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Financial stress and economic activity in Germany and the Euro Area

by Björn van Roye

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JEL classification: E5, E6, F3, G2, G14.

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Financial stress and economic activity in Germany and the Euro Area*

Björn van Roye
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1 Introduction

The financial crisis 2008-2009 has shown that turmoils in financial markets spilling over to the interbank market may have dramatic effects on the economy. The collapse of Lehman Brothers led to a full-blown systemic crisis of the financial system which finally provoqued the sharpest and severest downturn in economic activity since the great depression. The exacerbation of the European sovereign debt crisis - associated with a systemic crisis of the European banking system -, when government spreads of the peripheral countries rose sharply, strengthens the necessity for consideration of financial developments for the real economy. In general, there is evidence that financial imbalances commonly lead to widespread financial strains which may cause severe financial crises and recessions (Borio and Lowe (2002), Borio and Drehmann (2009), and Bloom (2009)). It is therefore a crucial challenge to monitor and to detect potential financial stress signals for the conduct of economic policy. The monitoring of financial stability has also become an increasingly important task for central banks. One major challenge is that monetary and financial factors are too peripheral in the standard macroeconomic models. Real-time indicators of the build-up of financial imbalances play a critical role for the improvement of these models. These indicators may be able to guide decision makers to tighten or loosen monetary and macroprudential policies even if inflation remains subdued. (Borio (2011a), Borio (2011b), and Goodhart (2011)). In practice, the European Central Bank (ECB) and the Federal Reserve have developed indicators that are aimed to "measure the current state of instability, i.e. the current level of frictions, stresses and strains in the financial system" (European Central Bank (2011)). The Federal Reserve Bank of Kansas City and the Federal Reserve Bank of St. Louis established the so-called *KCFSI* and *STLFSI* Indices (Davig and Hakkio (2009) and Kliesen and Smith (2010) in order have a single and comprehensive index measuring financial stress for the conduct of monetary policy "further down the road".

Also international institutions and private financial institutions such as the International Monetary Fund (IMF), The Organisation of Economic Co-operation and Development (OECD), the Bank for International Settlements (BIS), Goldman Sachs, Bloomberg and Citigroup have developed financial stress indicators in order to establish early warning indicators for financially erroneous trends. Until the Great Recession the majority of macroeconomic forecasting models did not include variables signaling financial market movements such as stock market volatility, capital market spreads or indicators for misalignments in the interbank market. As a consequence, the traditional macroeconomic models significantly underestimated the scope of the recession. The financial crisis has though brought the discussion of the inclusion of financial market variables strongly into focus again.

There is a whole new strand of literature that deals with financial stress indicators in order to capture the rupture of the financial system after the default of Lehman Brothers. The developed indicators are generally calculated using various financial variables such as stock and bond market developments and risk spreads. In the literature, these financial variables are then summarized in one indicator using either principal components analysis or a weighted-sum approach.[1] The great majority in the recent literature focus on the principal component approach. Illing and Liu (2006) were among the first to use a principal components analysis with regards to a financial stress indicator. They use a static factor model for Canada and show that their indicator provides an ordinal measures for financial stress in the financial system. For the United States there is a variety of different financial stress indicators. The Federal Reserve Bank of Kansas City and the Federal Reserve Bank of St. Louis established the so-called *KCFSI* and *STLFSI* Indices, using weekly US financial data (Davig and Hakkio (2009) and Kliesen and Smith (2010)). In a subsequent article, Davig and Hakkio (2010) analyze the effects of financial stress on real economic activity using the KCFSI. They find that the U.S. economy fluctuates between a normal regime, in which financial stress is low and economic activity is high, and a distressed regime, in which financial stress is high and economic activity is low. Hatzius et al. (2010) explore the link between financial conditions and economic activity in the United States. They calculate an alternative financial stress indicator using 45 variables and show that during most of the past two decades, including the last five years, the indicator shows a stronger link with future economic activity than existing indicators. One major innovation is that they allow for the estimation of an unbalanced panel which makes it possible to calculate the indicator back to 1970. Ng (2011) examines the predictive power of the indicators developed by Hatzius et al. (2010), the Basel Committee's Indicator (Bank for International Settlements (2010)) and another indicator developed by Domanski and Ng (2011). He comes to the conclusion that the regard of financial stress indicators as an additional predictor improves forecasting performance at horizons of 2 to 4 quarters on US GDP growth. A somewhat variant contribution for the impact of financial stress on economic activity in the United States is presented in Bloom (2009). He analyzes the impact of uncertainty shocks, measured by the volatility index (VIX) of the S&P500, on industrial production. He uses a vector autoregressive model (VAR) and finds significant effects of stock market volatility on industrial production.[2]

For the Euro Area, Holló et al. (2011) develop a composite indicator of systemic stress (CISS) which is thought to measure the current state of financial instability of the financial system. They employ a threshold bivariate VAR model including the CISS and industrial production. They show that impact of stress in financial markets depends on the regime, i.e. while the impact of financial stress on

[1] Examples for the weighted-sum approach are indicators developed by Cardarelli et al. (2011), Guichard et al. (2009), Goldman Sachs, Bloomberg and Citigroup.

[2] In fact, he does not calculate a financial stress indicator, but takes the S&P stock market volatility, which he interprets as a measure for uncertainty in the market.

economic activityin low-stress regimes is insignificant, the impact in high stress regimes significantly dampens economic activity considerably in the months after the shock. Mallick and Sousa (2011) use two identifications in a Bayesian VAR (BVAR) and a sign-restriction VAR to examine the real effects of financial stress. They emphasize that unexpected variation in financial stress leads to significant variations in output. Grimaldi (2010) discusses the performance of a financial stress indicator for the Euro Area. She finds that the indicator is able to efficiently extract information from an otherwise noisy signal and it can provide richer information than simple measures of volatility.

There are also several contributions regarding several comparable financial stress indicators across countries. The IMF recently uses these indicators developed by Matheson (2011) for the United States and the Euro Area and Unsal et al. (2011) for several Asian countries and Australia in order to improve the assessment of economic activity in the World Economic Outlook (International Monetary Fund (2011)). Cardarelli et al. (2011) examine why some financial stress periods lead to a downswing in economic activity in 17 advanced economies over 30 years using an augmented indicator including more variables from the banking sector. They find that financial stress is often but not always a precursor to a recession. Duca and Peltonen (2011) construct a financial stress indicatorcovering a set of 28 emerging market and advanced economies with quarterly data and find that taken into account jointly and global macrofinancial vulnerabilities improves the performance of discrete choice models in forecasting systemic events.

In the following, I calculate a Financial Market Stress Indicator (FMSI) for Germany and the Euro Area and estimate a model to explore the effects of financial stress on economic activity and the model's forecasting properties. I use a broad measure for financial stress including financial variables of the banking sector that proved to be relevant when explaining the sharp downturn during the financial crisis, the securities market, the stock market and the foreign exchange market. As Brave and Butters (2011), I allow for the estimation of an unbalanced panel and account for the issue of ragged data edges due to publication lags in order to cope with longer time series and real time data. Subsequently, I run an out-of-sample forecasting exercise using a small Bayesian VAR model with informative prior information on the steady state, as developed in Villani (2009), for German GDP and synthetic Euro Area GDP and show that forecasting accuracy can be improved taking into account the FMSI.

The remainder of the paper is organized as follows. In Section 2, I estimate the Financial Market Stress Indicator for Germany and the Euro Area, applying dynamic factor models. In Section 3, I present the BVAR model with the informative steady-state prior including the FMSI. In that section, I conduct an impulse-response analysis and a variance decomposition. In a forecasting comparison, I run a three to four variable BVAR with GDP, inflation, the short-term interest rate, and the FMSI and calculate root-mean-squared-errors (RMSE) for forecasts of one to eight quarters ahead. I then compare the RMSEs of the BVAR-

FMSI-model's forecasting accuracy of GDP growth with a standard BVAR without financial stress, and two forecast benchmarks, a recent mean forecast and a no-change forecast. Section 4 briefly concludes.

2 The Financial Market Stress Indicators (FMSI)

In this section I present the methodology for the calculation of the FMSI, the data sources and the resulting indicators for Germany and the Euro Area.

