53.33**	**61.96**
DAR(1)	3.91	2.01	**56.67**	42.48	4.81	1.85	**53.33**	32.54
RW	**3.22**	**1.84**	46.67	42.66	**3.41**	**1.55**	41.67	36.10
				$h = 3$				
no banking data	*6.80*	*3.52*	**63.33**	**73.59**	9.18	3.78	**56.67**	40.83
with banking data	7.42	3.67	60.00	63.28	*8.67*	*3.69*	51.67	**47.42**
DAR(1)	7.03	3.43	61.67	56.76	9.22	3.30	48.33	45.68
RW	**5.72**	**3.17**	**63.33**	49.87	**5.88**	**2.68**	31.67	13.36
				$h = 12$				
no banking data	*7.00*	**4.38**	**80.00**	**72.85**	6.75	3.86	**65.00**	45.74
with banking data	7.39	4.66	**80.00**	72.00	*6.61*	*3.76*	**65.00**	**47.94**
DAR(1)	6.67	4.68	78.33	69.17	6.66	3.80	45.00	22.46
RW	**6.33**	4.72	78.33	69.17	**6.19**	**3.48**	33.33	21.60

Bold figures indicate the best performance and *italic* figures indicate better performance between the cases when banking data are included in the financial index and when they are not.

given performances measure and a given forecast horizon). The closest to significant results are obtained for loss-based measures (for the euro area) for $h = 3$, when the null hypothesis is rejected at the 32% significance level from approximately mid-2019 onwards.

Table 7: Forecasting employment for Austria and the euro area.
We consider best vector error correction models including either the financial uncertainty index without banking data or the financial uncertainty index with banking data as well as two benchmark models, the random walk (RW) and the autoregressive model of order one in differences (DAR(1)). The time period used is April 2009 to December 2020, the out-of-sample period is January 2015 to December 2020.

	Employment, AT				Employment, EA			
	RMSE	MAE	DA	DV	RMSE	MAE	DA	DV
				$h = 1$				
no banking data	*38.06*	*17.01*	60.00	*53.99*	**0.54**	**0.27**	**93.33**	**95.96**
with banking data	39.97	18.67	*61.67*	49.68	0.60	0.28	91.67	95.51
DAR(1)	32.72	14.55	60.00	52.74	0.75	0.31	90.00	68.24
RW	**31.11**	**14.11**	**68.33**	**57.35**	0.58	**0.27**	88.33	67.31
				$h = 3$				
no banking data	*66.13*	*33.24*	**86.67**	*63.47*	**0.96**	**0.48**	**93.33**	**91.34**
with banking data	77.27	36.68	83.33	58.28	1.02	0.52	**93.33**	**91.34**
DAR(1)	**51.55**	**25.92**	85.00	**63.63**	2.10	0.83	88.33	64.19
RW	52.02	31.37	85.00	**63.63**	1.19	0.80	90.00	67.39
				$h = 12$				
no banking data	*80.03*	**48.53**	**83.33**	**75.73**	**2.09**	1.16	**86.67**	**80.01**
with banking data	83.54	53.74	**83.33**	**75.73**	2.10	**1.14**	**86.67**	**80.01**
DAR(1)	**75.16**	49.80	**83.33**	**75.73**	2.51	1.90	83.33	77.03
RW	77.46	70.76	**83.33**	**75.73**	2.45	2.31	78.33	72.65

Bold figures indicate the best performance and *italic* figures indicate better performance between the cases when banking data are included in the financial index and when they are not.

Table 8: Forecasting ATX and Euro Stoxx 50.
We consider best vector error correction models including either the financial uncertainty index without banking data or the financial uncertainty index with banking data as well as two benchmark models, the random walk (RW) and the autoregressive model of order one in differences (DAR(1)). The time period used is April 2009 to December 2020, the out-of-sample period is January 2015 to December 2020.

	ATX				Euro Stoxx 50			
	RMSE	MAE	DA	DV	RMSE	MAE	DA	DV
				$h = 1$				
no banking data	*204.93*	*128.38*	60.00	*60.82*	247.17	137.35	**61.67**	45.11
with banking data	208.05	129.28	**63.33**	59.29	*205.09*	*124.04*	**61.67**	**55.68**
DAR(1)	**163.42**	**99.00**	**63.33**	**69.41**	159.28	99.26	50.00	47.77
RW	163.88	100.80	45.00	34.85	**157.94**	**97.64**	48.33	39.03
				$h = 3$				
no banking data	434.57	301.19	**55.00**	48.54	405.98	270.81	51.67	*41.88*
with banking data	*418.53*	*296.75*	53.33	**50.21**	*363.03*	*246.77*	51.67	38.13
DAR(1)	311.97	223.57	45.00	32.40	295.64	207.61	50.00	32.93
RW	**298.39**	**214.57**	50.00	37.29	**281.52**	**200.11**	**53.33**	**44.80**
				$h = 12$				
no banking data	815.19	690.57	*50.00*	*48.60*	*368.96*	**311.00**	**66.67**	**69.08**
with banking data	*719.67*	*653.15*	48.33	44.79	437.25	377.54	50.00	46.68
DAR(1)	660.45	569.64	35.00	24.52	493.45	439.75	33.33	40.85
RW	**567.86**	**481.49**	**56.67**	**55.97**	**402.70**	338.78	50.00	56.93

Bold figures indicate the best performance and *italic* figures indicate better performance between the cases when banking data are included in the financial index and when they are not.

5 Conclusions

In this paper we obtain new indices measuring financial and economic (in)stability in Austria and in the euro area. Instead of estimating the *level* of (in)stability in a financial or economic system we measure the *degree of predictability* of (in)stability, where our methodological approach is based on the index of Jurado, Ludvigson and Ng (2015). We use monthly data comprising 199 time series for Austria and 196 time series for the euro area to construct our economic and financial stability indices. The data covers the time span from January 2000 to December 2020.

After estimating the financial and economic uncertainty indices, we perform impulse response analyses in a vector error correction framework, where we focus on the impact of an uncertainty shock on industrial production, employment and the stock market, for Austria and the euro area. We observe that our financial uncertainty index shows a strong and significant impact on the stock market index, for both Austria and the euro area, respectively. The impact observed with our index is stronger than with the composite indicator of systemic stress (CISS), which serves as a benchmark. For Austria the financial uncertainty index also has a significant impact on industrial production. Our economic uncertainty index shows a strong and significant impact on the economic variables, industrial production and employment, for the euro area, while for Austria the impact is hardly significant.

In addition, we perform a forecasting analysis, where we assess the value added of our uncertainty indices on forecasts of industrial production, employment and the stock market, i.e., we compare the forecast performance of these variables when the uncertainty index is included in the model and when it is not. We observe that both the financial and the macroeconomic uncertainty indices can improve the forecasting performance in some cases. However, results are not so clear, in particular for Austria, since the performance depends on the forecasting horizon, the forecasted variable and the performance measure used to evaluate the forecast. A certain pattern can be observed for the euro area. Models including *economic* uncertainty provide the best forecast performance with respect to the directional value when forecasting industrial production, and with respect to the mean squared error and the mean absolute error when forecasting employment. On the other hand, models including *financial* uncertainty give the best forecast performance with respect to the directional value when forecasting the Euro Stoxx 50. These results are somehow in line with the results obtained from the impulse response analysis. Namely, economic uncertainty improves the forecasts of macroeconomic variables (industrial production and employment) while financial uncertainty improves the forecasts of the stock market index.

In addition to existing literature we also use aggregate banking data to construct a further financial uncertainty index such that we are able to detect potential differences and, in particular, analyze whether banking data improves the predictive properties. Due to the limited availability of the banking data, namely from December 2008 onwards, we can derive an augmented financial uncertainty index only for a shorter time period. When comparing the forecasting performance of our financial uncertainty index with and without banking data, we observe that for Austria the results are ambiguous, while for the euro area banking data improve profit-based measures both in the short run and in the long run, when forecasting industrial production. When forecasting the stock market, however, the inclusion of banking data improves forecasting (with respect to all measures) only in the short run, while in the long run it deteriorates it.

References

[1] R. Bachmann, E. Steffen, E.R. Sims. 2013. Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics*, 5, 217–249.

[2] J. Bai, S. Ng. 2002. Determining the number of factors in approximate factor models. *Econometrica*, 70, 191–221.

[3] J. Bai, S. Ng. 2006. Confidence intervals for diffusion index forecasts and inference for factor-augmented regressions. *Econometrica*, 74, 1133–1150.

[4] J. Bai, S. Ng. 2008. Forecasting economic time series using targeted predictors. *Journal of Econometrics*, 146, 304–317.

[5] S.R. Baker, N. Bloom, S.J. Davis. 2016. Measuring economic policy uncertainty. *Quarterly Journal of Economics*, 131, 1593–1636.

[6] S. Basu, B. Bundick. 2017. Uncertainty shocks in a model of effective demand. NBER working paper No. 18420.

[7] T. Berger, S. Grabert, B. Kempa. 2016. Global and country-specific output growth uncertainty and macroeconomic performance. *Oxford Bulletin of Economics and Statistics*, 78, 694–716.

[8] M. Bijapur. 2021. Granular Uncertainty Shocks, SSRN working paper.

[9] N. Bloom. 2009. The impact of uncertainty shocks. *Econometrica*, 77, 623–685.

[10] N. Bloom. 2014. Fluctuations in uncertainty. *The Journal of Economic Perspectives*, 28, 153–175.

[11] W.A. Bomberger. 1996. Disagreement as a measure of uncertainty, *Journal of Money, Credit and Banking*, 28, 381–392.

[12] P.J. Brockwell, R.A. Davis. 2006. *Time Series: Theory and Methods*. Springer Series and Statistics. Springer, New York, 2nd edition.

[13] M. Böck, M. Feldkircher, B. Raunig. 2021. A view from outside: Sovereign CDS volatility as an indicator of economic uncertainty, OeNB WP No. 233.

[14] G. Caggiano, E. Castelnuovo, N. Groshenny. 2014. Uncertainty shocks and unemployment dynamics: An analysis of post-WWII US recessions. *Journal of Monetary Economics*, 67, 78–92.

