

Financial stress and economic activity in Germany *

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Abstract

The global financial crisis of 2008-2009 and the European sovereign debt crisis have shown that strongly increasing stress on financial markets is important for analyzing and forecasting economic activity. Since financial stress is not directly observable but is presumably reflected in many financial market variables, I derive a financial market stress indicator (FMSI) for Germany using a dynamic approximate factor model that summarizes the stress component of various financial variables. Subsequently, I use these indicators to analyze the effects of financial stress on economic activity in a small threshold Vector Autoregressive (TVAR) model. I find that if the indicator exceeds a certain threshold, an increase in financial stress causes economic activity to decelerate significantly, whereas if it is below this threshold financial stress does not significantly matter for economic activity. Further, I show that the indicator significantly improves out-of-sample forecasting accuracy for economic activity in Germany.

Keywords: Financial stress indicator; Financial Systems; Recessions; Financial Crises; Threshold Vector Autoregressive Model; Forecasting; Germany.

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

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1 Introduction

The global financial crisis of 2008-2009 showed that strong increases in financial stress have dramatic effects on the economy. The collapse of Lehman Brothers led to a full-blown systemic crisis in the financial system that triggered the sharpest and severest downturn in economic activity since the Great Depression. In the euro area, this crisis was exacerbated by a sovereign debt crisis, which is associated with a systemic crisis in the euro area banking system. Beside this very recent evidence from the worldwide financial crisis and the euro area sovereign debt crisis, there is also empirical and theoretical evidence that financial stress leads to widespread financial strains and financial instability, which may cause severe financial crises and recessions in general (Borio and Lowe (2002), Borio and Drehmann (2009), and Bloom (2009)). It is therefore a crucial challenge to monitor and to detect potential signs of financial stress for the conduct of economic policy. Hence, 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 for the build-up of financial imbalances play a critical role to improve 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". 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 all developed financial stress indicators in order to detect early signs for increases in financial stress.

Until the global financial crisis, the majority of macroeconomic forecasting models did not include variables signalling financial market movements, i.e. variables such as stock market volatility, capital market spreads, or indicators of misalignments in the interbank market were not considered in these models. As a consequence, the traditional macroeconomic models significantly underestimated the scope of the global financial crisis and this has focused the attention on including financial market variables in these models.

A whole new strand of literature has sprung up that uses financial stress indicators in order to capture the rupture of the financial system after the default

of Lehman Brothers. The financial stress indicators are generally calculated using various financial variables, such as stock and bond market developments and risk spreads. In the new strand of the literature, these financial variables have been summarized in one indicator using either principal components analysis or a weighted-sum approach. Illing and Liu (2006) were among the first to use a principal components analysis calculating a financial stress indicator. They use a static factor model for Canada and show that their indicator provides an ordinal measure for financial stress in the financial system. Davig and Hakkio (2009) and Kliesen and Smith (2010), for example, use this approach to calculate the so-called *KCFSI* and *STLFSI* Indices for the U.S. economy, which were established by The Federal Reserve Bank of Kansas City and the Federal Reserve Bank of St. Louis. 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) calculate an alternative financial stress indicator using 45 variables to explore the link between financial conditions and economic activity in the United States and show that during most of the past two decades, including the last five years, the indicator indicated future economic activity better than existing indicators. Their major innovation is that they estimate 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 using financial stress indicators as additional predictors improves forecasting U.S. GDP growth performance at horizons of 2 to 4 quarters. Bloom (2009) takes a somewhat different approach to exploring the link between financial stress and economic activity in the United States by analyzing 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 the stock market volatility affects industrial production significantly.¹

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 in the euro area. 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 economic activity in low-stress regimes is insignificant; the impact in high stress regimes significantly dampens economic activity considerably in the

¹In fact, he does not use a financial stress indicator, but instead uses the S&P stock market volatility, which he interprets as a measure of uncertainty in the market.

months after the shock. Mallick and Sousa (2011) use a financial stress indicator in a Bayesian VAR (BVAR) model and a sign-restriction VAR model to examine the real effects of financial stress. They find that unexpected variation in financial stress leads to significant variations in output. Grimaldi (2010) derives a financial stress indicator for the euro area and studies its ability to detect periods of financial stress. She finds that the indicator is able to extract information from an otherwise noisy signal and that it can provide richer information than simple measures of volatility.

There are also several articles in the recent literature that deal with various comparable financial stress indicators that can be used across countries. These indicators have been used recently by the IMF to improve the assessment of economic activity in the World Economic Outlook (International Monetary Fund (2011)). Matheson (2011), for example, developed the indicators for the United States and the euro area and Unsal et al. (2011) developed indicators for several Asian countries and Australia. Cardarelli et al. (2011) use an augmented indicator including more variables from the banking sector and examine why some financial stress periods lead to a downswing in economic activity in 17 advanced economies over 30 years. They find that financial stress often but not always precedes a recession.