2.1 Methodology

In general, financial stress is unobservable but is presumably reflected in various financial market variables. Therefore, usually for the construction of such an indicator, a batch of different financial market variables are taken into account. For this purpose, I follow a similar methodology as Davig and Hakkio (2009) and Brave and Butters (2011) and use a dynamic approximate factor model applying a principal components approach with dynamic behaviour of the common latent factor. This approach has the advantage that it allows for the treatment of ragged edges due to publication lags.[3] Specifically, I take a model that can be written in state space form. The measurement equation relates the observed data X_t to the state vector of latent factors F_t.

$$X_t = \Lambda F_t + C\varepsilon_t, \qquad \text{where} \;\; \varepsilon_t \;\; \sim \;\; iid\, \mathcal{N}(0, \sigma_\varepsilon) \tag{1}$$

where X_t is a matrix of stationary and standardized endogenous financial variables, F_t is a $1 \times T$ latent factor containing a time-varying common source of variation in the $N \times T$ matrix (the common volatility factor) and Λ is a $N \times 1$ vector of factor loadings of the time series. The values in the factor loading vector represent to what extent each financial variable time series is affected by the common factor. The $N \times 1$ vector ε_t represents the idiosyncratic component which is allowed to be slightly correlated at all leads and lags. The dynamics of the latent factor F_t are described in the transition equation, i.e.:

$$F_t = AF_{t-1} + B\xi_t, \qquad \text{where} \;\; \xi_t \;\; \sim \;\; iid\, \mathcal{N}(0, \Sigma_\xi) \tag{2}$$

where A is the transition matrix capturing the development of the latent factor F_t in a VAR model over time. In a first step I employ a PCA-based EM-algorithm proposed by Stock and Watson (2002). In this step, this algorithm allows for a consistent treatment of missing data by imputing the PCA estimations from the balanced panel on missing data. Due to the state space form of the model, the initial estimates of the parameters can be passed through the Kalman filter and smoother in order to estimate the latent factors $\hat{F}_t$. Afterwards, Λ and A are re-estimated by ordinary least squares.

[3]Therefore, this methodology is quite prominent in the forecasting literature (see Stock and Watson (2002), Giannone et al. (2008) and Doz et al.)

2.2 Data

I estimate the model using monthly data. However, some variables are not published at a monthly frequency. In order to get monthly values for quarterly data, I apply a linear interpolation as in Chow and Lin (1971).[4] For daily series, I use monthly averages. Many time series are not available over the whole sample period. Yet, according to our methodology, the FMSI can be estimated when some variables are still missing by virtue of publication lags and missing values in the past.

I collect data from various sources. In table 4 and 5 in the appendix all variables considered in the FMSI estimation for Germany and the Euro Area are listed. Detailed information on the calculation and transformation on the specific variables can also be found in the appendix. In general, the data can be summarized into three different sub-groups; i.e. banking sector variables, securities market variables, and foreign exchange variables.

2.2.1 A FMSI for Germany

The first group contains variables related to the banking sector. These include the TED spread, the money market spread (Euribor over Eurepo), the β of the banking sector (a measure for bank return volatility relative to overall volatility calculated with a standard capital-asset pricing model), the slope of the yield curve, stock market returns of banks, a banks risk premium indicator, the spread on bank securities, expected lending conditions of German banks surveyed in the the ECB's Bank Lending Survey, firms credit availability condition as surveyed by the ifo institute, credit default swaps on banks, the German contribution of the demand of the ECB's deposit facility as an indicator for excess liquidity as well as an indicator for the profit situation of banks from a ZEW survey. The second group contains variables related to the securities and stock market. These include a corporate bond and corporate credit spread, CDS on DAX30 non-financial firms, the performance of the DAX, DAX volatility (VDAX), the correlation of the REX and the DAX, credit default swaps on government bonds, the spread on forward rates over current money market rates, and a housing loan spread. Finally, in the third group foreign exchange market volatility – the volatility of the real effective exchange rate – is calculated through a GARCH (1,1) model. The dynamic factor model is estimated over a sample period from 1981Q1 to 2011Q3.

The Financial Market Stress Indicator is depicted in figure 1. The first period of elevated stress is the 1982 recession followed by the 1987 stock market crash. Financial stress increased again with the Russian and Asian Crisis in 1997/1998. A sharp increase of financial stress was due to the burst in the dotcom bubble

[4] The raw data together with the interpolated data of quarterly time series are shown in the appendix.

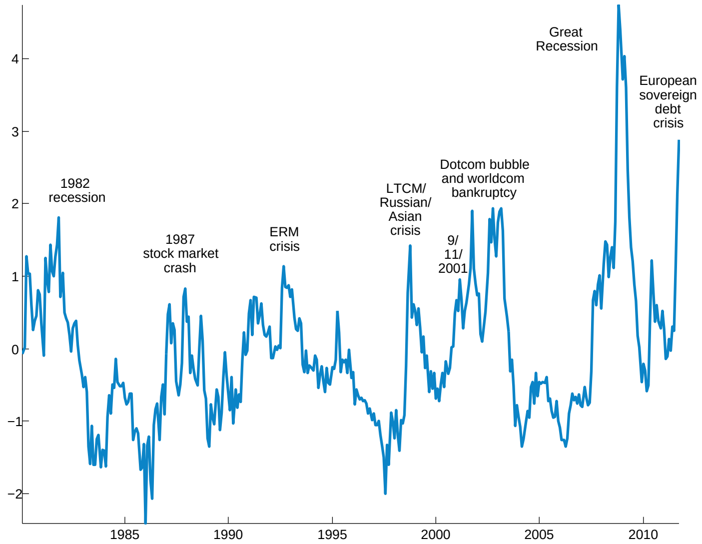


Figure 1: FMSI for Germany

at the beginning of the new millennium. However, the sharpest increase and the highest level of financial stress according to the indicator was the Great Recession 2008/2009 when spreads and volatilities in nearly all markets soared tremendously.

2.2.2 A FMSI for the Euro Area

For the Euro Area, variables for the banking sector include the TED spread, the money market spread (Euribor over Eurepo), the β of the banking sector , the slope of the yield curve, stock market returns of banks, a banks risk premium indicator, the spread on bank securities, credit default swaps on banks, banks lending standards from the ECB Bank Lending Survey, as well as an indicator for excess liquidity and the usage of the ECB's marginal lending facility. As far as the securities and stock market concerned, I include the spread of BBB rated corporate bonds over AAA rated bonds and a corporate credit spread, as well as credit default swaps on Eurostoxx50 non financial firms, the performance of the Eurostoxx50, Eurostoxx volatility (VSTOXX), the correlation of the EMTX and the Eurostoxx, credit default swaps on government bonds and spreads on Euro Area 16 (excluding Germany) over German Bunds, a housing loan spread. As for Germany, in the third group foreign exchange market volatility is calculated. The model is estimated over a sample from 1999Q1 to 2011Q3.

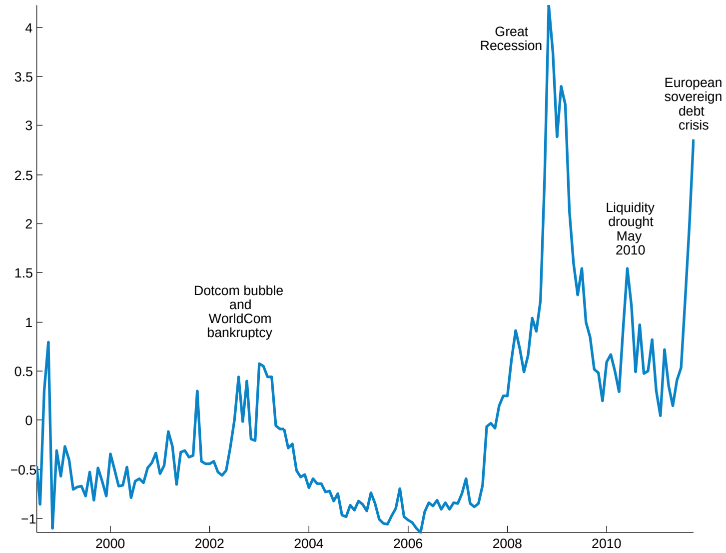


Figure 2: FMSI for the Euro Area

As in the case for Germany, financial stress arose with the burst of the dot-com bubble followed by the sharp increase in financial stress during the Great Recession. The European sovereign debt crisis has led to a divergence of the indicators since financial misalignments are primarily centered in Euro Area countries excluding Germany (see Figure 9 in the section sensitivity analysis).

3 A Bayesian VAR model with the FMSI

In order to to get insights of the effects of financial stress on economic activity, I estimate a BVAR model with an informative prior on the steady-state. I implement both one model without the FMSI and one including the FMSI. I run a variance decomposition in order to determine how much of GDP growth can be explained by a change in financial stress. Subsequently, an out-of-sample forecasting analysis is conducted.