[15] A. Carriero, T.E. Clark, M. Marcellino. 2018. Measuring uncertainty and its impact on the economy. *Review of Economics and Statistics*, 100, 799–815.

[16] H. Chuliá, M. Guillén, J.M. Uribe. 2017. Measuring uncertainty in the stock market. *International Review of Economics and Finance*, 48, 18–33.

[17] F.X. Diebold, R.S. Mariano. 1995. Comparing predictive accuracy. *Journal of Business & Economic Statistics*, 13, 253–263.

[18] S. Gilchrist, J.W. Sim, E. Zakrajsek. 2014. Uncertainty, financial frictions, and investment dynamics, NBER WP No. 20038.

[19] D. Holló, M. Kremer, M. Lo Duca. 2012. CISS – A composite indicator of systemic stress in the financial system. European Central Bank Working Paper No. 1426.

[20] International Monetary Fund. 2002. Financial soundness indicators: Analytical aspects and country practices. Occasional paper 212.

[21] K. Jurado, S.C. Ludvigson, S. Ng. 2015. Measuring uncertainty. *American Economic Review*, 105, 1177–1216.

[22] S.C. Ludvigson, S. Ma, S. Ng. 2021. Uncertainty and business cycles: Exogenous impulse or endogenous response? *American Economic Journal*, 13, 369–410.

[23] S.C. Ludvigson, S. Ng. 2007. The empirical risk-return relation: A factor analysis approach. *Journal of Financial Economics*, 83, 171–222.

[24] S.C. Ludvigson, S. Ng. 2009. Macro factors in bond risk premia. *Review of Financial Studies*, 22, 5027—5067.

[25] H. Lütkepohl. 2005. *New Introduction to Multiple Time Series Analysis.* Springer-Verlag, Berlin Heidelberg.

[26] G.J. McLachlan, T. Krishnan. 2008. *The EM Algorithm and Extensions*. Wiley Series in Probability and Statistics. John Wiley & Sons, New York, 2nd edition.

[27] M. Pietrzak. 2021. Can financial soundness indicators help predict financial sector distress? IMF Working Paper WP/21/197.

[28] B. Rossi, T. Sekhposyan. 2015. Macroeconomic uncertainty indices based on nowcast and forecast error distributions, *American Economic Review*, 105, 650–655.

[29] B. Seong, S.K. Ahn, P.A. Zadrozny. 2013. Estimation of vector error correction models with mixed-frequency data. *Journal of Time Series Analysis*, 34, 194–205.

[30] R.H. Shumway, D.S. Stoffer. 1982. An approach to time series smoothing and forecoasting using the EM algorithm. *Journal of Time Series Analysis*, 3, 253–264.

[31] C. Scotti. 2016. Surprise and uncertainty indexes: Real-time aggregation of real activity macro surprises. *Journal of Monetary Economics*, 82, 1–19.

[32] J.H. Stock, M.W. Watson. 2006. Forecasting with many predictors. In Handbook of Forecasting, edited by H.M. Pesaran and M. Weale, Amsterdam: Elsevier. 515–554.

[33] V. Zarnowitz, L.A. Lambros. 1987. Consensus and uncertainty in economic prediction, *Journal of Political Economy*, 95, 591–621.

A Data

A.1 Financial and macroeconomic data

In the following, we provide details on the financial and macroeonomic data for Austria and for the euro area, which we use for computing the financial (macroeconomic) uncertainty indices. The data are available either at monthly frequencies or at daily frequencies, where data are transformed to monthly frequencies by taking monthly averages. Table 9 lists the abbreviations used in the following tables (including financial and macroeconomic data). We consider 77 financial variables for Austria, and 74 financial variables for the euro area. In addition we have 122 macroeconomic variables for Austria and the euro area, respectively.

In order to ensure stationarity we perform various transformations. With respect to the financial data, we compute first differences (first diff) for interest rates, and spreads, i.e., differences (diff), for rates/yields. We calculate returns for stock/bond indices and foreign exchange rates in two ways: first we calculate returns of a month with respect to the previous month and annualize the results (monthly returns, m/m-1 (a)), second we calculate returns of a month with respect to the previous year (yearly returns, m/m-12). Finally we compute volatilities, namely stochastic volatilities (stoch vola), for the monthly returns of stock/bond indices and foreign exchange rates. We transform the macroeconomic data by taking yearly growth rates (m/m-12), the survey data are given in balances (difference between positive and negative answering options, measured as percentage points of total answers) and are not transformed.

The macroeconomic data include eight questions from the industry survey data collected by the DG ECFIN, for twelve different industries; hence, in total, 96 variables.[24] The industries are beverages, wood (wood and wood and cork products except furniture, straw and plaiting materials), paper (paper and paper products), printing (printing and reproduction of recorded media), chemicals (chemicals and chemical products), rubber (rubber and plastics products), other minerals (other non-metallic mineral products), basic materials, fabricated metals (fabricated metal products except machinery and equipment), machinery (machinery and equipment N.E.C.), motor vehicles (motor vehicles, trailers and semi-trailers), and other manufacturing. The questions relate to industrial confidence indi-

[24]Two variables of the survey data, employment expectations, are not available for the euro area because the data only start later than January 2000. These are the series related to the industries beverages and wood.

cator, production trend observed in recent months, order books, export order books, stocks of finished products, production expectations, selling price expectations, and employment expectations. The data used for calculating financial uncertainty indices are monthly and range from January 2000 to December 2020, i.e., 252 observations per variable.

Table 9: Abbreviations in tables with financial and macroeconomic data

Short	Name
AMS	Arbeitsmarktservice, Austrian Public Employment Service
BD	Bundesrepublik Deutschland, Germany
BIS	Bank for International Settlements
bo	bond
BP	basis points
CHF	Swiss franc
cor	corporates
cur	current prices
DG ECFIN	European Commission Directorate-General for Economic and Financial Affairs
DS	Datastream
EA	euro area
ECB	European Central Bank
EBF	EBF/ACI FMA, EBF – European Banking Federation/ACI – The Financial Markets Association
Eur3	Euribor 3m
exp orders	export order books
fin	financials
FX	foreign exchange rate
GBP	British pound sterling
Gov	government bond index
GovYie	government bond yield
IBOXX	EURO IBOXX (euro area IBOXX bonds)
ind	index
ind conf	industrial confidence indicator
IRS	interest rate swap
JPY	Japanes yen
m	month, months
m/m-1 (a)	monthly returns, annualized
m/m-12	yearly returns
mio	million
nsa	not seasonally adjusted
OE	Oesterreich, Austria
OeNB	Oesterreichische Nationalbank, Austrian central bank
orders	order books
OIS	overnight index swap
own	own calculations
perc	percent
prod trend	production trend observed in recent months
rat	ratio

Continued on next page

Table 9 – *Continued from previous page*

Short	Name
Ref	Refinitiv
RI	total return index
sa	seasonally adjusted
Spr	spread
STAT	Statistics Austria
stoch vol	stochastic volatility of returns
thous	thousand
Transform.	transformation
USD	US-dollar
vol	volumes (in macroeconomic data)
vol	volatility (in financial data)
w	week, weeks
WB	Wiener Börse (Vienna Stock Exchange)
yie	yield

A.1.1 Austria

Table 10: Financial data, Austria

	Name	Dimension	Transform.	Source	Code
1	Eonia	Perc	first diff	EBF	EUEONIA
2	Euribor, 1m	Perc	first diff	EBF	EIBOR1M
3	Euribor, 3m	Perc	first diff	EBF	EIBOR3M
4	Euribor, 6m	Perc	first diff	EBF	EIBOR6M
5	Euribor, 12m	Perc	first diff	EBF	EIBOR1Y
6	Overnight index swap, 1w	Perc	first diff	Ref	OIEURSW
7	Overnight index swap, 2w	Perc	first diff	Ref	OIEUR2W
8	Overnight index swap, 3w	Perc	first diff	Ref	OIEUR3W
9	Overnight index swap, 1m	Perc	first diff	Ref	OIEUR1M
10	Overnight index swap, 2m	Perc	first diff	Ref	OIEUR2M
11	Overnight index swap, 3m	Perc	first diff	Ref	OIEUR3M
12	Overnight index swap, 4m	Perc	first diff	Ref	OIEUR4M
13	Overnight index swap, 5m	Perc	first diff	Ref	OIEUR5M
14	Overnight index swap, 6m	Perc	first diff	Ref	OIEUR6M
15	Overnight index swap, 7m	Perc	first diff	Ref	OIEUR7M
16	Overnight index swap, 8m	Perc	first diff	Ref	OIEUR8M
17	Overnight index swap, 9m	Perc	first diff	Ref	OIEUR9M
18	Overnight index swap, 10m	Perc	first diff	Ref	OIEUR10
19	Overnight index swap, 11m	Perc	first diff	Ref	OIEUR11
20	Overnight index swap, 12m	Perc	first diff	Ref	OIEUR1Y
21	Gov bond yield, OE, 2y	Perc	first diff	DS	BMOE02Y(RY)
22	Gov bond yield, OE, 3y	Perc	first diff	DS	BMOE03Y(RY)