This paper contributes to the recent literature in several ways. First, I estimate a financial market stress indicator (FMSI) for Germany using a dynamic approximate factor model. I use a broad measure of financial stress considering financial variables from the banking sector that proved to be relevant when explaining the sharp downturn during the financial crisis, financial variables from the securities and stock market, and financial variables of the foreign exchange market. As Brave and Butters (2011), I estimate an unbalanced panel and account for the issue of ragged data edges due to publication lags in order to apply long time series. Subsequently, I estimate a small threshold VAR model in order to account for nonlinear effects. Finally, I show that the model outperforms alternative forecasting models such as a threshold autoregressive model and a standard VAR with respect to out-of-sample forecasting accuracy for industrial production in Germany. The paper is organized as follows. In section 2, I estimate the FMSI for Germany, applying a dynamic approximate factor model. In Section 3, I present the TVAR model. Further, I show the results of the impulse-response analysis from the TVAR model and compare them to the linear impulse response function of a traditional VAR. In a forecasting comparison, I run an alternative threshold autoregression for industrial production and a standard VAR and calculate root-mean-squared-errors (RMSE) for forecasts of one to twelve months ahead. In section 4 I briefly present conclusions.

2 The Financial Market Stress Indicator (FMSI)

2.1 Methodology

In general, financial stress is unobservable but is presumably reflected in various financial market variables. Therefore, a batch of various financial market variables are usually taken into account when constructing an indicator of financial stress. 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 methodology has the advantage that it allows for the treatment of ragged edges caused by publication lags.² Specifically, I construct 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 .

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

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 the time series' factor loadings. The values in the factor loading vector represent the extent to which 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.:

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

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 . Subsequently, Λ and A are re-estimated by ordinary least squares.

2.2 Data

I estimate the model using monthly data over a sample period from 1980M2 until 2011M11. However, some variables are not published monthly. In order to obtain monthly values for quarterly data, I apply a linear interpolation, as in Chow and

²Therefore, this methodology is quite prominent in the forecasting literature (see Stock and Watson (2002), Giannone et al. (2008) and Doz et al.)

Lin (1971).³ 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 have collected data from various sources. In table 1 all variables considered in the FMSI estimation are listed. Detailed information on the calculation and transformation of the specific variables can also be found in the Appendix.

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

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

Table 1: Data description

In general, the data can be summarized into three different groups: banking sector variables, securities and stock market variables, and foreign exchange variables.

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 of bank return volatility relative to overall volatility calculated with the standard capital-asset pricing model), the slope of the yield curve, stock market returns of banks, an indicator of banks' risk premium, the spread on bank securities, expected lending conditions for German banks surveyed by the ECB's Bank Lending Survey, the availability of credit to firms as surveyed by the ifo Institute, credit default swaps on banks, an indicator of excess liquidity that is based on Germany's contribution to the ECB's deposit facility and an indicator for the profit situation of banks as surveyed by the ZEW. The second group contains variables related to the securities and stock market. These include a corporate bond and corporate credit spread, credit default swaps on

³The raw data together with the interpolated data of the quarterly time series are shown in the Appendix.

DAX30 non-financial firms, the yearly 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, the third group contains variables related to the foreign exchange market volatility, which is estimated using a GARCH(1,1) model.

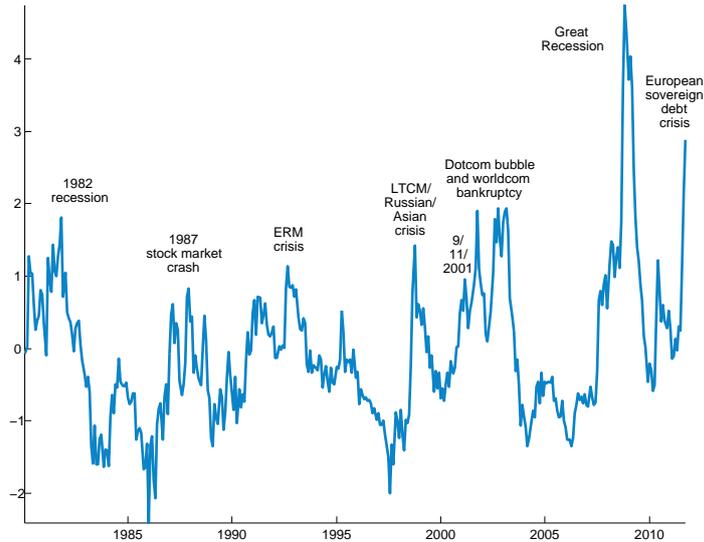


Figure 1: Financial market stress indicator

The results obtained using the FMSI are shown in Figure 1. As can be seen in the figure, several periods of increased financial stress occurred in the sample time period: during the 1982 recession, during the 1987 stock market crash, during the Russian Asian crisis in 1997/1998, during the bankruptcy of worldcom and the burst of the dotcom bubble, and especially during the Great Recession of 2008/2009, when the spreads and volatilities soared in nearly all markets. The financial market turmoils associated with the sovereign debt crisis in the euro area recently led to a sharp increase of the indicator anew.