3.1 Methodology

The majority of literature finds that Bayesian VAR models are superior with respect to out-of-sample forecasting accuracy compared to traditional VAR models.[5] In general, the root-mean-squared-error can be reduced using prior information on the dynamic coefficients on the model. In this paper I take a step further and use a BVAR with an informative prior on the steady-state. Various articles have shown that this methodology can further improve forecasting accuracy by using valuable prior information on the variables steady-state.[6]
Within a Bayesian estimation, a prior probability density function is specified for the parameters to be estimated. The specification is based on non sample information. A prior probability distribution is considered to be informative when the main part of the probability mass is centered relatively tight around a particular value. Accordingly, the distribution is considered non informative when this is not the case. Sample information is summarized in the likelihood function. From the combination of prior and data sample density functions, an updated density function is derived for the parameters. The specific shape of this posterior probability density function depends on the sample observations.
The general Bayesian VAR model has the following form:

$$G(L)Y_t = \mu + \eta_t, \tag{3}$$

where $G(L) = I - G_1 L - \cdots - G_p L^p$ is a lag polynomial of order p, Y_t is an $(n \times 1)$ vector of stationary macroeconomic variables, and η_t is an $(n \times 1)$ vector of i.i.d. error terms fulfilling $E(\eta_t) = 0$ and $E(\eta_t \eta_t') = \Sigma$.
However, with the general VAR model (3) it is difficult to come up with a prior distribution for μ. This problem has typically been solved by imposing a non informative prior on these parameters. Indeed, it is possible to specify an analogous informative prior if the parameterization of the model is altered in a particular way. Consider the following model:

[5] See for example Christoffel et al. (2010) and Litterman (1986).

[6] Österholm (2008), Beechey and Österholm (2008), Österholm and Zettelmeyer (2008), Barrera and Duttagupta (2010), and Christoffel et al. (2010).

$$G(L)(Y_t - \Psi) = \eta_t, \tag{4}$$

where $G(L)$, x_t, and η_t are defined as above. This model is a special case of the so-called mean-adjusted VAR model used by Villani (2009).[7]

The prior on the dynamic coefficients is supposed to follow a multivariate normal distribution. I impose a slightly modified version of the Minnesota prior suggested by Litterman (1986). In the traditional Minnesota prior, means on the first own lag of variables modeled in levels are set to one. However, within this framework it is set to 0.9 to make the prior theoretically consistent with the mean-adjusted VAR (4). In this model, this level specification is applied for the FMSI and the interest rate. All remaining means (GDP growth and inflation) are set to zero, i.e., means on the first own lag of variables modeled in differences, means on all higher-order lags, and means on all cross-coefficients. The coefficients are assumed to be independent from one another so that all covariances are zero.

Overall, the vector of endogenous variables in the VAR has the following form:

$$\mathbf{Y}_t = \begin{pmatrix} FMSI_t \\ \pi_t \\ i_t \\ \Delta y_t \end{pmatrix}, \tag{5}$$

where $FMSI_t$ is the financial market stress indicator, Δy_t is the GDP growth rate, π_t is the quarterly inflation rate and i_t is the 3-month Euribor. In order to identify independent standard normal shocks based on the estimated reduced form shocks, a standard Cholesky decomposition of the variance-covariance matrix is applied. The FMSI is contemporaneously independent of all shocks exluding its own. This ordering approach has become standard in the literature. It is for example also employed by Bloom (2009), Matheson (2011), Cardarelli et al. (2011) and Holló et al. (2011).[8] The structural shock identification can be justified from a consideration of information availability. Data on real GDP growth is published with a significant lag in Germany and the Euro Area. This information is thus not available for financial market participants in real time. Therefore, it cannot be reflected in contemporenous asset prices and other financial market variables.[9].

According to the methodology of the mean-adjusted BVAR I impose prior information on the steady-state of the variables. Since I do not have prior information from theory for the FMSI, I impose a rather diffuse prior with a wide distribution

[7] I will refer to model (4) as the mean-adjusted VAR in the following.

[8] An alternative ordering, where GDP growth is independent and the FMSI is contemporanously dependent of all other shocks, yields qualitatively similar results, which are available upon request.

[9] See Holló et al. (2011)

around the prior mean. The prior for steady-state growth for Germany follows the medium term projection from the (International Monetary Fund (2011)), the prior on the inflation rate is set to the target rate of the ECB and the prior information on the short-term interest rate follows insights from theoretical models.[10]

		Prior		Posterior	
		Mean	95 % interval	Mean	95 % interval
Germany					
FMSI	$FMSI$	0.0	[-8.0; 8.0]	0.18	[-2.51; 2.69]
GDP	Δy_t	1.2	[0.5; 1.9]	1.41	[1.10; 1.72]
Inflation	π_t	1.9	[0.0; 4.0]	1.73	[1.30;2.10]
Short-term interest rate	i_t	3.5	[2.0; 5.0]	3.48	[2.84;4.12]
Euro Area					
FMSI	$FMSI$	0.0	[-8.0; 8.0]	-0.54	[-1.23; 0.24]
GDP	Δy_t	2.0	[-2.0; 6.0]	1.21	[0.81; 1.61]
Inflation	π_t	1.9	[0.0; 4.0]	1.91	[2.21;1.61]
Short-term interest rate	i_t	4.4	[0.6; 9.4]	2.83	[3.51;2.18]

Source: Authors' calculations.
Notes: The values for GDP and inflation are expressed in percent at annualized rates. The data for the short-term interest rate is expressed in percent.

Table 1: Prior and posterior distributions of the BVAR

For the Euro Area, I follow Christoffel et al. (2010) and set GDP growth to 2 percent, the inflation rate to 1.9 percent and the short-term interest rate to 4.4 percent. An overview of the prior information and the estimated posterior distribution is presented in table (1).

[10] See for example Clarida et al. (1999).

3.2 Impulse Responses and Variance Decomposition

In this section I present an impulse response analysis and a variance decomposition in order to analyze the effects of financial stress on economic activity in Germany and the Euro Area. The 50 percent and 95 percent Bayesian confidence bands are plotted around the impulse response functions.

3.2.1 Germany

The impulse response analysis shows that increases in financial stress are very persistent. The inital level after a financial stress shock is reached only 8 quarters after the shock occurred. The increase of financial stress has also significant effects in economic activity. One standard deviation increase in the FMSI leads to a reduction in real GDP growth of about annualized 0.2 percentage points on impact. After 4 quarters the effect is the strongest, reducing real GDP growth by 0.6 percentage points. The effects on the inflation rate are more modest, reducing headline inflation only about 0.2 percentage points after 3-4 quarters. The short-term interest rate reduces slightly but persistently in response to a shock in financial stress. After 4 quarters, the interest rate is 0.4 percentage points lower. At a longer horizon, the interest rate converges back to its initial level.

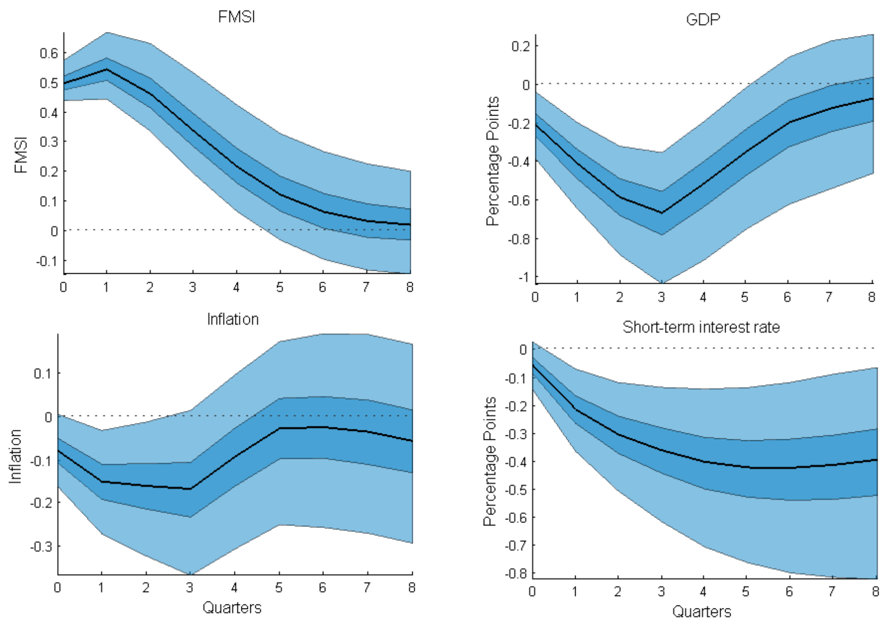


Figure 3: Impulse responses after a shock to the financial market stress indicator (Germany)