Continued on next page

Table 10 – *Continued from previous page*

	Name	Dimension	Transform.	Source	Code
23	Gov bond yield, OE, 5y	Perc	first diff	DS	BMOE05Y(RY)
24	Gov bond yield, OE, 7y	Perc	first diff	DS	BMOE07Y(RY)
25	Gov bond yield, OE, 10y	Perc	first diff	DS	BMOE10Y(RY)
26	Gov bond yield, OE, 30y	Perc	first diff	DS	BMOE30Y(RY)
27	Interest rate swap, OE, 3m, 1y	Perc	first diff	Ref	ICATS1Y
28	Interest rate swap, OE, 3m, 2y	Perc	first diff	Ref	ICATS2Y
29	Interest rate swap, OE, 3m, 3y	Perc	first diff	Ref	ICATS3Y
30	Interest rate swap, OE, 3m, 4y	Perc	first diff	Ref	ICATS4Y
31	Interest rate swap, OE, 3m, 5y	Perc	first diff	Ref	ICATS5Y
32	Interest rate swap, OE, 3m, 6y	Perc	first diff	Ref	ICATS6Y
33	Interest rate swap, OE, 3m, 7y	Perc	first diff	Ref	ICATS7Y
34	Interest rate swap, OE, 3m, 8y	Perc	first diff	Ref	ICATS8Y
35	Interest rate swap, OE, 3m, 9y	Perc	first diff	Ref	ICATS9Y
36	Interest rate swap, OE, 3m, 10y	Perc	first diff	Ref	ICATS10
37	Interest rate swap, OE, 3m, 12y	Perc	first diff	Ref	ICATS12
38	Interest rate swap, OE, 3m, 15y	Perc	first diff	Ref	ICATS15
39	Interest rate swap, OE, 3m, 20y	Perc	first diff	Ref	ICATS20
40	Interest rate swap, OE, 3m, 25y	Perc	first diff	Ref	ICATS25
41	Interest rate swap, OE, 3m, 30y	Perc	first diff	Ref	ICATS30
42	ATX index	Index	m/m-1 (a)	WB	ATXINDX
43	ATX dividend yield	Ratio	no	WB/DS	ATXINDX(DSDY)
44	ATX price earn ratio	Ratio	no	WB/DS	ATXINDX(DSPE)
45	ATX Prime index	Index	m/m-1 (a)	WB	ATXIN50
46	Gov bond index, OE, 5y	RI	m/m-1 (a)	DS	BMOE05Y(RI)
47	Gov bond index, OE, 10y	RI	m/m-1 (a)	DS	BMOE10Y(RI)
48	Gov bond index, OE, 30y	RI	m/m-1 (a)	DS	BMOE30Y(RI)
49	USD/EUR	FX	m/m-1 (a)	ECB	USECBSP
50	JPY/EUR	FX	m/m-1 (a)	ECB	JPECBSP
51	CHF/EUR	FX	m/m-1 (a)	ECB	SWECBSP
52	GBP/EUR	FX	m/m-1 (a)	ECB	UKECBSP
53	ATX index	Index	m/m-12	WB	ATXINDX
54	ATX Prime index	Index	m/m-12	WB	ATXIN50
55	Gov bond index, OE, 5y	RI	m/m-12	DS	BMOE05Y(RI)
56	Gov bond index, OE, 10y	RI	m/m-12	DS	BMOE10Y(RI)
57	Gov bond index, OE, 30y	RI	m/m-12	DS	BMOE30Y(RI)
58	USD/EUR	FX	m/m-12	ECB	USECBSP
59	JPY/EUR	FX	m/m-12	ECB	JPECBSP
60	CHF/EUR	FX	m/m-12	ECB	SWECBSP
61	GBP/EUR	FX	m/m-12	ECB	UKECBSP
62	Spread GovYie, 5y, OE-BD	BP	diff	DS	BMOE05Y(RY), BMBD05Y(RY)
63	Spread GovYie, 10y, OE-BD	BP	diff	DS	BMOE10Y(RY), BMBD10Y(RY)
64	Spread GovYie, 30y, OE-BD	BP	diff	DS	BMOE30Y(RY), BMBD30Y(RY)
65	Spread GovYie (OE, 10y)-Eur3	BP	diff	DS, EBF	BMOE10Y(RY), EIBOR3M
66	Libor-OIS-Spread, 1m	BP	diff	EBF, Ref	EIBOR1M, OIEUR1M
67	Libor-OIS-Spread, 3m	BP	diff	EBF, Ref	EIBOR3M, OIEUR3M
68	Libor-OIS-Spread, 6m	BP	diff	EBF, Ref	EIBOR6M, OIEUR6M
69	Libor-OIS-Spread, 1y	BP	diff	EBF, Ref	EIBOR1Y, OIEUR1Y

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Table 10 – *Continued from previous page*

	Name	Dimension	Transform.	Source	Code
70	ATX index, vola	Vola	stoch vola	WB, own	ATXINDX
71	ATX Prime index, vola	Vola	stoch vola	WB, own	ATXIN50
72	Gov bond index, OE, 5y, vola	Vola	stoch vola	DS, own	BMOE05Y(RI)
73	Gov bond index, OE, 10y, vola	Vola	stoch vola	DS, own	BMOE10Y(RI)
74	USD/EUR vola	Vola	stoch vola	ECB, own	USECBSP
75	JPY/EUR vola	Vola	stoch vola	ECB, own	JPECBSP
76	CHF/EUR vola	Vola	stoch vola	ECB, own	SWECBSP
77	GBP/EUR vola	Vola	stoch vola	ECB, own	UKECBSP

When we compute the macroeconomic uncertainty indicator for Austria the following financial variables are grouped with the macroeconomic variables, not with the financial variables: Euribor, 3m; Euribor, 6m; Euribor 12m; Government bond yield, OE, 2y; Government bond yield, OE, 5y; Government bond yield, OE, 10y; ATX index, m/m-1 (a); ATX dividend yield; ATX price earnings ratio; growth rates, m/m-1 (a), of USD/EUR, JPY/EUR, CHF/EUR, and GBP/EUR; ATX index, m/m-12; Spread government bond yield, 10y, OE-BD; Spread government bond yield (OE, 10y)-Euribor, 3m.

Table 11: Macroeconomic data, Austria

	Name	Dimension	Transform.	Source	Code
1	Consumer confidence indicator	sa	no	OeNB	OECNFCONQ
2	Economic sentiment indicator	index around 100	no	DG ECFIN	OECNFBUSG
3	Exports	nsa, cur (mio euro)	m/m-12	STAT	OEEXPGDSA
4	Imports	nsa, cur (mio euro)	m/m-12	STAT	OEIMPGDSA
5	Real effective exchange rate	index	m/m-12	BIS	OEBISRXNR
6	Trade balance	nsa, cur (mio euro)	no	STAT	OEVISGDSA
7	Bank loans to households	nsa, cur (mio euro)	m/m-12	OeNB	OECRDCONA
8	New car registrations	nsa, number	m/m-12	STAT	OECAR...P
9	Retail sales	nsa, constant prices	m/m-12	STAT	OERETTOTE
10	Employment	nsa, volume (thous)	m/m-12	STAT	OEEMPTOTP
11	Labour force	nsa, volume (thous)	m/m-12	STAT	OELABFRCP
12	Unemployed	nsa, persons	m/m-12	AMS	OEUNPTOTP
13	Unemployment rate	sa	no	STAT	OEUN%TOTQ
14	Job vacancies	nsa, volume	m/m-12	AMS	OEVACTOTP
15	Minimum wages in manufacturing	nsa, price index	m/m-12	STAT	OEWAGMANF
16	Bank lending to private sector	nsa, cur (mio euro)	m/m-12	OeNB	OEBANKLPA
17	Harmonized index of consumer prices	nsa, price index	m/m-12	STAT	OECPHARMF
18	Consumer price index	nsa, price index	m/m-12	STAT/Ref	OECPALLRF
19	Wholesale price index	nsa, price index	m/m-12	STAT	OEWPI...F
20	Exports	nsa, prices	m/m-12	Refinitiv	OEEXPGD%A
21	Tourist arrivals	nsa, vol (thous)	m/m-12	STAT	OETOURISP
22	Overnight stays	nsa, vol (thous)	m/m-12	STAT	OEOVN...P

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Table 11 – *Continued from previous page*

	Name	Dimension	Transform.	Source	Code
23	Overnight stays in Vienna	nsa, vol (thous)	m/m-12	STAT	OEOVNLIEP
24	Overnight stays in hotels	nsa, vol (thous)	m/m-12	STAT	OEOVNCTLP
25	Industrial production	sa, volume index	m/m-12	Eurostat	OEESQR59G
26	Industrial production: manufacturing	sa, volume index	m/m-12	Eurostat	OEES493KG
27	Industrial confidence, beverages	sa, balance	no	DG ECFIN	OE11.COBQ
28	Industrial confidence, wood	sa, balance	no	DG ECFIN	OE16.COBQ
29	Industrial confidence, paper	sa, balance	no	DG ECFIN	OE17.COBQ
30	Industrial confidence, printing	sa, balance	no	DG ECFIN	OE18.COBQ
31	Industrial confidence, chemicals	sa, balance	no	DG ECFIN	OE20.COBQ
32	Industrial confidence, rubber	sa, balance	no	DG ECFIN	OE22.COBQ
33	Industrial confidence, other minerals	sa, balance	no	DG ECFIN	OE23.COBQ
34	Industrial confidence, basic metals	sa, balance	no	DG ECFIN	OE24.COBQ
35	Industrial confidence, fabricated metals	sa, balance	no	DG ECFIN	OE25.COBQ
36	Industrial confidence, machinery	sa, balance	no	DG ECFIN	OE28.COBQ
37	Industrial confidence, motor vehicles	sa, balance	no	DG ECFIN	OE29.COBQ
38	Industrial confidence, other manufacturing	sa, balance	no	DG ECFIN	OE32.COBQ
39	Recent production trend, beverages	sa, balance	no	DG ECFIN	OE11.1.BQ
40	Recent production trend, wood	sa, balance	no	DG ECFIN	OE16.1.BQ
41	Recent production trend, paper	sa, balance	no	DG ECFIN	OE17.1.BQ
42	Recent production trend, printing	sa, balance	no	DG ECFIN	OE18.1.BQ
43	Recent production trend, chemicals	sa, balance	no	DG ECFIN	OE20.1.BQ
44	Recent production trend, rubber	sa, balance	no	DG ECFIN	OE22.1.BQ
45	Recent production trend, other minerals	sa, balance	no	DG ECFIN	OE23.1.BQ
46	Recent production trend, basic metals	sa, balance	no	DG ECFIN	OE24.1.BQ
47	Recent production trend, fabricated metals	sa, balance	no	DG ECFIN	OE25.1.BQ
48	Recent production trend, machinery	sa, balance	no	DG ECFIN	OE28.1.BQ
49	Recent production trend, motor vehicles	sa, balance	no	DG ECFIN	OE29.1.BQ
50	Recent production trend, other manufacturing	sa, balance	no	DG ECFIN	OE32.1.BQ
51	Order books, beverages	sa, balance	no	DG ECFIN	OE11.2.BQ
52	Order books, wood	sa, balance	no	DG ECFIN	OE16.2.BQ
53	Order books, paper	sa, balance	no	DG ECFIN	OE17.2.BQ
54	Order books, printing	sa, balance	no	DG ECFIN	OE18.2.BQ
55	Order books, chemicals	sa, balance	no	DG ECFIN	OE20.2.BQ
56	Order books, rubber	sa, balance	no	DG ECFIN	OE22.2.BQ
57	Order books, other minerals	sa, balance	no	DG ECFIN	OE23.2.BQ
58	Order books, basic metals	sa, balance	no	DG ECFIN	OE24.2.BQ
59	Order books, fabricated metals	sa, balance	no	DG ECFIN	OE25.2.BQ
60	Order books, machinery	sa, balance	no	DG ECFIN	OE28.2.BQ
61	Order books, motor vehicles	sa, balance	no	DG ECFIN	OE29.2.BQ
62	Order books, other manufacturing	sa, balance	no	DG ECFIN	OE32.2.BQ
63	Export order books, beverages	sa, balance	no	DG ECFIN	OE11.3.BQ
64	Export order books, wood	sa, balance	no	DG ECFIN	OE16.3.BQ
65	Export order books, paper	sa, balance	no	DG ECFIN	OE17.3.BQ
66	Export order books, printing	sa, balance	no	DG ECFIN	OE18.3.BQ
67	Export order books, chemicals	sa, balance	no	DG ECFIN	OE20.3.BQ
68	Export order books, rubber	sa, balance	no	DG ECFIN	OE22.3.BQ
69	Export order books, other minerals	sa, balance	no	DG ECFIN	OE23.3.BQ