3 A threshold VAR model with the FMSI

In order to obtain insights into the effects of financial stress on economic activity, I estimate a simple threshold VAR model, which consists of the FMSI, the 12-month growth rate of industrial production, the inflation rate and the short-term interest rate. The advantage of the threshold VAR model is that it allows to account for nonlinear effects. Particularly, asymmetric behavior of certain variables in response to shocks and a framework of multiple equilibria can be captured using this model framework. I closely follow the methodology of Balke (2000), who estimates the effects of credit growth on economic using a TVAR model. First, I test for threshold effects and present regime dependent impulse response functions. Finally, I conduct an out-of-sample forecasting analysis, comparing the root-mean-squared error of a TAR model, a simple VAR model and a recent-mean forecast.

3.1 Methodology

A threshold VAR model is a simple extension of a threshold AR model, firstly introduced by Tong (1978). The basic model consists of the FMSI, the growth rate of industrial production (ΔIP_t), the inflation rate (π_t), and the short-term interest rate i_t .

The threshold VAR model has the following form:

$$Y_t = \Lambda_1 Y_{t-1} + \Lambda_2 Y_{t-1} I[z_{t-d} \geq z^*] + \eta_t, \quad (3)$$

where $Y_t = [FMSI_t \ \Delta IP_t \ \pi_t \ i_t]'$ is a 4×1 vector of endogenous variables at time t , z_t is a scalar regime indicator and z^* the estimated threshold value. The function $I[\cdot]$ is an indicator function which takes the value 1 if the threshold variable z_{t-d} is above the estimated threshold value z^* . η_t is an $(n \times 1)$ vector of i.i.d. error terms fulfilling $E(\eta_t) = 0$ and $E(\eta_t \eta_t') = \Sigma$.

In order to identify independent standard normal shocks based on the estimated reduced form shocks, I apply a standard Cholesky decomposition of the variance-covariance matrix. The FMSI is contemporaneously independent of all shocks excluding 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).⁴ The structural shock identification can be justified from a consideration of information availability. Data on industrial production is published with a significant lag in Germany. This information is thus not available for financial market participants in real time. Therefore, it is unlikely to be reflected in contemporaneous asset prices and other financial

⁴An alternative ordering, where industrial production is independent and the FMSI is contemporaneously dependent of all other shocks, yields qualitatively similar results, which are available upon request.

market variables.⁵.

I assume that the threshold model is determined by a single regime indicator z_t . In general, this indicator is specified as a moving average of one variable in the VAR model. The lag-length of the TVAR is determined jointly with the delay of the threshold variables. In my case, the regime indicator is the first lag of the FMSI. In the subsection below, I report the critical values of the threshold tests.

3.2 Threshold Tests

In order to estimate the VAR model it is essential to test for threshold effects. These effects can be formally tested using the two-step conditional least squares procedure proposed by Tsay (1998) and alternatively by a Wald test proposed by Hansen (1999). In both tests the null hypothesis of a linear VAR can be tested against the alternative hypothesis of a non-linear VAR.

Table 2: Threshold Tests

d	Tsay-test			Wald test
	Test Statistic	p-value	Estimated threshold value	Estimated threshold value
1	35.44	0.00001	-0.0154	-0.0514
2	34.87	0.00006	-0.0284	-0.0522

Source: Authors' calculations.
Notes: H_0 : linear VAR, H_1 : threshold VAR

One problem that arises is that the threshold value z is not identified under the null-hypothesis. Therefore the tests consist of a running a grid search of the threshold variables z_t . Tsay (1998) developed a test simultaneously determining the delay of the threshold variable and the threshold value z . In both cases, with a threshold delay of $d=1$ and $d=2$ the test rejects the null hypothesis of a linear VAR (Table 2). The results of this test show that the threshold value are in both cases close to zero. The Wald test supports this finding.

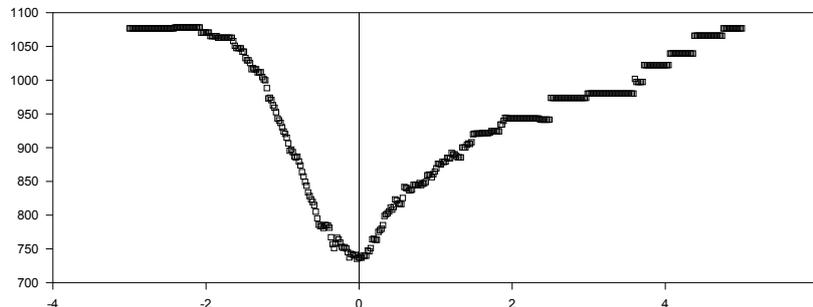


Figure 2: Threshold estimation based on AIC for TVAR(2) against VAR(2)

⁵See Holló et al. (2011)

In Figure 2 I present the Akaike Information Criteria (AIC) with respect to various potential threshold values for the FMSI with two lags (TVAR(2)). In the analysis, I find that the optimal specification is a TVAR(2) model with the first lag of the FMSI (z_{t-1}) as a threshold variable.

3.3 Impulse Response Analysis

In this section, I present an impulse response analysis in order to analyze the effects of financial stress on economic activity. The impulse response analysis shows that increases in financial stress are very persistent. The initial level of the FMSI after a financial stress shock is reached only 8 quarters after the shock occurred. Increases in financial stress have significant effects in economic activity. One positive standard deviation increase in the FMSI causes real GDP growth to reduce about annualized 0.2 percentage points. 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 falls 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.