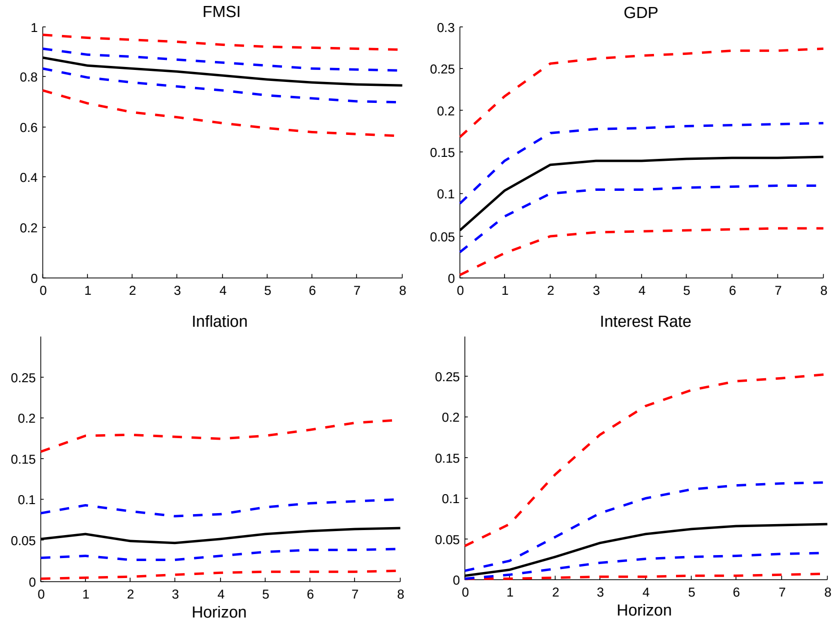


Figure 4: Variance Decomposition (Germany)

A variance decomposition underlines the role of macroeconomic importance of financial stress. At a horizon of 8 quarters shocks in financial market stress explain about 15 percent of variation in real GDP growth, 7 percent of the variation in the inflation rate and 5 percent of changes in the interest rate.

3.2.2 Euro Area

An analogous impulse response analysis with respect to the Euro Area yields similar qualitative results. The FMSI is similarly persistent and returns to its initial level just after 8 quarters. The negative impact on GDP growth is comparable with that to Germany, whereas the reduction in the inflation rate is significantly stronger. The short-term interest rate declines persistently and converges back to its inital level after approximately 12 quarters.

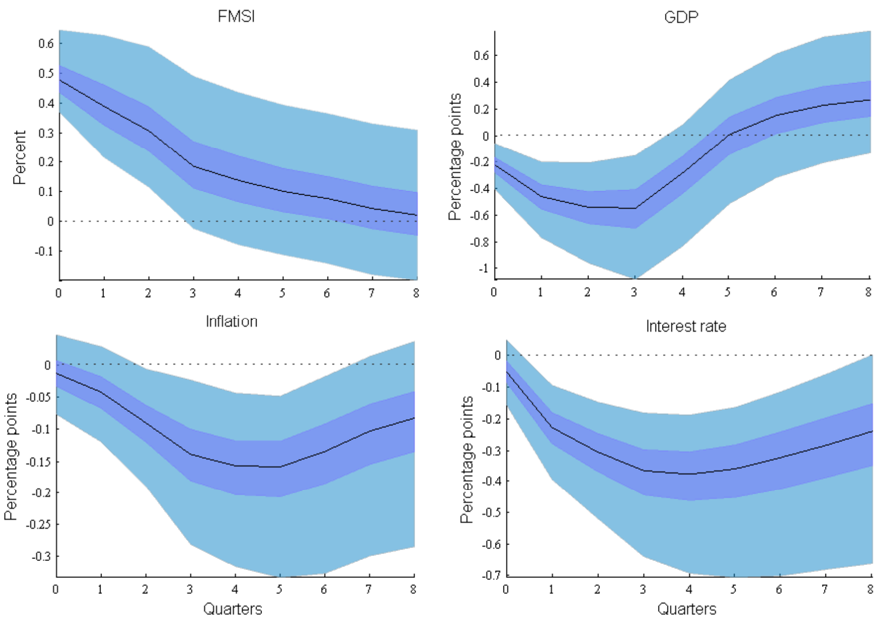


Figure 5: Impulse responses after a shock to the financial market stress indicator (Euro Area)

As the variance decomposition is concerned, about 30 percent of variation of GDP growth can be explained by an increase in financial stress. The contribution to the inflation rate amounts up to 18 percent and the short-term interest rate 50 percent after 8 quarters.

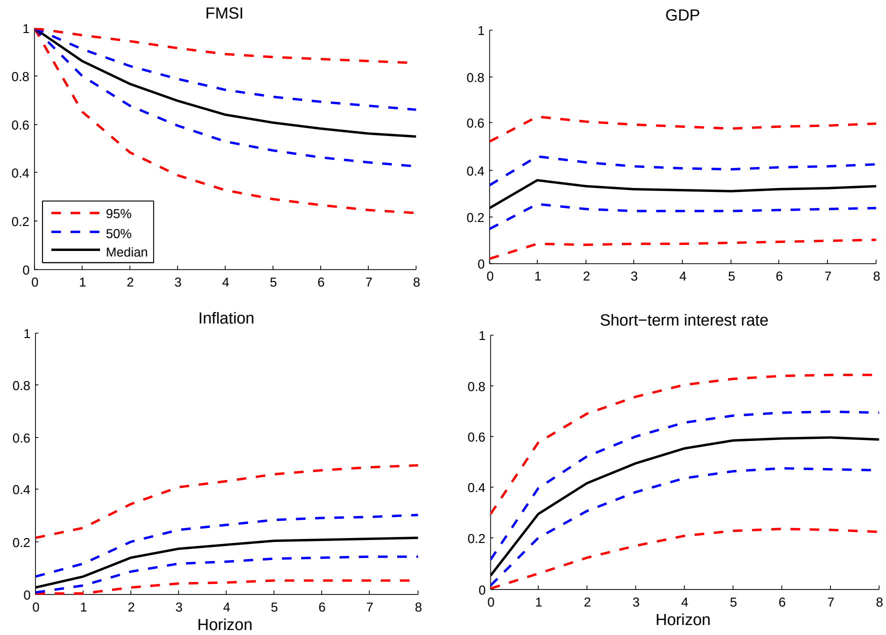


Figure 6: Variance Decomposition (Euro Area)

3.3 Out-of-sample forecasting performance

In order to determine the information gain when including financial stress in a small macroeconomic model, a forecast comparison between different model specifications is implemented below, i.e. with and without the FMSI for Germany.[11] The forecasting performance of the models is evaluated using the horizon h root mean squared error (RMSE), given by

$$RMSE_h = \sqrt{N_h^{-1} \sum_{t=1}^{N_h} (x_{t+h} - \hat{x}_{t+h,t})^2} \tag{6}$$

where x_{t+h} is the actual value of variable x at time $t+h$ and $\hat{x}_{t+h}$ is an h step ahead forecast of x implemented at time t.

I want to evaluate the forecasting performances for all quarterly horizons between 1 and 8. Therefore, I first estimate all models using data from 1980:Q4 to 2003:Q2 and generate forecasts over all 8 horizons. Then I consecutively extend the estimation sample by one quarter and do the same until the estimation sample comprises 2009:Q2. Thereafter, I forecast over consecutively shorter periods since from this point on there would be no data to compare the longer forecasts

[11] The out-of-sample forecasting accury evaluation is solely implemented for the FMSI for Germany. Due to the short estimation period, the respective analysis for the Euro Area is at least problematic.

Horizon	BVAR	BVAR with stress	No change	Recent mean
1Q	1.071	**0.901**	1.072	1.101
2Q	1.840	**1.624**	2.165	2.046
3Q	2.941	**2.223**	3.301	2.961
4Q	3.081	**2.827**	4.612	4.003
5Q	3.203	**3.210**	5.300	4.409
6Q	3.467	**3.361**	5.708	4.665
7Q	3.487	**3.447**	5.876	4.846
8Q	3.542	**3.390**	5.960	4.864

Source: Authors' calculations.

Table 2: Root-mean-squared-error for German GDP growth

with. I get 25 forecasts and therewith 25 squared errors at the 8 quarter horizon, 29 squared errors at the 7 quarter horizon, 30 squared errors at the 6 quarter horizon, and so on. At the one-quarter horizon, I finally get 35 squared errors. Using all of these, I compute the corresponding mean squared errors for all 8 horizons (Table 2). The RMSE are then compared to the BVAR model without the financial market stress indicator and two other benchmark forecasts, a no-change forecast ($\hat{x}_{t+h|t} = x_t$ where $h = 1, \ldots 8$ and) such that the growth rate from period $t + 1$ is assumed to equal the growth rate in t and a recent mean forecast ($\hat{x}^{(r)}_{t+h|t} = r^{-1} \sum_{i=1}^{r} x_{t-i+1}$) such that the growth rate depends on the mean of the r most recent realized values.[12] The general picture is unambiguous: the mean-adjusted BVAR with financial stress outperforms the BVAR without financial stress and the two benchmark forecasts at all considered horizons.