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Table 11 – *Continued from previous page*

	Name	Dimension	Transform.	Source	Code
70	Export order books, basic metals	sa, balance	no	DG ECFIN	OE24.3.BQ
71	Export order books, fabricated metals	sa, balance	no	DG ECFIN	OE25.3.BQ
72	Export order books, machinery	sa, balance	no	DG ECFIN	OE28.3.BQ
73	Export order books, motor vehicles	sa, balance	no	DG ECFIN	OE29.3.BQ
74	Export order books, other manufacturing	sa, balance	no	DG ECFIN	OE32.3.BQ
75	Stocks of finished products, beverages, stocks	sa, balance	no	DG ECFIN	OE11.4.BQ
76	Stocks of finished products, wood	sa, balance	no	DG ECFIN	OE16.4.BQ
77	Stocks of finished products, paper	sa, balance	no	DG ECFIN	OE17.4.BQ
78	Stocks of finished products, printing	sa, balance	no	DG ECFIN	OE18.4.BQ
79	Stocks of finished products, chemicals	sa, balance	no	DG ECFIN	OE20.4.BQ
80	Stocks of finished products, rubber	sa, balance	no	DG ECFIN	OE22.4.BQ
81	Stocks of finished products, other minerals	sa, balance	no	DG ECFIN	OE23.4.BQ
82	Stocks of finished products, basic metals	sa, balance	no	DG ECFIN	OE24.4.BQ
83	Stocks of finished products, fabricated metals	sa, balance	no	DG ECFIN	OE25.4.BQ
84	Stocks of finished products, machinery	sa, balance	no	DG ECFIN	OE28.4.BQ
85	Stocks of finished products, motor vehicles	sa, balance	no	DG ECFIN	OE29.4.BQ
86	Stocks of finished products, other manufacturing	sa, balance	no	DG ECFIN	OE32.4.BQ
87	Production expectations, beverages	sa, balance	no	DG ECFIN	OE11.5.BQ
88	Production expectations, wood	sa, balance	no	DG ECFIN	OE16.5.BQ
89	Production expectations, paper	sa, balance	no	DG ECFIN	OE17.5.BQ
90	Production expectations, printing	sa, balance	no	DG ECFIN	OE18.5.BQ
91	Production expectations, chemicals	sa, balance	no	DG ECFIN	OE20.5.BQ
92	Production expectations, rubber	sa, balance	no	DG ECFIN	OE22.5.BQ
93	Production expectations, other minerals	sa, balance	no	DG ECFIN	OE23.5.BQ
94	Production expectations, basic metals	sa, balance	no	DG ECFIN	OE24.5.BQ
95	Production expectations, fabricated metals	sa, balance	no	DG ECFIN	OE25.5.BQ
96	Production expectations, machinery	sa, balance	no	DG ECFIN	OE28.5.BQ
97	Production expectations, motor vehicles	sa, balance	no	DG ECFIN	OE29.5.BQ
98	Production expectations, other manufacturing	sa, balance	no	DG ECFIN	OE32.5.BQ
99	Selling price expectations, beverages	sa, balance	no	DG ECFIN	OE11.6.BQ
100	Selling price expectations, wood	sa, balance	no	DG ECFIN	OE16.6.BQ
101	Selling price expectations, paper	sa, balance	no	DG ECFIN	OE17.6.BQ
102	Selling price expectations, printing	sa, balance	no	DG ECFIN	OE18.6.BQ
103	Selling price expectations, chemicals	sa, balance	no	DG ECFIN	OE20.6.BQ
104	Selling price expectations, rubber	sa, balance	no	DG ECFIN	OE22.6.BQ
105	Selling price expectations, other minerals	sa, balance	no	DG ECFIN	OE23.6.BQ
106	Selling price expectations, basic metals	sa, balance	no	DG ECFIN	OE24.6.BQ
107	Selling price expectations, fabricated metals	sa, balance	no	DG ECFIN	OE25.6.BQ
108	Selling price expectations, machinery	sa, balance	no	DG ECFIN	OE28.6.BQ
109	Selling price expectations, motor vehicles	sa, balance	no	DG ECFIN	OE29.6.BQ
110	Selling price expectations, other manufacturing	sa, balance	no	DG ECFIN	OE32.6.BQ
111	Employment expectations, beverages	sa, balance	no	DG ECFIN	OE11.7.BQ
112	Employment expectations, wood	sa, balance	no	DG ECFIN	OE16.7.BQ
113	Employment expectations, paper	sa, balance	no	DG ECFIN	OE17.7.BQ
114	Employment expectations, printing	sa, balance	no	DG ECFIN	OE18.7.BQ
115	Employment expectations, chemicals	sa, balance	no	DG ECFIN	OE20.7.BQ
116	Employment expectations, rubber	sa, balance	no	DG ECFIN	OE22.7.BQ

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Table 11 – *Continued from previous page*

	Name	Dimension	Transform.	Source	Code
117	Employment expectations, other minerals	sa, balance	no	DG ECFIN	OE23.7.BQ
118	Employment expectations, basic metals	sa, balance	no	DG ECFIN	OE24.7.BQ
119	Employment expectations, fabricated metals	sa, balance	no	DG ECFIN	OE25.7.BQ
120	Employment expectations, machinery	sa, balance	no	DG ECFIN	OE28.7.BQ
121	Employment expectations, motor vehicles	sa, balance	no	DG ECFIN	OE29.7.BQ
122	Employment expectations, other manufacturing	sa, balance	no	DG ECFIN	OE32.7.BQ

A.1.2 Euro area

Table 12: Financial data, euro area

	Name	Dimension	Transform.	Source	Code
1	Eonia	Perc	first diff	EBF	EUEONIA
2	Euribor, 1m	Perc	first diff	EBF	EIBOR1M
3	Euribor, 3m	Perc	first diff	EBF	EIBOR3M
4	Euribor, 6m	Perc	first diff	EBF	EIBOR6M
5	Euribor, 12m	Perc	first diff	EBF	EIBOR1Y
6	Overnight index swap, 1w	Perc	first diff	Ref	OIEURSW
7	Overnight index swap, 2w	Perc	first diff	Ref	OIEUR2W
8	Overnight index swap, 3w	Perc	first diff	Ref	OIEUR3W
9	Overnight index swap, 1m	Perc	first diff	Ref	OIEUR1M
10	Overnight index swap, 2m	Perc	first diff	Ref	OIEUR2M
11	Overnight index swap, 3m	Perc	first diff	Ref	OIEUR3M
12	Overnight index swap, 4m	Perc	first diff	Ref	OIEUR4M
13	Overnight index swap, 5m	Perc	first diff	Ref	OIEUR5M
14	Overnight index swap, 6m	Perc	first diff	Ref	OIEUR6M
15	Overnight index swap, 7m	Perc	first diff	Ref	OIEUR7M
16	Overnight index swap, 8m	Perc	first diff	Ref	OIEUR8M
17	Overnight index swap, 9m	Perc	first diff	Ref	OIEUR9M
18	Overnight index swap, 10m	Perc	first diff	Ref	OIEUR10
19	Overnight index swap, 11m	Perc	first diff	Ref	OIEUR11
20	Overnight index swap, 12m	Perc	first diff	Ref	OIEUR1Y
21	Gov bond yield, EA, 5-7y	Perc	first diff	DS	AEMGVG3(RY)
22	Gov bond yield, EA, 7-10y	Perc	first diff	DS	AEMGVG4(RY)
23	Gov bond yield, EA, >10y	Perc	first diff	DS	AEMGVG5(RY)
24	Gov bond yield, EA, 10y	Perc	first diff	ECB	EMGBOND.
25	IBOXX Euro Fin	Perc	first diff	iBoxx	IBCFNAL(RY)
26	IBOXX Fin AAA	Perc	first diff	iBoxx	IBEFN3A(RY)
27	IBOXX Fin BBB	Perc	first diff	iBoxx	IBEFN3B(RY)
28	IBOXX Cor	Perc	first diff	iBoxx	IBCRPAL(RY)
29	IBOXX Cor AAA	Perc	first diff	iBoxx	IBC3AAL(RY)
30	IBOXX Cor BBB	Perc	first diff	iBoxx	IBC3BAL(RY)

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Table 12 – *Continued from previous page*