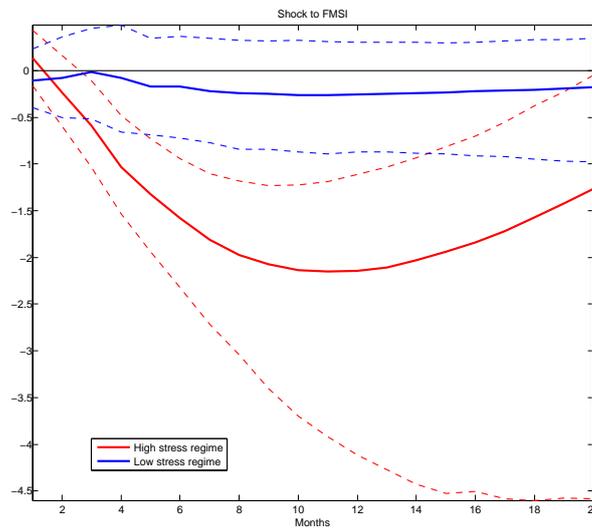


Figure 3: Impulse responses after a shock to the financial market stress indicator

3.4 Out-of-sample forecasting performance

In order to determine the information gain when including financial stress in a small macroeconomic model, I implement a forecast comparison between different model specifications. The forecasting performance of the models is evaluated using the horizon h root-mean-squared-error (RMSE), given by

$$RMSE_h = \sqrt{N_h^{-1} \sum_{t=1}^{N_h} (x_{t+h} - \hat{x}_{t+h,t})^2}, \quad (4)$$

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 .

Horizon	TAR	TVAR with stress	No change	Recent mean
1Q	1.022	0.801	1.172	1.121
2Q	1.580	1.421	2.265	2.046
3Q	2.651	2.125	3.401	2.961
4Q	3.042	2.527	4.512	4.003
5Q	3.525	3.010	5.500	4.409
6Q	3.667	3.121	5.908	4.665
7Q	3.668	3.287	5.976	4.846
8Q	3.742	3.525	5.999	4.864

Source: Authors' calculations.

Table 3: Root-mean-squared-error for growth in industrial production

Since I would like to evaluate the forecasting performances for all quarterly horizons between 1 and 8, I first estimate all the 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 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 3). The RMSE are then compared to the TAR model two other benchmark forecasts, a no-change forecast ($\hat{x}_{t+h|t} = x_t$ where $h = 1, \dots, 8$) such that the growth rate from period $t + 1$ is assumed to equal the growth rate in t and a recent mean forecast ($\hat{x}_{t+h|t}^{(r)} = r^{-1} \sum_{i=1}^r x_{t-i+1}$) such that the growth rate depends on the mean of the r most recent realized values.⁶ The general picture

⁶In this paper I used 4 quarters for the recent mean forecast.

is unambiguous: the TVAR with financial stress outperforms the TAR and the two benchmark forecasts at all considered horizons.

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 a financial market stress indicators that should be taken into account when analyzing business cycles in Germany. This indicator is developed using a panel of various financial market variables that are available in real time by applying a dynamic factor model. An increase in this indicator can be considered as an additional early warning variables for a deceleration of economic activity. Particularly, it can be shown that an increase in financial stress, if it is above a certain threshold indicates economic activity to dampen. Subsequently, I show forecasting accuracy of industrial production can be improved when I include the indicator into a small scale threshold 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 indicator significantly reduces the root-mean-squared error and therefore can improve forecasting accuracy in the short-to medium-term.

5 Appendix

5.0.1 Variables related to the banking sector

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

Money market spread The money market spread is the difference between 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.

Beta of the banking sector The beta 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 the standard capital asset pricing model (CAPM). A beta larger than one indicates that banking stocks shift more than proportionally than the overall stock market and that the banking sector is thus risky (see also Balakrishnan et al. (2009)).

Bank stock market returns This indicator measures the stock market returns of commercial bank shares. I use an equity index of the ten largest German commercial banks. A decrease in banks' stock market returns causes the financial market stress indicator to increase in magnitude.

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

Bank securities spread This indicator is measured by the difference between bank securities with the maturity of 2 years and AAA-rated (German) government bonds with the same maturity. An increase in the spread reflects that

investors perceive the risk in the banking sector to be on the rise. The time series for bank securities is taken from the banking statistics from the Bundesbank.

Expected lending This indicator comes from the ECB’s Bank Lending Survey. In this survey, banks are asked to report their assessment of how credit lending standards will evolve within the next three months. The Bundesbank reports the national results for the survey. The survey is conducted on a quarterly basis and is 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.