[12] In this paper I used 4 quarters for the recent mean forecast.

3.4 Sensitivity analysis

In this section I test for robustness varying the sample period. In a first robustness test, I estimate the model until the second quarter of 2008, omitting the events associated with the default of Lehman Brothers.

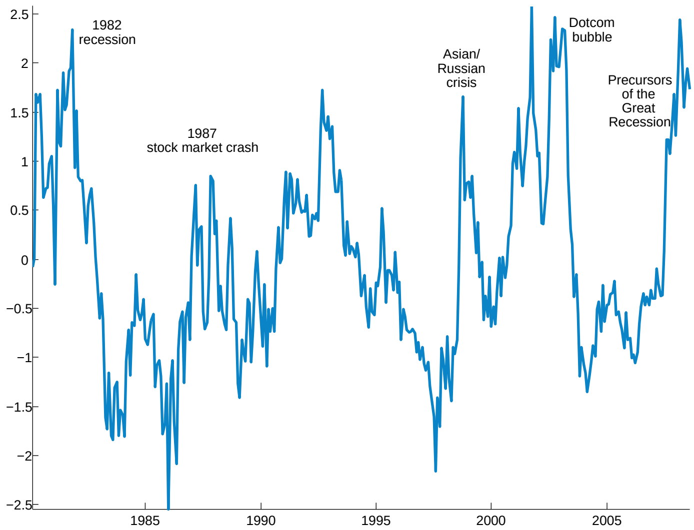


Figure 7: FMSI Germany (excluding the Great Recession)

The qualitative results remain unchainched, the significance and magnitute of the impact is reduced, however. In particular, the negative reaction of the inflation rate and the decrease in the short-term interest rate after a shock to the financial market stress indicator are not significant anymore. Additionally, the contemporaneous decline in GDP growth after the shock is only significant at a 50 percent confidence level. The magnitude of the GDP growth reduction reduces to 0.4 percentage points after three quarters on average, compared to 0.7 percentage points in the sample period including the Great Recession. However, this can be partially explained by the shock volatility reduction of the financial market stress indicator when it is estimated omitting the Great Recession.

The results from the increase in out-of-sample forecasting accuracy is not changed in this sensitivity analysis either. The root-mean-squared-error is lower for the model including the financial market stress indicator at all considered horizons.

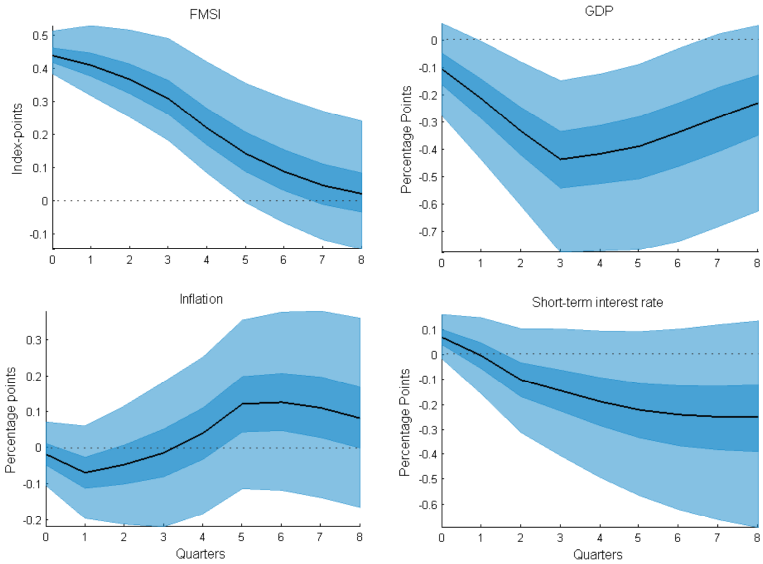


Figure 8: Impulse response after a shock to the financial market stress indicator Germany (excluding the Great Recession)

Horizon	BVAR	BVAR with stress	No change	Recent mean
1Q	0.590	**0.565**	0.642	0.585
2Q	1.168	**1.053**	1.153	1.216
3Q	2.181	**1.916**	2.182	2.308
4Q	2.877	**2.470**	3.268	3.151
5Q	3.154	**2.777**	3.587	3.524
6Q	3.261	**2.948**	3.930	3.797
7Q	3.287	**3.114**	4.093	3.977
8Q	3.320	**3.239**	4.224	4.201

Source: Authors' calculations.

Table 3: Root-mean-squared-error for German GDP growth

In a second robustness check, I estimate the financial stress indicator for Germany from the beginning of the monetary union in 1999. The shorter sample period mitigates the estimation problem due to the unobserved panel since nearly all data is available from 1999.[13] Additionally, the shorter sample period allows for an approximate comparison of financial stress between Germany and the aggregate Euro Area.[14] The disadvantage of the shorter time period is the increase of generous parametrization when estimating the VAR model due to the shorter time period. However, since we estimate the model using Bayesian techniques, the shorter time horizon does not alter the estimation precision as much as under a traditional VAR. With the shorter estimation period, the shape of the FMSI slightly changes.

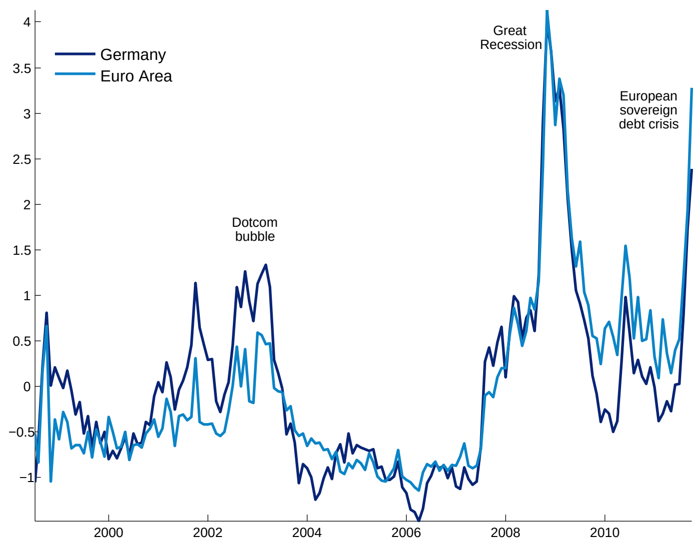


Figure 9: Financial stress indicator short sample

When estimating the impact of financial stress on economic activity, the results remain unchanged qualitatively. An increase in the financial market stress indicator leads to a dampening in GDP growth and a slightly significant deceleration of inflation and a decreasing short-term interest rate.[15]

[13] An exception are Credit Default Swaps, which are available not earlier than from the beginning of 2008.

[14] To be clear, since the FMSI is estimated for the aggregate Euro Area, Germany is included in the Euro Area indicator.

[15] The detailed impulse response functions and the variance decomposition are available upon request.

4 Conclusion

The disruptive events in financial markets over the past three years increased the necessity in taking into account financial misalignments for forecasting and analyzing economic activity in macroeconomic models. The aim of this paper is to establish financial market stress indicators that should be taken into account when analyzing business cycles in Germany and the Euro Area. These indicators are developed using a panel of various financial market variables applying a dynamic factor model. An increase in these indicators can be considered as additional early warning variables for a decelaration of economic activity. Particularly, it can be shown that an increase in financial stress dampens overall economic activity. A variance decomposition shows that about 15 percent of variation in German GDP growth can be accounted for financial stress, whereas the share for the Euro Area is significantly higher. Subsequently, I show the improvement of forecasting accuracy of German GDP growth when including the indicator into a small scale Bayesian VAR model. In particular, I compare the root mean squared errors of two estimation samples and diverse time horizons including and excluding financial stress. The analysis shows that the inclusion of the indicator significantly reduces the root-mean-squared error of a small Bayesian VAR for the German economy and therefore can improve forecasting accuracy in the short- to medium-term.