	Name	Dimension	Transform.	Source	Code
31	IBOXX Non-Fin	Perc	first diff	iBoxx	IBCNFAL(RY)
32	IBOXX Non-Fin AAA	Perc	first diff	iBoxx	IBENF3A(RY)
33	IBOXX Non-Fin BBB	Perc	first diff	iBoxx	IBENF3B(RY)
34	IBOXX Sovereigns	Perc	first diff	iBoxx	IBSEUAL(RY)
35	Euro Stoxx index	Index	m/m-1 (a)	STOXX	DJEURST
36	Euro Stoxx dividend yield	Ratio	no	STOXX	DJEURST(DY)
37	Euro Stoxx price earn ratio	Ratio	no	STOXX	DJEURST(PE)
38	Euro Stoxx 50 index	Index	m/m-1 (a)	STOXX	DJES50I
39	Gov bond index, EA, 5-7y	RI	m/m-1 (a)	DS	AEMGVG3(RI)
40	Gov bond index, EA, 7-10y	RI	m/m-1 (a)	DS	AEMGVG4(RI)
41	Gov bond index, EA, g10y	RI	m/m-1 (a)	DS	AEMGVG5(RI)
42	USD/EUR	FX	m/m-1 (a)	ECB	USECBSP
43	JPY/EUR	FX	m/m-1 (a)	ECB	JPECBSP
44	CHF/EUR	FX	m/m-1 (a)	ECB	SWECBSP
45	GBP/EUR	FX	m/m-1 (a)	ECB	UKECBSP
46	Euro Stoxx index	Index	m/m-12	STOXX	DJEURST
47	Euro Stoxx 50 index	Index	m/m-12	STOXX	DJES50I
48	Gov bond index, EA, 5-7y	RI	m/m-12	DS	AEMGVG3(RI)
49	Gov bond index, EA, 7-10y	RI	m/m-12	DS	AEMGVG4(RI)
50	Gov bond index, EA, g10y	RI	m/m-12	DS	AEMGVG5(RI)
51	USD/EUR	FX	m/m-12	ECB	USECBSP
52	JPY/EUR	FX	m/m-12	ECB	JPECBSP
53	CHF/EUR	FX	m/m-12	ECB	SWECBSP
54	GBP/EUR	FX	m/m-12	ECB	UKECBSP
55	Spread GovYie, 10y, EA-BD	BP	diff	ECB, DS	EMGBOND., BMBD10Y(RY)
56	Spread GovYie (EA, 10y)-Eur3	BP	diff	ECB, EBF	EMGBOND., EIBOR3M
57	Spread GovYie, 10y, GR-BD	BP	diff	DS	BMBD10Y(RY), BMBD10Y(RY)
58	Spread GovYie, 10y, IT-BD	BP	diff	DS	BMIT10Y(RY) BMBD10Y(RY)
59	Libor-OIS-Spread, 1m	BP	diff	EBF, Ref	EIBOR1M, OIEUR1M
60	Libor-OIS-Spread, 3m	BP	diff	EBF, Ref	EIBOR3M, OIEUR3M
61	Libor-OIS-Spread, 6m	BP	diff	EBF, Ref	EIBOR6M, OIEUR6M
62	Libor-OIS-Spread, 1y	BP	diff	EBF, Ref	EIBOR1Y, OIEUR1Y
63	Spread fin: BBB-AAA	BP	diff	iBoxx	IBEFN3B(RY), IBEFN3A(RY)
64	Spread cor: BBB-AAA	BP	diff	iBoxx	IBC3BAL(RY), IBC3AAL(RY)
65	Spread non-fin: BBB-AAA	BP	diff	iBoxx	IBENF3B(RY), IBENF3A(RY)
66	Spread fin-sovereign	BP	diff	iBoxx	IBCFNAL(RY), IBSEUAL(RY)
67	Euro Stoxx vola	Vola	stoch vola	STOXX, own	DJEURST
68	Euro Stoxx 50 vola	Vola	stoch vola	STOXX, own	DJES50I
69	Gov bond index, EA, 5-7y, vola	Vola	stoch vola	DS, own	AEMGVG3(RI)
70	Gov bond index, EA, 7-10y, vola	Vola	stoch vola	DS, own	AEMGVG4(RI)
71	USD/EUR vola	Vola	stoch vola	ECB, own	USECBSP
72	JPY/EUR vola	Vola	stoch vola	ECB, own	JPECBSP
73	CHF/EUR vola	Vola	stoch vola	ECB, own	SWECBSP
74	GBP/EUR vola	Vola	stoch vola	ECB, own	UKECBSP

When we compute the macroeconomic uncertainty indicator for the euro area the following financial variables are grouped with the macroeconomic variables, not with the financial variables: Euribor, 3m; Euribor, 6m; Euribor 12m; Government bond yield, EA, 5-7y; Government bond yield, EA, 7-10y; Government bond yield, EA, >10y; Euro Stoxx index, m/m-1 (a); Euro Stoxx dividend yield; Euro Stoxx price earnings ratio; growth rates, m/m-1 (a), of USD/EUR, JPY/EUR, CHF/EUR, and GBP/EUR.

Table 13: Macroeconomic data, euro area

	Name	Dimension	Transform.	Source	Code
1	Industrial confidence indicator	sa, balance	no	DG ECFIN	EKCNFBUSQ
2	Consumer confidence indicator	sa, balance	no	DG ECFIN	EKEUSCCIQ
3	Economic sentiment indicator	sa, index around 100	no	DG ECFIN	EKEUSESIG
4	Exports	sa, cur (mio euro)	m/m-12	Eurostat	EKEXPGDSB
5	Imports	sa, cur (mio euro)	m/m-12	Eurostat	EKIMPGDSB
6	Real effective exchange rate	index	m/m-12	ECB	EMXTW..RF
7	Money M3	sa, cur (mio euro)	m/m-12	ECB	EMM3....B
8	Bank loans for household consumption	nsa, cur (mio euro)	m/m-12	ECB	EMCRDCONA
9	Bank loans to non-fin corporations	nsa, cur (mio euro)	m/m-12	ECB	EMEBMC0.A
					EMEBMC1.A
					EMEBMC5.A
10	New car registrations	sa, volume (thous)	m/m-12	ECB	EKEBCARRO
11	Retail sales excl. motor veh & fuel	sa, turnover (index)	m/m-12	Eurostat	EKEW47MTG
12	Retail sales, nonfood prod excl. fuel	sa, turnover (index)	m/m-12	Eurostat	EKEW47PTG
13	Unemployed	sa, volume (thous)	m/m-12	Eurostat	EKESTUNPO
14	Unemployed, <25	sa, volume (thous)	m/m-12	Eurostat	Z8ES46XRO
15	Unemployed, females	sa, volume (thous)	m/m-12	Eurostat	Z8ESZAKBO
16	Unemployed, males	sa, volume (thous)	m/m-12	Eurostat	Z8ESQ6UQO
17	Unemployment rate	sa, percent	no	Eurostat	EKUN%TOTQ
18	Unemployment rate, <25	sa, percent	no	Eurostat	Z8ESZKEOQ
19	Unemployment rate, females	sa, percent	no	Eurostat	Z8ESJLSFQ
20	Unemployment rate, males	sa, percent	no	Eurostat	Z8ES29KYQ
21	Industrial production	sa, volume index	m/m-12	Eurostat	Z8ESQR59G
22	Industrial prod excl. construction	sa, volume index	m/m-12	Eurostat	EKIPTOT.G
23	Industrial prod manufacturing	sa, volume index	m/m-12	Eurostat	EKIPMAN.G
24	New order, manufacturing	sa, volume index	m/m-12	ECB	EKEBREMKG
25	New order, consumer durables	sa, volume index	m/m-12	ECB	EKEBREMHG
26	Harmonized index of cons prices	nsa, price index	m/m-12	Eurostat	EKCPHARMF
27	Producer price ind, mfc, dom mkts	nsa, price index	m/m-12	Eurostat	Z8ESR1E3F
28	Producer price ind, ind excl. constr	nsa, price index	m/m-12	Eurostat	EKPROPRCF
29	Industrial confidence, beverages	sa, balance	no	DG ECFIN	EK11.COBQ
30	Industrial confidence, wood	sa, balance	no	DG ECFIN	EK16.COBQ
31	Industrial confidence, paper	sa, balance	no	DG ECFIN	EK17.COBQ
32	Industrial confidence, printing	sa, balance	no	DG ECFIN	EK18.COBQ
33	Industrial confidence, chemicals	sa, balance	no	DG ECFIN	EK20.COBQ
34	Industrial confidence, rubber	sa, balance	no	DG ECFIN	EK22.COBQ
35	Industrial confidence, other minerals	sa, balance	no	DG ECFIN	EK23.COBQ
36	Industrial confidence, basic metals	sa, balance	no	DG ECFIN	EK24.COBQ