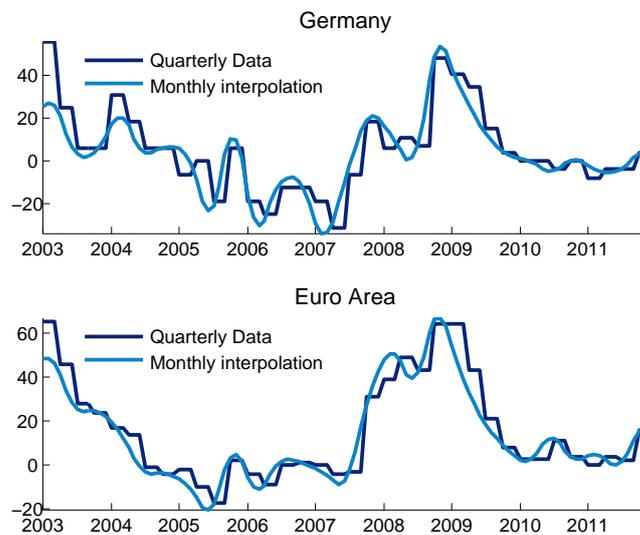


Figure 4: Interpolated series. Source: ECB, *Bank Lending Survey*

ifo credit conditions This indicator comes from a survey conducted by the ifo Institute. In this survey, firms are asked to report their assessment of how credit lending standards are currently evolving. Increasing values of the indicator reflect a tightening of credit standards, which contributes positively to the FMSI. The ifo credit conditions indicator is reported on a monthly basis.

Credit default swaps on financial corporations This index is an average of 5-year credit default swaps on the most important (largest ten) financial corporations, i.e. commercial banks. Increasing values of the index reflects that investors perceive the risk in the non-financial corporate sector to be on the rise.

Excess liquidity Value of bank deposits at the ECB that exceed the minimum reserve requirements. High use of the ECB deposit facility reflects uncertainty in

the interbank market. Banks prefer to hold their excess reserves with the ECB rather than to lend it to the nonfinancial sector or to other banks in the interbank market.

ZEW bank survey 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 institutions. Decreasing values indicate a worsened profit stance, which contributes positively to the FMSI. The indicator is published on a monthly basis.

5.0.2 Variables related to securities market

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

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

Credit default swaps on corporate sector This index is an average of 5-year credit default swaps on the DAX 30 nonfinancial 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. Increasing values of this index indicate that investors perceive the risk that nonfinancial corporate will default on their debt to be on the rise.

Housing spread The housing spread measures the difference between the interest rate on all housing loans to private households and the interest rate for secured money market transactions (3m Eurepo).

Credit default swap on 1Y Government Bonds The credit default swap reflects market expectations that the government will default on its 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 The VDAX measures stock return volatility. Usually, an increase in stock market volatility reflects a higher degree of uncertainty and risk perception. This time series is available from 1996M1. I calculate it back to 1980M1 by estimating a GARCH(1,1) model of the realized stock return volatility of the DAX before 1996. The correlation of this time series between 1996 and 2011 is over 90 percent.

DAX yoy % change This variable measures the inverted monthly year-on-year yield of the DAX. Increasing values cause the value of the FMSI to increase.

Slope of the yield curve The slope of the yield curve reflects bank profitability. I determine this indicator by taking the difference between the short- and long-term yields on government bonds. It can be seen as a measurement for the possible degree of maturity transformation. Usually, banks generate profits by intermediating from short-term liabilities (deposits) to long-term assets (loans). A negative slope of the yield curve, i.e. a negative term spread, therefore indicates a decrease in bank profitability.⁷

Correlation of REX and DAX The REX is a fixed-income performance index. Increasing interest rates imply a decreasing REX index. Hence, a negative correlation between REX and DAX indicates a positive correlation between DAX and the general level of interest rates.

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

⁷See Cardarelli et al. (2011).

5.0.3 Variables related to the foreign exchange market

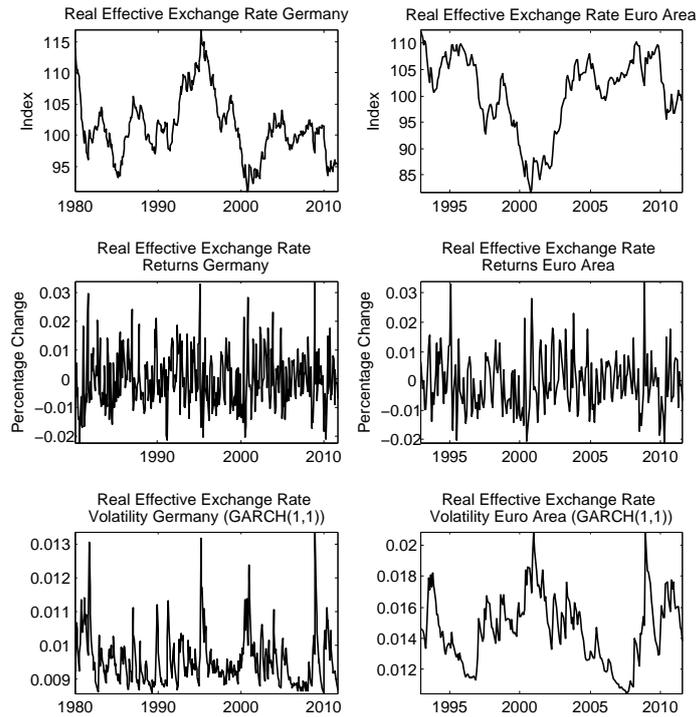
Real effective exchange rate This index measures the volatility of the real effective exchange rate (REER). The REER is deflated by the consumer price index with respect to 20 trading partners. An ARCH-test rejected the null hypothesis of the lack of GARCH effects at a significance level of 95 percent.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

Table 4: Estimation Results of the GARCH(1,1) model

Parameter	Value	Standard Error	t-Statistic
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

Source: Authors' calculations.