5 Appendix

5.1 Detailed description of the data and data transformations

Indicators	Native frequency	First observation	Category	Transform	Source
		Banking indices			
TED spread	monthly	$1994M01$	Spreads	Level	Deutsche Bundesbank
Money market spread	daily	$1999M01$	Spreads	Level	Deutsche Bundesbank
β of banking sector	daily	$1980M03$	Spreads	Level	Deutsche Bundesbank
Bank stock market returns	daily	$1980M02$	Prices	Growth	Thomson Financial
Banking equity risk index	daily	$1980M02$	Spreads	Growth	Thomson Financial
Bank securities spread	monthly	$1980M01$	Spreads	Level	Deutsche Bundesbank
Expected Lending (BLS)	quarterly	$2003M01$	Index	Level	Deutsche Bundesbank
ifo-credit conditions	monthly	$2004M05$	Index	Level	ifo institute
CDS on banking sector	monthly	$2007M01$	Index	Level	Thomson Financial
Excess liquidity	monthly	$1999M01$	Value Euro	Level	Deutsche Bundesbank
ZEW Bank Index	monthly	$1991M12$	Index	Level	ZEW
		Securities market indices			
Corporate Bond Spread	monthly	$1980M01$	Spreads	Level	Deutsche Bundesbank
Corporate Credit Spread	monthly	$1980M01$	Spreads	Level	Deutsche Bundesbank
Housing Spread	monthly	$2003M01$	Spreads	Level	European Central Bank
CDS on Corporate Sector	monthly	$2008M01$	Spreads	Level	Thomson Financial
CDS on 1Y Government Bonds	daily	$2007M12$	Spreads	Level	Thomson Financial
Consumer Credit spread	monthly	$1980M01$	Spreads	Level	Deutsche Bundesbank
VDAX	monthly	$1984M01$	Prices	Level	Deutsche Bundesbank
% Change of DAX	daily	$1980M01$	Prices	Growth	Deutsche Bundesbank
Slope of Yield Curve	monthly	$1994M01$	Spreads	Level	Deutsche Bundesbank
$Corr(REX, DAX)$	daily	$1980M01$	Correlations	Level	Deutsche Bundesbank
Forward Spread	daily	$2003M04$	Spreads	Level	European Central Bank
		Foreign exchange indices			
REER (GARCH(1,1))	monthly	$1994M01$	Prices	Level	Deutsche Bundesbank

Source: European Central Bank, Deutsche Bundesbank, ifo institute, Thomson Financial Datastream, own calculations.

Table 4: Data description Germany

Indicators	Native frequency	First observation	Category	Transform	Source
		Banking indices			
TED spread	monthly	$1999M01$	Spreads	Level	European Central Bank
Money market spread	daily	$1999M01$	Spreads	Level	European Central Bank
β of banking sector	daily	$1999M01$	Spreads	Level	European Central Bank
Bank stock market returns	daily	$1999M01$	Prices	Growth	Thomson Financial
Bank equity risk index	daily	$1999M01$	Spreads	Level	Thomson Financial
Bank securities spread	monthly	$1999M01$	Spreads	Level	Merrill Lynch
Expected Lending (BLS)	quarterly	$2003M01$	Index	Level	European Central Bank
CDS on banking sector	monthly	$2007M01$	Index	Level	Thomson Financial
Excess liquidity	weekly	$1999M01$	Value Euro	Level	European Central Bank
Marginal Lending Facility	weekly	$1999M01$	Value Euro	Level	European Central Bank
		Securities market indices			
Corporate Bond Spread	monthly	$1999M01$	Spreads	Level	Merrill Lynch
Corporate Credit Spread	monthly	$2003M01$	Spreads	Level	European Central Bank
CDS on Corporate Sector	monthly	$2008M01$	Spreads	Level	Thomson Financial
Housing Spread	monthly	$2003M01$	Spreads	Level	European Central Bank
CDS on 1Y Government Bonds	daily	$2007M12$	Spreads	Level	Thomson Financial
Government Bond Spread	daily	$1999M01$	Spreads	Level	Thomson Financial
Consumer Credit spread	monthly	$2003M01$	Spreads	Level	European Central Bank
VStoxx	monthly	$1999M01$	Prices	Level	Thomson Financial
% Change of Eurostoxx	daily	$1999M01$	Prices	Growth	Deutsche Bundesbank
Slope of Yield Curve	monthly	$1999M01$	Spreads	Level	Deutsche Bundesbank
$Corr(EMTX, Eurostoxx)$	daily	$1999M01$	Correlations	Level	Thomson Financial
		Foreign exchange indices			
REER (GARCH(1,1))	monthly	$1999M01$	Prices	Level	Deutsche Bundesbank

Source: European Central Bank, Deutsche Bundesbank, Thomson Financial Datastream, Merrill Lynch, own calculations.

Table 5: Data description Euro Area

5.1.1 Variables related to the banking sector

TED spread The TED spread is calculated as the difference of the one-month and twelve-month money market rate (Fibor/Euribor) The spread is an important money market indicator, indicating the liquidity and confidence in the banking sector. A shortage of liquidity leads to a decrease of supply in the money market, leading to an increase in the TED spread.

Money market spread The money market spread is the difference of the 3-month Euro Interbank Offered Rate (Euribor, which is the average interest rate at which European banks lend unsecured funds to other market participants) and the Eurepo (the benchmark for secured money market operations). An increase in the spread reflects an increase in uncertainty in the money market and can be interpreted as a risk premium.

β **of the banking sector** The β of the banking sector is determined as the covariance of stock market and banking returns over the standard deviation of stock market returns. It follows from a standard capital asset pricing model (CAPM). A β larger than one indicates that banking stocks shift more than proportional with the overall stock market (see also Balakrishnan et al. (2009)).

Bank stock market returns This indicator measures the stock market returns for commercial bank shares. For Germany I use an equity index of the ten largest commercial banks. For the Euro Area, a bank equity index from Thomson Financial Datastream is chosen (Datastream code: BANKSEM). A decrease in banks stock market returns leads to an increase in the financial market stress indicator.

Banking equity risk index The banking equity index Germany is a capital weighted total return index calculated by Thomson Financial Datastream. It consists of eight German Banks that are continously included in the index since 1973 and further 10 banks that gradually were included in the course of the sample period. The risk premium is calculated as in Behr and Steffen (2006), where it is constructed as a fraction bank stock returns over a risk-free interest rate. The yield of the banking equity index is determined using daily log-differences of the time series. The yield is then subtracted from a risk-free interest rate. In this case, I use the one-month secured money market rate (1m Eurepo). For the Euro Area I use a comparable banking equity index (the indicator used in the calculation of bank stock market returns).

Bank securities spread This indicator is measured by the difference of bank securities with the maturity of 2 years over AAA-rated (German) government bonds with the same maturity. An increase in the spread reflects higher risk perception of the banking sector. For Germany, the time series for bank securities is taken from the banking statistics from the Bundesbank, for the Euro Area it is calculated using data from Merrill Lynch.

Expected Lending (BLS) This indicator comes from the ECB's bank lending survey. In this survey banks are asked to report their assessment how credit lending standards will evolve within the coming three months. For Germany the Bundesbank is reporting the national results of the survey. It is reported on a quarterly basis and therefore linearly interpolated using the Chow and Lin (1971) methodology. The interpolated data is depicted below. Increasing values indicate an expected tightening in lending standards which contributes positively to the FMSI.

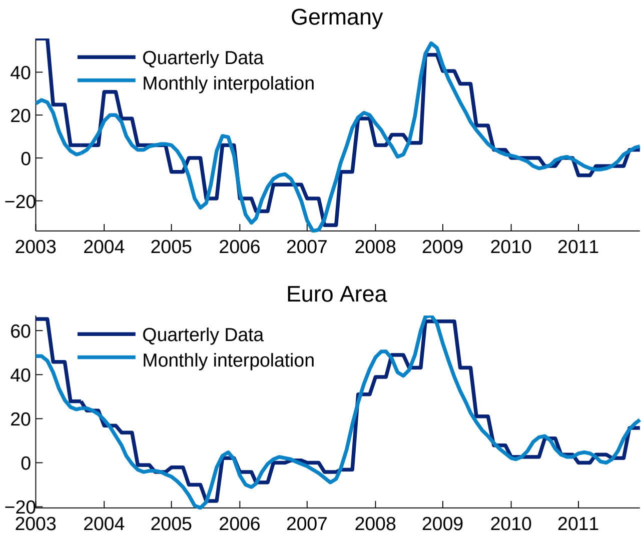


Figure 10: Interpolated series from the ECB Bank Lending Survey

ifo credit conditions This indicator is surveyed by the ifo institute. In this survey firms are asked to report their assessment how credit lending standards are evolving currently. Increasing values reflect a tightening in credit standards, which contributes positively to the FMSI. It is reported on a monthly basis and only available for Germany.