Continued on next page

Table 13 – *Continued from previous page*

	Name	Dimension	Transform.	Source	Code
37	Industrial confidence, fabricated metals	sa, balance	no	DG ECFIN	EK25.COBQ
38	Industrial confidence, machinery	sa, balance	no	DG ECFIN	EK28.COBQ
39	Industrial confidence, motor vehicles	sa, balance	no	DG ECFIN	EK29.COBQ
40	Industrial confidence, other manufacturing	sa, balance	no	DG ECFIN	EK32.COBQ
41	Recent production trend, beverages	sa, balance	no	DG ECFIN	EK11.1.BQ
42	Recent production trend, wood	sa, balance	no	DG ECFIN	EK16.1.BQ
43	Recent production trend, paper	sa, balance	no	DG ECFIN	EK17.1.BQ
44	Recent production trend, printing	sa, balance	no	DG ECFIN	EK18.1.BQ
45	Recent production trend, chemicals	sa, balance	no	DG ECFIN	EK20.1.BQ
46	Recent production trend, rubber	sa, balance	no	DG ECFIN	EK22.1.BQ
47	Recent production trend, other minerals	sa, balance	no	DG ECFIN	EK23.1.BQ
48	Recent production trend, basic metals	sa, balance	no	DG ECFIN	EK24.1.BQ
49	Recent production trend, fabricated metals	sa, balance	no	DG ECFIN	EK25.1.BQ
50	Recent production trend, machinery	sa, balance	no	DG ECFIN	EK28.1.BQ
51	Recent production trend, motor vehicles	sa, balance	no	DG ECFIN	EK29.1.BQ
52	Recent production trend, other manufacturing	sa, balance	no	DG ECFIN	EK32.1.BQ
53	Order books, beverages	sa, balance	no	DG ECFIN	EK11.2.BQ
54	Order books, wood	sa, balance	no	DG ECFIN	EK16.2.BQ
55	Order books, paper	sa, balance	no	DG ECFIN	EK17.2.BQ
56	Order books, printing	sa, balance	no	DG ECFIN	EK18.2.BQ
57	Order books, chemicals	sa, balance	no	DG ECFIN	EK20.2.BQ
58	Order books, rubber	sa, balance	no	DG ECFIN	EK22.2.BQ
59	Order books, other minerals	sa, balance	no	DG ECFIN	EK23.2.BQ
60	Order books, basic metals	sa, balance	no	DG ECFIN	EK24.2.BQ
61	Order books, fabricated metals	sa, balance	no	DG ECFIN	EK25.2.BQ
62	Order books, machinery	sa, balance	no	DG ECFIN	EK28.2.BQ
63	Order books, motor vehicles	sa, balance	no	DG ECFIN	EK29.2.BQ
64	Order books, other manufacturing	sa, balance	no	DG ECFIN	EK32.2.BQ
65	Export order books, beverages	sa, balance	no	DG ECFIN	EK11.3.BQ
66	Export order books, wood	sa, balance	no	DG ECFIN	EK16.3.BQ
67	Export order books, paper	sa, balance	no	DG ECFIN	EK17.3.BQ
68	Export order books, printing	sa, balance	no	DG ECFIN	EK18.3.BQ
69	Export order books, chemicals	sa, balance	no	DG ECFIN	EK20.3.BQ
70	Export order books, rubber	sa, balance	no	DG ECFIN	EK22.3.BQ
71	Export order books, other minerals	sa, balance	no	DG ECFIN	EK23.3.BQ
72	Export order books, basic metals	sa, balance	no	DG ECFIN	EK24.3.BQ
73	Export order books, fabricated metals	sa, balance	no	DG ECFIN	EK25.3.BQ
74	Export order books, machinery	sa, balance	no	DG ECFIN	EK28.3.BQ
75	Export order books, motor vehicles	sa, balance	no	DG ECFIN	EK29.3.BQ
76	Export order books, other manufacturing	sa, balance	no	DG ECFIN	EK32.3.BQ
77	Stocks of finished products, beverages	sa, balance	no	DG ECFIN	EK11.4.BQ
78	Stocks of finished products, wood	sa, balance	no	DG ECFIN	EK16.4.BQ
79	Stocks of finished products, paper	sa, balance	no	DG ECFIN	EK17.4.BQ
80	Stocks of finished products, printing	sa, balance	no	DG ECFIN	EK18.4.BQ
81	Stocks of finished products, chemicals	sa, balance	no	DG ECFIN	EK20.4.BQ
82	Stocks of finished products, rubber	sa, balance	no	DG ECFIN	EK22.4.BQ
83	Stocks of finished products, other minerals	sa, balance	no	DG ECFIN	EK23.4.BQ

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Table 13 – *Continued from previous page*

	Name	Dimension	Transform.	Source	Code
84	Stocks of finished products, basic metals	sa, balance	no	DG ECFIN	EK24.4.BQ
85	Stocks of finished products, fabricated metals	sa, balance	no	DG ECFIN	EK25.4.BQ
86	Stocks of finished products, machinery	sa, balance	no	DG ECFIN	EK28.4.BQ
87	Stocks of finished products, motor vehicles	sa, balance	no	DG ECFIN	EK29.4.BQ
88	Stocks of finished products, other manufacturing	sa, balance	no	DG ECFIN	EK32.4.BQ
89	Production expectations, beverages	sa, balance	no	DG ECFIN	EK11.5.BQ
90	Production expectations, wood	sa, balance	no	DG ECFIN	EK16.5.BQ
91	Production expectations, paper	sa, balance	no	DG ECFIN	EK17.5.BQ
92	Production expectations, printing	sa, balance	no	DG ECFIN	EK18.5.BQ
93	Production expectations, chemicals	sa, balance	no	DG ECFIN	EK20.5.BQ
94	Production expectations, rubber	sa, balance	no	DG ECFIN	EK22.5.BQ
95	Production expectations, other minerals	sa, balance	no	DG ECFIN	EK23.5.BQ
96	Production expectations, basic metals	sa, balance	no	DG ECFIN	EK24.5.BQ
97	Production expectations, fabricated metals	sa, balance	no	DG ECFIN	EK25.5.BQ
98	Production expectations, machinery	sa, balance	no	DG ECFIN	EK28.5.BQ
99	Production expectations, motor vehicles	sa, balance	no	DG ECFIN	EK29.5.BQ
100	Production expectations, other manufacturing	sa, balance	no	DG ECFIN	EK32.5.BQ
101	Selling price expectations, beverages	sa, balance	no	DG ECFIN	EK11.6.BQ
102	Selling price expectations, wood	sa, balance	no	DG ECFIN	EK16.6.BQ
103	Selling price expectations, paper	sa, balance	no	DG ECFIN	EK17.6.BQ
104	Selling price expectations, printing	sa, balance	no	DG ECFIN	EK18.6.BQ
105	Selling price expectations, chemicals	sa, balance	no	DG ECFIN	EK20.6.BQ
106	Selling price expectations, rubber	sa, balance	no	DG ECFIN	EK22.6.BQ
107	Selling price expectations, other minerals	sa, balance	no	DG ECFIN	EK23.6.BQ
108	Selling price expectations, basic metals	sa, balance	no	DG ECFIN	EK24.6.BQ
109	Selling price expectations, fabricated metals	sa, balance	no	DG ECFIN	EK25.6.BQ
110	Selling price expectations, machinery	sa, balance	no	DG ECFIN	EK28.6.BQ
111	Selling price expectations, motor vehicles	sa, balance	no	DG ECFIN	EK29.6.BQ
112	Selling price expectations, other manufacturing	sa, balance	no	DG ECFIN	EK32.6.BQ
113	Employment expectations, paper	sa, balance	no	DG ECFIN	EK17.7.BQ
114	Employment expectations, printing	sa, balance	no	DG ECFIN	EK18.7.BQ
115	Employment expectations, chemicals	sa, balance	no	DG ECFIN	EK20.7.BQ
116	Employment expectations, rubber	sa, balance	no	DG ECFIN	EK22.7.BQ
117	Employment expectations, other minerals	sa, balance	no	DG ECFIN	EK23.7.BQ
118	Employment expectations, basic metals	sa, balance	no	DG ECFIN	EK24.7.BQ
119	Employment expectations, fabricated metals	sa, balance	no	DG ECFIN	EK25.7.BQ
120	Employment expectations, machinery	sa, balance	no	DG ECFIN	EK28.7.BQ
121	Employment expectations, motor vehicles	sa, balance	no	DG ECFIN	EK29.7.BQ
122	Employment expectations, other manufacturing	sa, balance	no	DG ECFIN	EK32.7.BQ

The variable bank loans to non-financial corporations is created by summing the three variables bank loans to non-financial corporations <1 year (EMEBMC0.A), bank loans to non-financial corporations 1–4 years (EMEBMC1.A), and bank loans to non-financial corporations >4 years (EMEBMC5.A), and then computing growth rates. Two variables of the survey data, employment expectations, are not available for the euro area because the data only start later than January

2000. These are the series related to beverages (EK11.7.BQ) and wood (EK16.7.BQ).

A.2 Banking data

In addition to market data, we use the consolidated banking data collected and published by the European Central Bank (ECB). They contain information on the aggregate consolidated profitability, balance sheets, asset quality, liquidity and solvency of EU banks, and refer to all EU Member States. A new framework for consolidated banking data has been in place since the implementation of the European Banking Authority's Implementing Technical Standards (ITS) on supervisory reporting, i.e., since end 2014. While the ITS ensure that supervisory data across Europe are fully harmonised, some gaps remain in the reporting of financial information and the extent to which some banks continue to be subject to national reporting requirements. From end 2014, the consolidated banking data are based on the new EBA ITS on supervisory reporting; hence, the data structure definition for the CBD changed. When methodologically sound, the old CBD series (annual or semi-annual data up to end 2013) were joined to the new CBD ones.[25] The "old" CBD data range from 2007 to 2013 for annual data, and from 2010H2 to 2014H1 for semi-annual data while the "new" CBD data range from 2014Q4 onwards, where some series are only available at an annual basis. Series starting in 2007 correspond to series with data from 2007 to 2014Q4 coming from the CBD dataset, mapped into the CBD2 dataset.[26]

We cannot be fully sure that the "joined" series behave exactly like the shorter series (based on the new EBA ITS on supervisory reporting) would. However we had to opt for the longer series starting at the end of 2007, as the other option would have resulted in time series being too short for our analysis. Optimally, we would repeat the analysis in ten years and then only use only the consolidated banking data starting end 2014.

We consider a number of series for Austria and for the euro area, where the reporting sector is the domestic banking groups and stand-alone banks and we consider all institutions, irrespective of their accounting/supervisory framework (IFRS or non-IFRS). In principle we use all variables available for Austria and the euro area, which start in 2007,

[25] The ECB database of the "old" data is called CBD, the ECB database of the "new" data is called CBD2.

[26] More details on the consolidated banking data released by the ECB can be found on the CBD website, see `https://www.ecb.europa.eu/stats/supervisory_prudential_statistics/consolidated_banking_data/html/index.en.html`, the data can be accessed at ECB's Statistical Data Warehouse, see `https://sdw.ecb.europa.eu/browse.do?node=9689685`.

not in 2014, and which are given as stock data. Quarterly flow data are not annualized and are thus not considered except when are reported in percent of other quarterly flow data. For the variables which are given in euro we perform two different transformations to ensure stationarity. We first compute growth rates (m/m-1) and second ratios, where the latter are computed by dividing the given amount in euro by some reference value in euro, namely total assets. This yields a total of 45 variables for Austria and a total of 37 variables for the euro area.[27]

The quarterly time series are transformed to monthly time series by employing the Kalman filter and Kalman smoother, see Appendix B. Alternatively, we used simple linear interpolation to fill the missing data, where the results were not fundamentally different from using the Kalman filter and smoother. The final monthly data used for calculating the financial uncertainty indices range from December 2008 to December 2020, i.e., 145 observations per variable.