Notes: The conditional probability distribution was chosen to be Gaussian.



5.1 Contributions to the FMSI

5.1.1 Long sample (1980M01-2011M07)

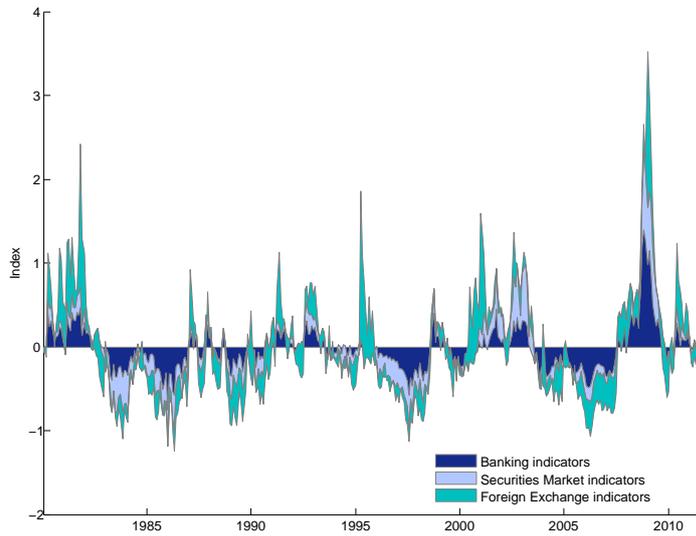


Figure 5: Contribution of indicator groups

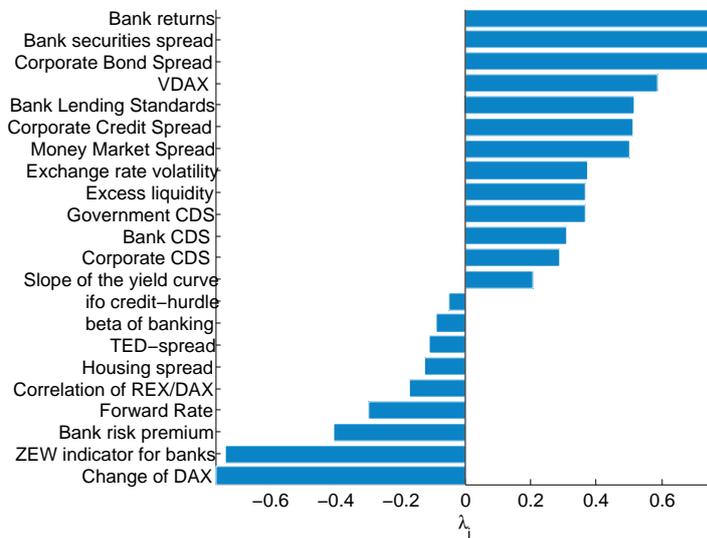


Figure 6: Factor loadings