CDS on financial corporations For Germany, this index is an average of 5-year credit default swaps on the most important (largest ten) financial corporations, i.e. commercial banks. For the Euro Area, an aggregate European Monetary Union 5-year CDS-banking index published by Thomson Financial

Datastream is used (Datastream code: DSEBK5E). An increase in this index reflects a higher risk perception with respect to the non-financial corporate sector.

Excess liquidity Value of bank deposits at the ECB that exceed the minimum reserve requirements. A high usage of the ECB deposit facility reflects uncertainty in the interbank market. Banks prefer to hold their excess resserves with the ECB rather than lending it to the non-financial sector or to other banks in the interbank market.

Marginal Lending Facility Value of bank lending at the ECB that is demanded outside the main refinancing operations at a higher interest rate.

ZEW survey on banks This is a survey based indicator from the Center for European Policy Research (ZEW). In this survey, bank managers are asked how they evaluate the current profit situation of their credit institution. Decreasing values indicate a worsened profit stance, which contributes positively to the FMSI. The indicator is published on a monthly basis and is solely available for Germany.

5.1.2 Variables related to securities market

Corporate bond spread The corporate bond spread is the yield on BBB-rated corporate bonds with a maturity of 5 years over the yield on AAA-rated (German) government bond yield with the same maturity. The spread increases with higher risk perception in the corporate bond market. This spreads contains credit, liquidity and market risk premia.

Corporate credit spread The credit spread measures the difference between the yield on one to two year loans to non-financial corporations and the rate for secured money market transactions (Eurepo).

CDS on corporate sector This index is an average of 5-year credit default swaps on the DAX 30 non-financial corporations outstanding debt. For the Euro Area, it is a simple average of non-financial firms, using data for different sectors from Thomson Financial Datstream. An increase in this index reflects a higher risk perception with respect to the non-financial corporate sector.

Housing spread The housing spread measures the difference between the interest rate all housing loans to private households over the interest rate for secured money market transactions (Eurepo).

Government Bond Spreads The Government Bond Spread for the Euro Area is calculated as a weighted average of 10Y government bond yields of all non-AAA rated countries over AAA rated countries. Increasing values indicate a higher risk perception of investors to outstanding government debt in certain countries of EMU. Since government debt of Germany itself holds a triple AAA rating, no government bond yield spread over high quality bonds are calculated for Germany.

CDS on 1Y Government Bonds The Credit Default Swap reflects market expectations of a default in government debt. Increasing values indicate a higher risk perception of investors to outstanding government debt.

Consumer credit spread The credit spread measures the difference between the yield on one to two year loans to households and the rate for secured money market transactions (Eurepo).

VDAX and VSTOXX The VDAX and VSTOXX measures stock return volatility. Usually an increase in stock market volatility reflects a higher degree of uncertainty and risk perception.

DAX and Eurostoxx yoy % change These variables measures the inverted monthly year-on-year yield of the DAX and the Eurostoxx. Increasing values lead to an increase of the FMSI.

Slope of the yield curve The slope of the yield curve reflects bank profitability. It is determined taking differences between the short- and long-term yields on goverment issued securities. It measures the possible degree of maturity transformation. Usually, banks generate profit by intermediation from short-term liabilities (deposits) to long-term assets (loans). A negative slope of the yield curve, i.e. a negative term spread, therefore stands for an increase of bank profitability.[16]

Corr(REX,DAX) and Corr(EMTX,Eurostoxx) The REX and the EMTX are fixed-income performance indexes. The EMTX is a euro government bond benchmark calculated and disseminated by EuroMTS. Increasing interest rates implies a decreasing REX/EMTX index. Hence, a negative correlation between REX (resp. EMTX) and DAX (resp. Eurostoxx) indicates a positive correlation between DAX (resp. Eurostoxx) and the general level of interest rates.

Forward Spread The forward spread is calculated as the market forward rate for 3-months Euribor 1-4 months ahead minus the current 3-months Euribor. Increasing forward rates indicate an expected interest rate increase.

[16] See Cardarelli et al. (2011).

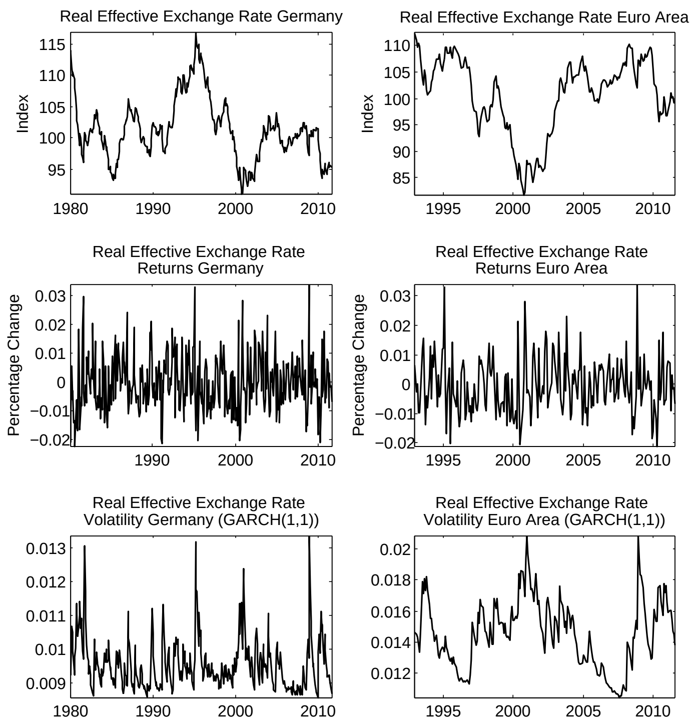
5.1.3 Variables related to the foreign exchange market

Real effective exchange rate This index measures the volatility of the real effective exchange rate (REER). The REER is deflated on the CPI-basis with respect to 20 trading partners. An ARCH-test rejected the null hypothesis of the lack of GARCH effects on a significance level of 95 percent. Hence, in order to determine real exchange rate volatility, we use a GARCH(1,1) model. The results are displayed below.

Table 6: Estimation Results of the GARCH(1,1) model

Parameter	Value	Standard Error	t-Statstic
Germany			
C	-0.00021261	0.00052026	-0.4087
K	2.3958e-005	2.0728e-005	1.1559
GARCH(1)	0.66342	0.25992	2.5524
ARCH(1)	0.076276	0.05643	1.3517
Euro Area			
C	0.00015911	0.00097406	0.1633
K	1.4787e-005	1.17e-005	1.2639
GARCH(1)	0.83714	0.094745	8.8357
ARCH(1)	0.095456	0.056987	1.6750

Source: Authors' calculations.
Notes: The conditional probability distribution was chosen to be Gaussian.