Table 14: Banking data, Austria

	Name	Unit	Percent of	Code
1	Total risk exp am / tot exp	Eur		CBD2.Q.AT.W0.11._Z._Z.A.A.E0000._X.ALL.RW._Z.LE._T.EUR
2	Exposures to credit risk, SA	Eur		CBD2.Q.AT.W0.11._Z._Z.A.A.E2000._X.ALL.OE._Z.LE._T.EUR
3	Total risk exp am for pos. fx etc	Eur		CBD2.Q.AT.W0.11._Z._Z.A.A.E5000._X.ALL.RW._Z.LE._T.EUR
4	Net interest income	%	tot inc	CBD2.Q.AT.W0.11._Z._Z.A.A.I2510._Z._Z._Z._Z._Z._Z.PC
5	Net fee and commission income	%	tot inc	CBD2.Q.AT.W0.11._Z._Z.A.A.I2530._Z._Z._Z._Z._Z._Z.PC
6	Financial assets	%	tot ass	CBD2.Q.AT.W0.11._Z._Z.A.A.I3100._Z._Z._Z._Z._Z._Z.PC
7	Total loans and advances	%	tot ass	CBD2.Q.AT.W0.11._Z._Z.A.A.I3160._Z._Z._Z._Z._Z._Z.PC
8	Total debt securities	%	tot ass	CBD2.Q.AT.W0.11._Z._Z.A.A.I3170._Z._Z._Z._Z._Z._Z.PC
9	Total equity instruments	%	tot ass	CBD2.Q.AT.W0.11._Z._Z.A.A.I3180._Z._Z._Z._Z._Z._Z.PC
10	Total equity	%	tot ass	CBD2.Q.AT.W0.11._Z._Z.A.A.I3300._Z._Z._Z._Z._Z._Z.PC
11	Total assets / Total equity	ratio		CBD2.Q.AT.W0.11._Z._Z.A.A.I3400._Z._Z._Z._Z._Z._Z.PN
12	Gross non-performing debt instruments	%	tot debt	CBD2.Q.AT.W0.11._Z._Z.A.A.I3614._Z._Z._Z._Z._Z._Z.PC
13	Net non-performing debt instruments	%	tot sol fu	CBD2.Q.AT.W0.11._Z._Z.A.A.I3616._Z._Z._Z._Z._Z._Z.PC
14	Cash and trading assets	%	tot ass	CBD2.Q.AT.W0.11._Z._Z.A.I.I3002._Z._Z._Z._Z._Z._Z.PC
15	Exposures to credit risk, IRB	Eur		CBD2.Q.AT.W0.11._Z._Z.A.A.E3000._X.ALL.OE._Z.LE._T.EUR
16	Total risk exp am for operational risk	Eur		CBD2.Q.AT.W0.11._Z._Z.A.A.E6000._X.ALL.RW._Z.LE._T.EUR
17	Risk weighted exp am for credit risk	Eur		CBD2.Q.AT.W0.11._Z._Z.A.A.ECR00._X.ALL.RW._Z.LE._T.EUR
18	Risk weighted exp am for other risks	Eur		CBD2.Q.AT.W0.11._Z._Z.A.A.EOR00._X.ALL.RW._Z.LE._T.EUR
19	Solvency ratio	%		CBD2.Q.AT.W0.11._Z._Z.A.A.I4001._Z._Z._Z._Z._Z._Z.PC
20	Tier 1 ratio	%		CBD2.Q.AT.W0.11._Z._Z.A.A.I4002._Z._Z._Z._Z._Z._Z.PC

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[27] The number of original series is 35 and 31, for Austria and the euro area, respectively. This number includes the variables given in percent and in euro, where the latter are then transformed to reflect growth rates and ratios with respect to a reference value (total assets).

Table 14 – *Continued from previous page*

	Name	Unit	Percent of	Code
21	Capital buffer	%		CBD2.Q.AT.W0.11._Z._Z.A.A.I4003._Z._Z._Z._Z._Z._Z.PC
22	Tier 1 buffer	%		CBD2.Q.AT.W0.11._Z._Z.A.A.I4009._Z._Z._Z._Z._Z._Z.PC
23	Risk-weighted assets	%	tot ass	CBD2.Q.AT.W0.11._Z._Z.A.A.I4011._Z._Z._Z._Z._Z._Z.PC
24	Tier 1 capital	%	own fu	CBD2.Q.AT.W0.11._Z._Z.A.A.I4100._Z._Z._Z._Z._Z._Z.PC
25	Tier 2 capital	%	own fu	CBD2.Q.AT.W0.11._Z._Z.A.A.I4130._Z._Z._Z._Z._Z._Z.PC
26	Total risk weighted exp am for credit etc	%		CBD2.Q.AT.W0.11._Z._Z.A.A.I4210._Z._Z._Z._Z._Z._Z.PC
27	Credit risk – SA	%		CBD2.Q.AT.W0.11._Z._Z.A.A.I4211._Z._Z._Z._Z._Z._Z.PC
28	Credit risk – IRB	%		CBD2.Q.AT.W0.11._Z._Z.A.A.I4216._Z._Z._Z._Z._Z._Z.PC
29	Total risk exp am for pos, FX etc	%		CBD2.Q.AT.W0.11._Z._Z.A.A.I4230._Z._Z._Z._Z._Z._Z.PC
30	Total risk exp am for operational risks	%		CBD2.Q.AT.W0.11._Z._Z.A.A.I4240._Z._Z._Z._Z._Z._Z.PC
31	Original exposure IRB	%	tot or exp	CBD2.Q.AT.W0.11._Z._Z.A.A.I4300._Z._Z._Z._Z._Z._Z.PC
32	Own funds	Eur		CBD2.Q.AT.W0.11._Z._Z.A.A.O0000._X.ALL.CM._Z.LE._T.EUR
33	Tier 1 capital	Eur		CBD2.Q.AT.W0.11._Z._Z.A.A.O1000._X.ALL.CM._Z.LE._T.EUR
34	Tier 2 capital	Eur		CBD2.Q.AT.W0.11._Z._Z.A.A.O2000._X.ALL.CM._Z.LE._T.EUR
35	Total assets	Eur		CBD2.Q.AT.W0.11._Z._Z.A.A.A0000._X.ALL.CA._Z.LE._T.EUR

The table uses the following abbreviations: exp am = exposure amount; tot exp = total exposures; pos, fx etc = position, foreign exchange and commodity risks; tot inc = total income; tot ass = total assets; tot debt = total gross debt instruments; tot sol fu = total own funds for solvency purposes; own fu = own funds; credit, etc. = credit, counterparty credit, dilution and delivery risks; SA = standardised approach; IRB = internal ratings based approach; tot or exp = total original exposure; % = percent; Eur = euro.

Table 15: Banking data, euro area

	Name	Unit	Percent of	Code
1	Total risk exp am / tot exp	Eur		CBD2.Q.U2.W0.11._Z._Z.A.A.E0000._X.ALL.RW._Z.LE._T.EUR
2	Total risk exp am for pos. fx etc	Eur		CBD2.Q.U2.W0.11._Z._Z.A.A.E5000._X.ALL.RW._Z.LE._T.EUR
3	Net interest income	%	tot inc	CBD2.Q.U2.W0.11._Z._Z.A.A.I2510._Z._Z._Z._Z._Z._Z.PC
4	Net fee and commission income	%	tot inc	CBD2.Q.U2.W0.11._Z._Z.A.A.I2530._Z._Z._Z._Z._Z._Z.PC
5	Financial assets	%	tot ass	CBD2.Q.U2.W0.11._Z._Z.A.A.I3100._Z._Z._Z._Z._Z._Z.PC
6	Total loans and advances	%	tot ass	CBD2.Q.U2.W0.11._Z._Z.A.A.I3160._Z._Z._Z._Z._Z._Z.PC
7	Total debt securities	%	tot ass	CBD2.Q.U2.W0.11._Z._Z.A.A.I3170._Z._Z._Z._Z._Z._Z.PC
8	Total equity instruments	%	tot ass	CBD2.Q.U2.W0.11._Z._Z.A.A.I3180._Z._Z._Z._Z._Z._Z.PC
9	Total equity	%	tot ass	CBD2.Q.U2.W0.11._Z._Z.A.A.I3300._Z._Z._Z._Z._Z._Z.PC
10	Total assets / Total equity	ratio		CBD2.Q.U2.W0.11._Z._Z.A.A.I3400._Z._Z._Z._Z._Z._Z.PN
11	Gross non-performing debt instruments	%	tot debt	CBD2.Q.U2.W0.11._Z._Z.A.A.I3614._Z._Z._Z._Z._Z._Z.PC
12	Net non-performing debt instruments	%	tot sol fu	CBD2.Q.U2.W0.11._Z._Z.A.A.I3616._Z._Z._Z._Z._Z._Z.PC
13	Cash and trading assets	%	tot ass	CBD2.Q.U2.W0.11._Z._Z.A.I.I3002._Z._Z._Z._Z._Z._Z.PC
14	Risk weighted exp am for credit risk	Eur		CBD2.Q.U2.W0.11._Z._Z.A.A.ECR00._X.ALL.RW._Z.LE._T.EUR
15	Risk weighted exp am for other risks	Eur		CBD2.Q.U2.W0.11._Z._Z.A.A.EOR00._X.ALL.RW._Z.LE._T.EUR
16	Solvency ratio	%		CBD2.Q.U2.W0.11._Z._Z.A.A.I4001._Z._Z._Z._Z._Z._Z.PC

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Table 15 – *Continued from previous page*