5.1.2 Short sample (1999M01-2011M07)

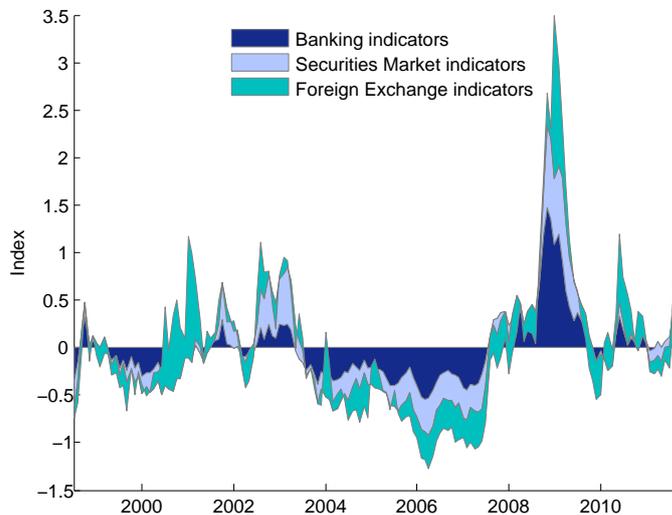


Figure 7: Contribution of indicator groups

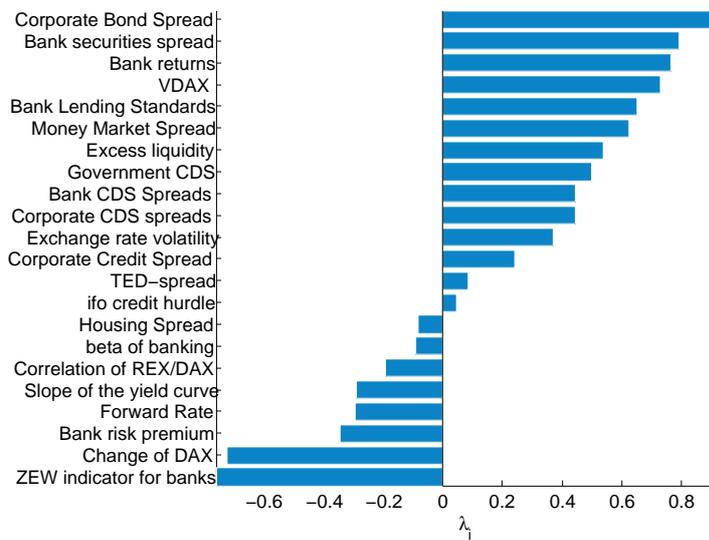


Figure 8: Factor loadings

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

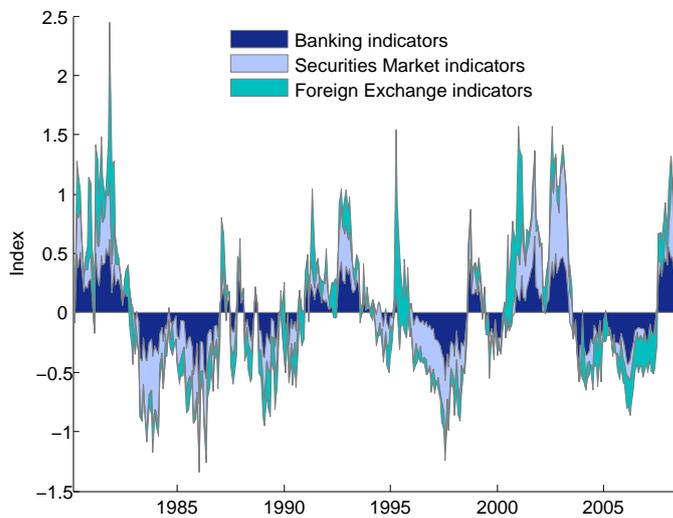


Figure 9: Contribution of indicator groups