5.2 Contributions to the FMSI

5.2.1 Long sample (1980M01-2011M07)

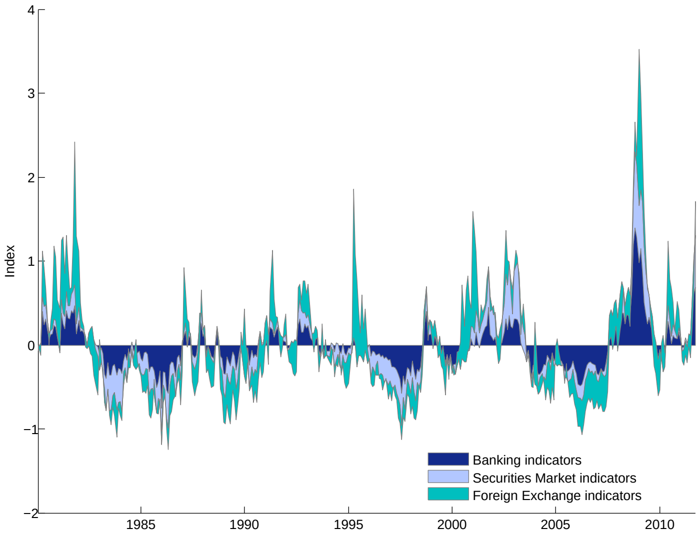


Figure 11: Contribution of indicator groups

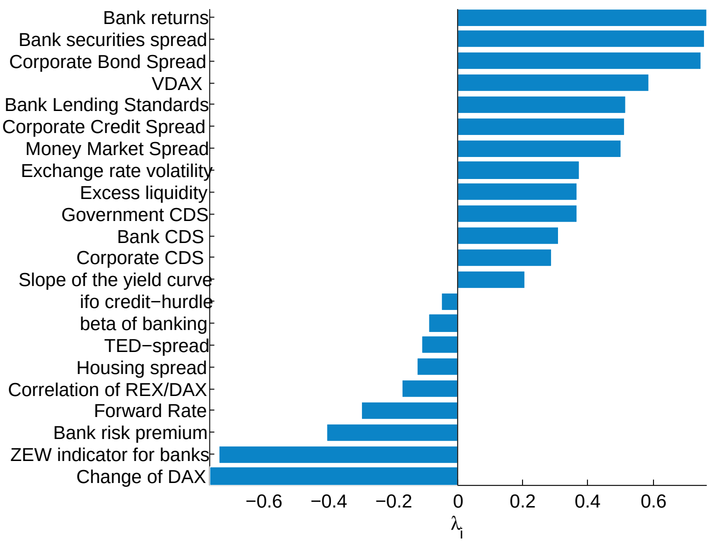


Figure 12: Factor loadings

5.2.2 Short sample (1999M01-2011M07)

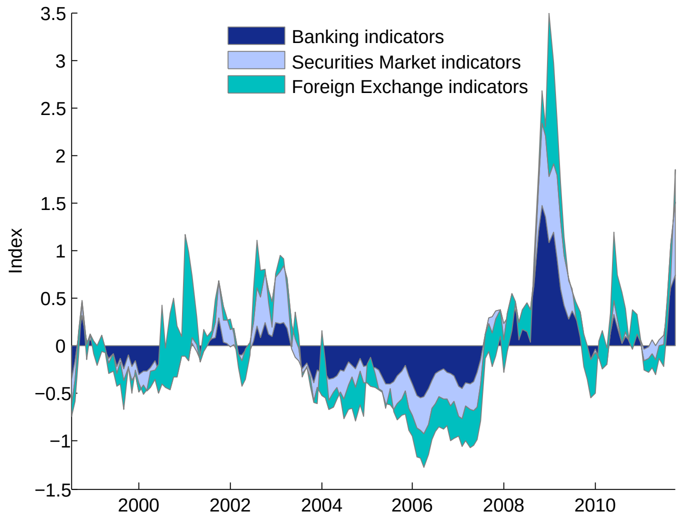


Figure 13: Contribution of indicator groups

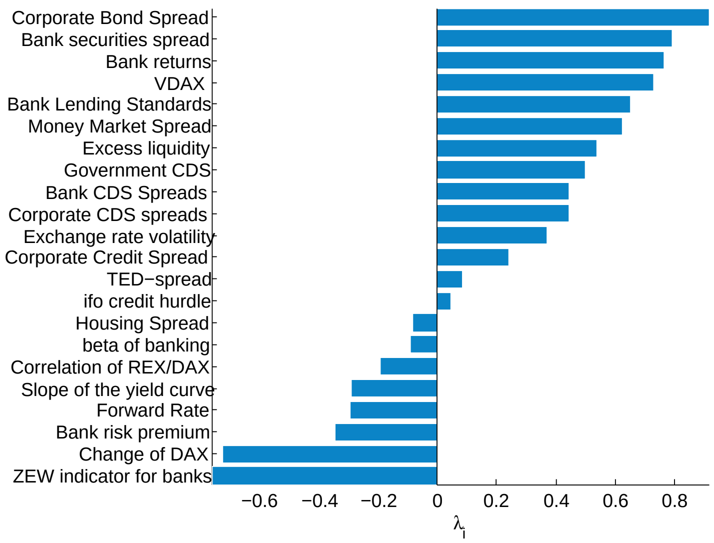


Figure 14: Factor loadings

5.2.3 Excluding the Great Recession (1980M01-2008M05)

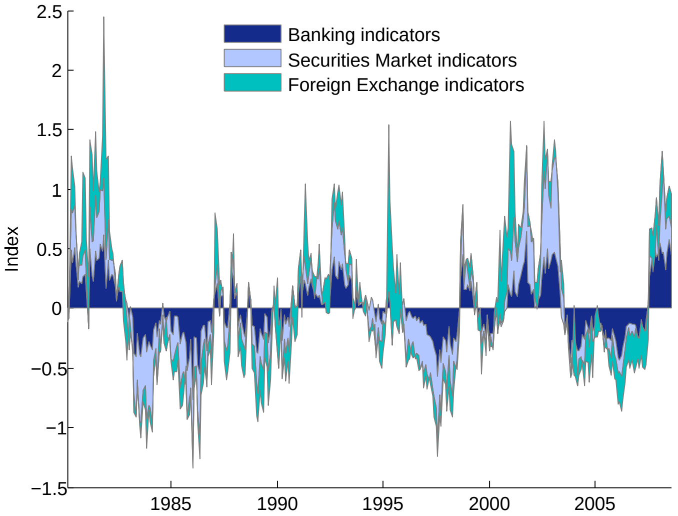


Figure 15: Contribution of indicator groups

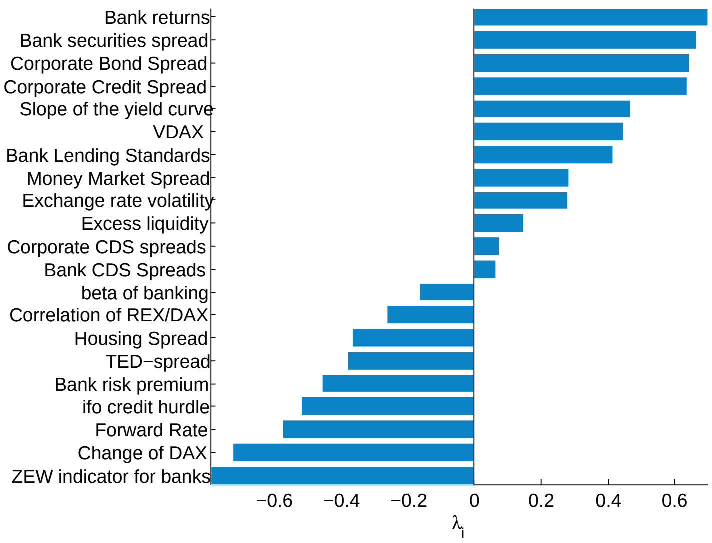


Figure 16: Factor loadings

5.2.4 Contributions to the indicator for the Euro Area

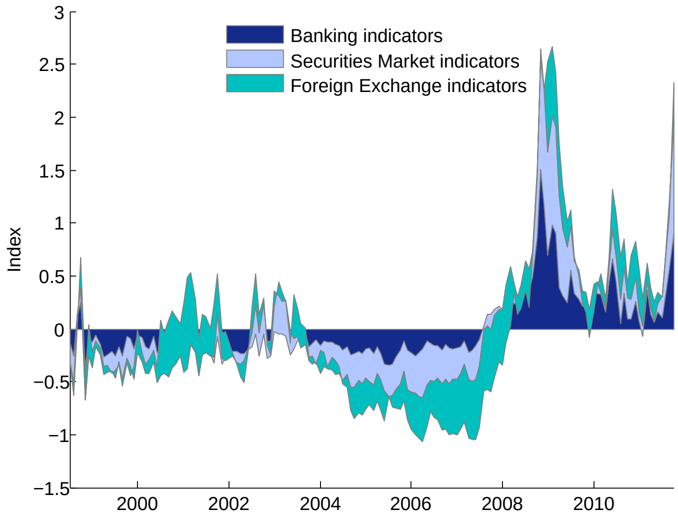


Figure 17: Contribution of indicator groups

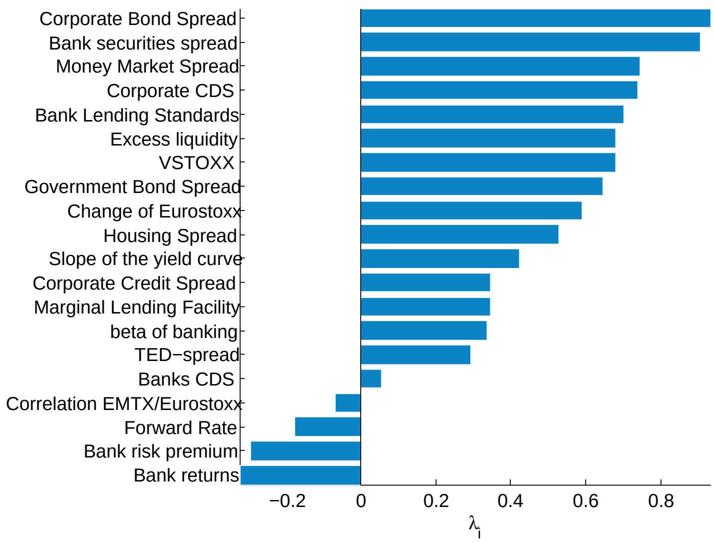


Figure 18: Factor loadings

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