	Name	Unit	Percent of	Code
17	Tier 1 ratio	%		CBD2.Q.U2.W0.11._Z._Z.A.A.I4002._Z._Z._Z._Z._Z._Z.PC
18	Capital buffer	%		CBD2.Q.U2.W0.11._Z._Z.A.A.I4003._Z._Z._Z._Z._Z._Z.PC
19	Tier 1 buffer	%		CBD2.Q.U2.W0.11._Z._Z.A.A.I4009._Z._Z._Z._Z._Z._Z.PC
20	Risk-weighted assets	%	tot ass	CBD2.Q.U2.W0.11._Z._Z.A.A.I4011._Z._Z._Z._Z._Z._Z.PC
21	Tier 1 capital	%	own fu	CBD2.Q.U2.W0.11._Z._Z.A.A.I4100._Z._Z._Z._Z._Z._Z.PC
22	Tier 2 capital	%	own fu	CBD2.Q.U2.W0.11._Z._Z.A.A.I4130._Z._Z._Z._Z._Z._Z.PC
23	Total risk weighted exp am for credit etc	%		CBD2.Q.U2.W0.11._Z._Z.A.A.I4210._Z._Z._Z._Z._Z._Z.PC
24	Credit risk – SA	%		CBD2.Q.U2.W0.11._Z._Z.A.A.I4211._Z._Z._Z._Z._Z._Z.PC
25	Credit risk – IRB	%		CBD2.Q.U2.W0.11._Z._Z.A.A.I4216._Z._Z._Z._Z._Z._Z.PC
26	Total risk exp am for pos, FX etc	%		CBD2.Q.U2.W0.11._Z._Z.A.A.I4230._Z._Z._Z._Z._Z._Z.PC
27	Total risk exp am for operational risks	%		CBD2.Q.U2.W0.11._Z._Z.A.A.I4240._Z._Z._Z._Z._Z._Z.PC
28	Original Exposure IRB	%	tot or exp	CBD2.Q.U2.W0.11._Z._Z.A.A.I4300._Z._Z._Z._Z._Z._Z.PC
29	Own funds	Eur		CBD2.Q.U2.W0.11._Z._Z.A.A.O0000._X.ALL.CM._Z.LE._T.EUR
30	Tier 1 capital	Eur		CBD2.Q.U2.W0.11._Z._Z.A.A.O1000._X.ALL.CM._Z.LE._T.EUR
31	Total assets	Eur		CBD2.Q.U2.W0.11._Z._Z.A.A.A0000._X.ALL.CA._Z.LE._T.EUR

The table uses the following abbreviations: exp am = exposure amount; tot exp = total exposures; pos, fx etc = position, foreign exchange and commodity risks; tot inc = total income; tot ass = total assets; tot debt = total gross debt instruments; tot sol fu = total own funds for solvency purposes; own fu = own funds; credit, etc. = credit, counterparty credit, dilution and delivery risks; SA = standardised approach; IRB = internal ratings based approach; tot or exp = total original exposure; % = percent; Eur = euro.

B Missing banking data

To work with monthly instead of quarterly data, missing values have to be estimated when the corresponding time series is only observed on a quarterly frequency. To do this we follow Shumway and Stoffer (1982), Brockwell and Davis (2006) [Chapter 12.3.] and Seong, Ahn and Zadrozny (2013). Consider the stochastic process (y_t), $y_t \in \mathbb{R}$, which is assumed to be trend stationary.[28] This process is assumed to be generated by a model of the form

$$\Delta y_t \quad = \quad \delta_0 + \delta_1 t + \sum_{j=1}^{q-1} \gamma_j \Delta y_{t-j} + u_t \tag{12}$$

where the time series dimension is denoted by $t = 1, \dots, T$. The "short run dynamics" are described by the parameters γ_j, $j = 1, \dots, q-1$, and u_t is a white noise process with mean zero and variance σ^2, $0 < \sigma^2 < \infty$.

With missing observations, $(y_t)_{t=1,\dots,T}$ is observed every $N^f > 1$ periods. In our case $N^f = 3$ as we observe the banking data at a quarterly frequency and plan to work with a monthly frequency. The subset of periods where all coordinates of y_t are observed is $\mathbb{T}_{obs}$. In the following we briefly describe how missing y_t can be estimated by applying the expectation-maximization algorithm (see, e.g., Mclachlan and Krishnan, 1997).

The corresponding $VAR(q)$ representation of (12) is

$$y_t \quad = \quad \delta_0 + \delta_1 t + \sum_{j=1}^{q} \Phi_j y_{t-j} + u_t \tag{13}$$

where $\Phi_1 = 1 + \gamma_1$, $\Phi_j = \gamma_j - \gamma_{j-1}$, $j = 2, \dots, q-1$ and $\Phi_q = -\gamma_{q-1}$. Let $\mathbf{y}_t = (y_t, \dots, y_{t-\kappa+1})' \in \mathbb{R}^\kappa$, where $\kappa = \max\{q, N^f\}$. By using (13) we get

$$\mathbf{y}_t \quad = \quad \bar{\mathbf{D}}_t + \mathbf{F}\mathbf{y}_{t-1} + \mathbf{e}_1 u_t \text{ , where}$$

$$\bar{\mathbf{D}}_t = \begin{pmatrix} \delta_0 + \delta_1 t \\ \mathbf{0}_{\kappa-1\times 1} \end{pmatrix} \in \mathbb{R}^{\kappa\times 1}, \quad \mathbf{F} = \begin{pmatrix} \Phi_1 & \Phi_2 & \dots & \Phi_{\kappa-1} & \Phi_\kappa \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{pmatrix} \in \mathbb{R}^{\kappa\times\kappa} \tag{14}$$

[28]We make this assumption as the banking data we consider are ratios and growth rates, which should actually be stationary. Due to the short time-series dimension this assumption can hardly be tested.

$\Phi_j = 0$ for $j > q$ and $\mathbf{e}_1 \in \mathbb{R}^{\kappa\times 1}$ is a basis vector with one being as the first element and zeros otherwise. The initial values $\mathbf{y}_0 \in \mathbb{R}^{\kappa}$ are assumed to be uncorrelated with the noise terms u_t and standard normally distributed.

For mixed-frequency data we define y_t^+, where $y_t^+ = y_t$ for any t where a (*stock*) variable y_t is actually observed, while $y_t^+ = \omega_t$ for any t where y_t is not observed; ω_t is standard normally distributed.[29] To express y_t^+ in terms of $\mathbf{y}_t$ let us introduce the following notation

$$\mathbf{H}_t = \begin{cases} \mathbf{e}_1', & \text{for },\ t \in \mathbb{T}_{obs} \\ \mathbf{0}_{1\times\kappa}, & t \notin \mathbb{T}_{obs} \end{cases} \tag{15}$$

$$\tilde{\mathbf{H}}_t = (\mathbf{0}_{1\times 2}, \mathbf{H}_t) \in \mathbb{R}^{1\times 2+\kappa} \tag{16}$$

where vector $(1, 1, \ldots, 1, 0, \ldots, 0)_{1\times\kappa}$ has ones on the first $N^f - 1$ positions and zeros otherwise and

$$Q_t = \begin{cases} 0, & t \in \mathbb{T}_{obs} \\ 1, & t \notin \mathbb{T}_{obs} \end{cases} \tag{17}$$

Endowed with this notation we define $\tilde{\mathbf{y}}_t = (1, t, \mathbf{y}_t')' \in \mathbb{R}^{2+\kappa}$, and obtain

$$\tilde{\mathbf{y}}_t = \tilde{\mathbf{F}}\tilde{\mathbf{y}}_{t-1} + \mathbf{e}_3 u_t\ , \tag{18}$$

where

$$\tilde{\mathbf{F}} = \left[\begin{array}{c|c} \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} & \mathbf{0}_{2\times 1} \\ \hline \begin{pmatrix} \delta_0 & \delta_1 \\ \mathbf{0}_{\kappa-1\times 1} & \mathbf{0}_{\kappa-1\times 1} \end{pmatrix} & \mathbf{F} \end{array}\right] \tag{19}$$

and $\mathbf{e}_3 \in \mathbb{R}^{\kappa+2\times 1}$ is a basis vector with one being as the third element and zeros otherwise.

[29] For a *flow* variable in levels temporal aggregates are observed, that is $y_t^+ = \sum_{j=1}^{N^f-1} y_{t-j}$. Since the banking data considered comprises stock variables only, we restrict our description of the procedure to the stock case in this section.

This results in the following state space form

$$\begin{aligned} &\tilde{\mathbf{y}}_t = \tilde{\mathbf{F}}\tilde{\mathbf{y}}_{t-1} + \mathbf{e}_3 u_t && \text{state equation} \\ &y_t^+ = \tilde{\mathbf{H}}_t\tilde{\mathbf{y}}_t + Q_t\omega_t = \tilde{\mathbf{H}}_t\left(\tilde{\mathbf{F}}\tilde{\mathbf{y}}_{t-1} + \mathbf{e}_3 u_t\right) + Q_t\omega_t && \text{observation equation} \end{aligned} \tag{20}$$

As already stated above, the random vector ω_t follows a standard normal distribution.

Let $\mathbf{Y}_T^+ = \left(y_1^+, y_2^+, \ldots, y_T^+\right)$ and $\boldsymbol{\theta}$ collect the model parameters. Then, the incomplete-data log-likelihood function is given by

$$\mathscr{L}(\boldsymbol{\theta}, \mathbf{Y}_T^+) \quad = \quad -\frac{1}{2}\sum_{t=1}^{T}\left[\ln\left|\tilde{\mathbf{H}}_t\mathbf{P}_{t|t-1}\tilde{\mathbf{H}}_t + Q_t^2\right| + \frac{\left(y_t^+ - \tilde{\mathbf{H}}_t\tilde{\mathbf{y}}_t\right)^2}{\tilde{\mathbf{H}}_t\mathbf{P}_{t|t-1}\tilde{\mathbf{H}}_t' + Q_t^2}\right] \tag{21}$$

where $\mathbf{P}_{t|t-1}$ follows from the Kalman filter recursions and depends on model parameters from the previous iteration.[30] By taking partial derivatives of (21) with respect to the corresponding model parameter we obtain maximum likelihood estimates.[31] To obtain these estimates conditional expectations of $\tilde{\mathbf{y}}_{t-j}\tilde{\mathbf{y}}_{t-k}'$, $j, k \in \{0, 1\}$, have to be calculated. To do this, we run the Kalman filter and the Kalman smoother. Hence, parameter estimates can be obtained by means of the expectation-maximization algorithm, where we commute between updating of the parameter estimates and updates of the conditional expectations by running the Kalman filter and Kalman smoother.

[30] See Seong, Ahn and Zadrozny (2013), appendix B, where $n = 1$ and $r = 0$ in their notation.
[31] See Seong, Ahn and Zadrozny (2013), equations (13)–(15).