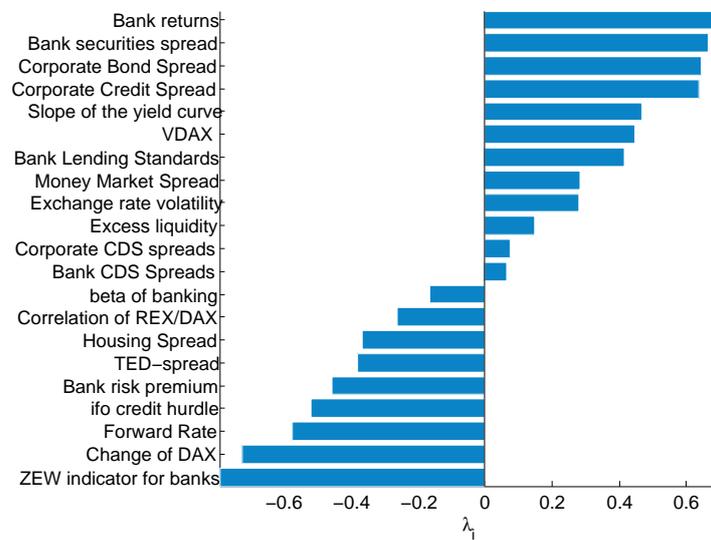


Figure 10: Factor loadings

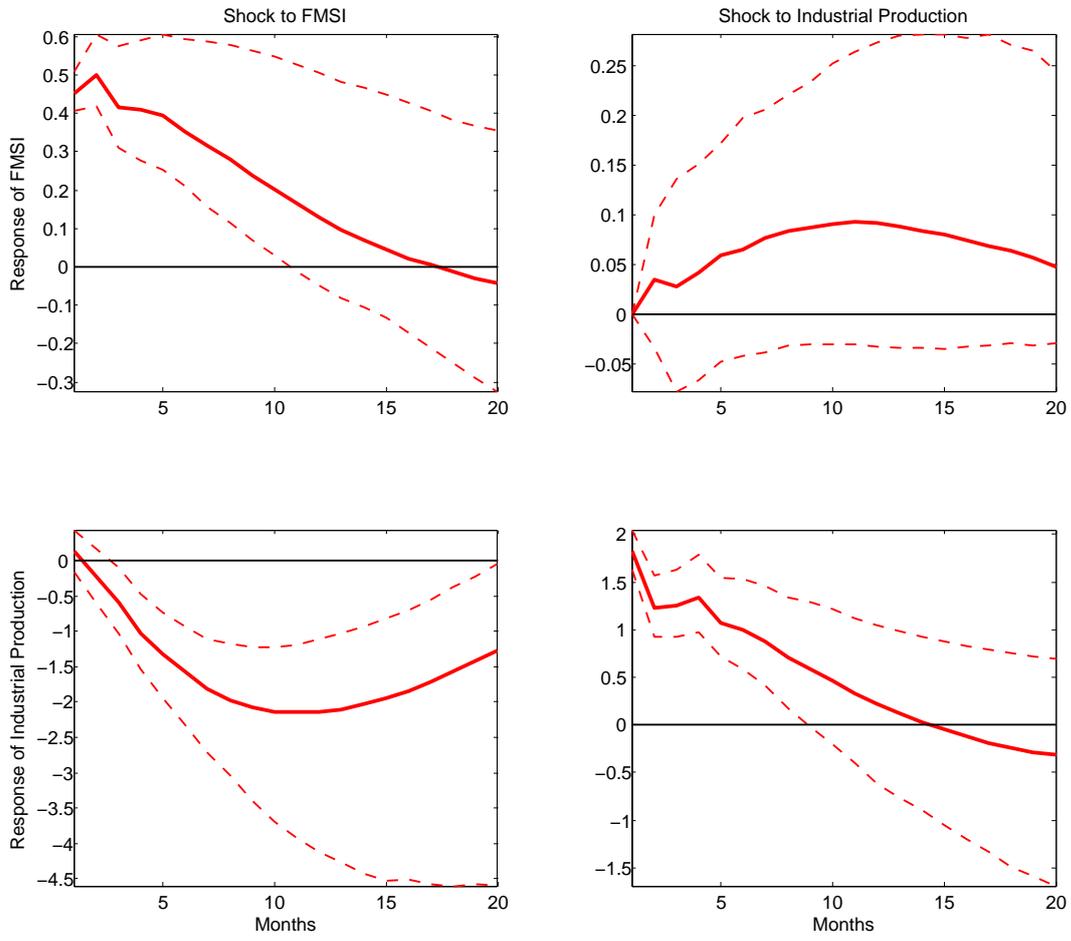


Figure 11: Impulse response function high stress regime

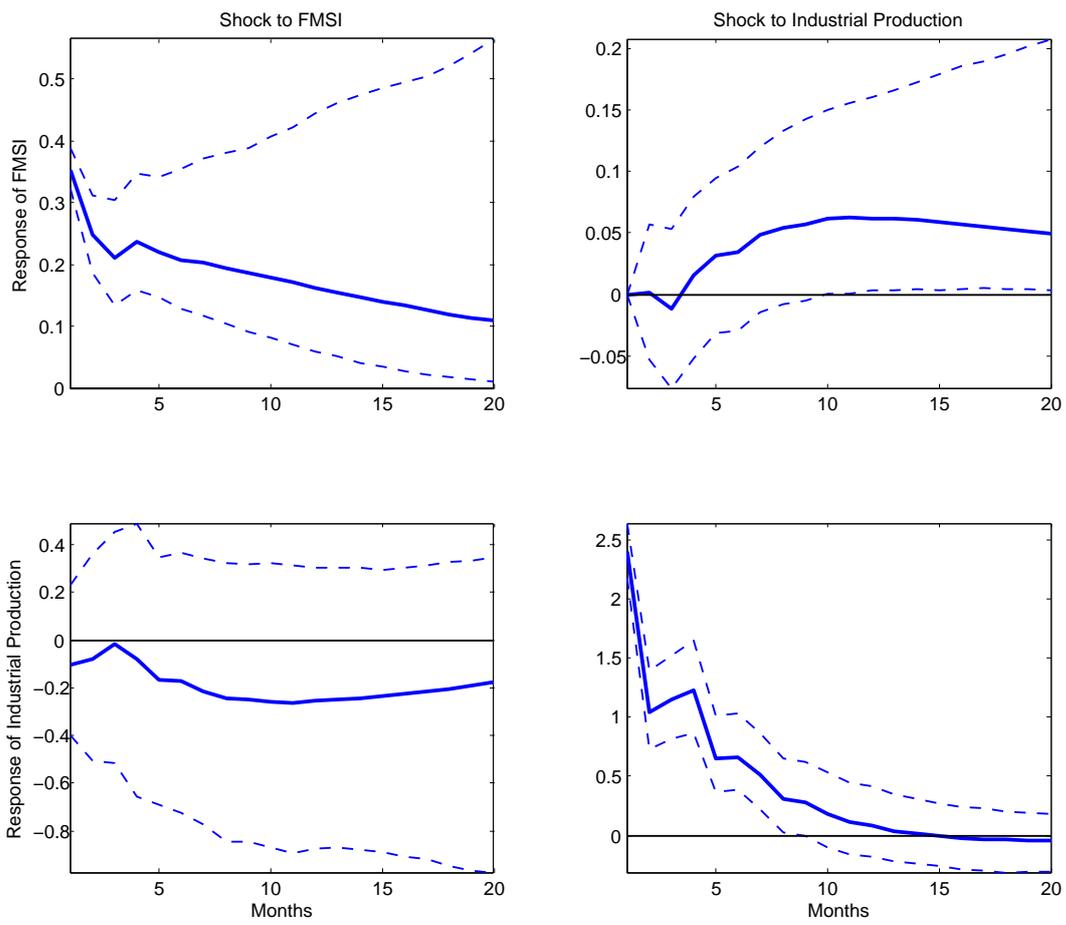


Figure 12: Impulse response function low stress regime

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