Stock Market Price Indices Modelling by a Small Scale Bayesian VAR: The Case of British FTSE and German DAX Index[1]

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Abstract

This article examines the behaviour and responses of stock market indices to various macroeconomic determinants by using small scale Bayesian VAR model. Our objective is to investigate the extent to which various macroeconomic shocks contribute to changes in stock market conditions. We focus on the German DAX 30 index and British FTSE 100 indices which serve as indicators for the development of the German and British economy as well as an illustration to evaluate the performance of the model. We have confirmed the general view that BVAR model outperforms a standard VAR model when the forecasting accuracy improved from 5% to 12%. We have also confirmed that any increase in risk-premium negatively influences stock markets in both case studies. However, the structure of the economies and capital also makes a difference, as found from different market reactions to supply shock.

Keywords: *Bayesian VAR, forecasting, stock market indices*

JEL Classification: C51, G11, G15

Introduction

Over the last couple of years financial markets went through volatile times, as we have seen extremes such as overvalued stock prices created bubbles up to crash of stock exchanges followed by recessions and crises. Nevertheless,

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financial markets attract daily millions of individuals and institutional investors in order to assess available resources and bring new added value. Historically, market movements reflected in stock price indices whose serve as an indicator and benchmarks for portfolio managers and single individual investors. The stock markets have always been one of the most popular investments due to their high returns. In that connection, stock index forecasting has always been a subject of interest a particular interest to investors, speculators, economist and governments.

Stock markets can be characterised by non-linearity in asset prices, stock returns, and volatility, and they are influenced by many other factors like interest rates, inflation, commodity prices, large corporate results, futures and options prices and during the last years by the monetary policies of major central banks. Stock market predictions are based on either fundamental or technical analyses. Fundamental analysis is related to the analysis of assets, economical values of securities and major macro economical fundaments, while technical analysis tries to find supports and resistances build on trends and shapes of historical prices. Still, no one can consistently predict the stock market movement. That is why any kind of prediction requires an iterative process of knowledge discovery and system improvement through knowledge engineering, data mining, theoretical and data-driven modelling, as well as trial and error (Hassan and Nath, 2005).

This article builds on the referenced work of Bańbura, Giannone and Reichlin (2010) and uses their model framework to analyse the role of macroeconomic determinants of stock market dynamics on the example of German DAX and British FTSE indices. Our objective is to investigate the extent to which various macroeconomic shocks contribute to changes in stock market conditions. First, we build a small scale Bayesian VAR model and use it to simulate the development of stock market indices. Then we perform impulse response analysis in order to show which macroeconomic determinants have the potential strength to influence the stock market dynamics in a short-run. The defined system also allows us to simulate the behaviour of stock markets in case of choosing scenario set-up, such as a 1% increase in the inter-bank interest rates.

The remainder of this article is organized as follows:

In Section 1 we present some issues linked to the interpretation of forecasting models.

Section 2 presents the used data and methodological framework.

In Section 3 we perform the forecast evaluation and present our model results and last Section concludes.

1. Conceptual Issues Interpreting Models for Stock Market Price Predictions

Financial market prediction has been one of the most challenging goals for the research community. Most scientific studies focused on the prediction problem from the perspective of prediction accuracy. Conceptual views on stock market price predictions differ and point out striking differences in outputs and model interpretations.

In developing a stock market prediction system, one of the most important tasks is to select the input variables. There are several methods used for stock indices prediction: Linear Regression, Time Series Models: Autoregressive Integrated Moving Average (ARIMA), Double Exponential Smoothing and Bayesian vector autoregressive models (BVAR), Artificial Neural Networks (ANNs), Generalised autoregressive conditional heteroscedasticity (GARCH), and Bootstrapping Simulations.

Several authors predicted stock returns with Bayesian vector autoregressive models. Avramov (2002) used Bayesian model averaging to analyse the sample evidence on return predictability in the presence of uncertainty about the return forecasting model. He found that incorporating model uncertainty can weaken the predictive power of economic variables. Among exercised variables, term and the market risk premium are relatively robust predictors and together with inflation, size premium and the value premium possess lower or no autocorrelation, while dividend yield and book-to-market, among others, have relatively small posterior probabilities of being correlated with future returns. Cremers (2002) introduced a methodology that explicitly takes model uncertainty into account by comparing all possible models simultaneously and in which the priors are calibrated to reflect economically meaningful prior information. The out-of-sample results for the Bayesian average models showed improved forecasts relative to classical statistical model selection methods, which are consistent with in-sample results and show some, albeit small evidence of predictability. Bessler and Lūckoff (2008) applied a model to forecast the returns of a portfolio of large German firms. They found that there is a certain degree of predictability of the BVAR when they use the returns of single stocks instead of macroeconomics variables, with no variables, with the recommendation to take a closer look at the cross-correlation structure of stock returns over monthly horizons.

ARIMA modelling was subject of the research study of Jarrett and Kyper (2011) with the aim to assess the prediction of Chinese stock market prices over a lengthy enough period of time where stock prices fluctuated during varying temporal economic movements. They came to a conclusion, that the ARIMA

Intervention Model is very useful for explanation of the dynamics of the impact of serious interruptions in an economy and the changes in the time series of a price index in a precise and detailed manner. Liao and Wang (2010) developed a model forecasting the global stock index by stochastic time effective neural network. They introduced the Brownian motion in order to make the model to have some effect on random movement while maintain the original trend. They tested the forecasting performance of the model by using different volatility parameters and showed some results of the analyses for the fluctuations of the global stock indices using the model. As confirmed by the study of Pino et al. (2008), Hamm and Brorsen (2000) and Schachmurove and Witkowska (2001), stock prices can be seen as a random time sequence with noise. Artificial neural networks, as large scale parallel processing, nonlinear systems that depend on their own intrinsic link data, provide methods and techniques that can approximate any nonlinear continuous function without a priori assumptions about the nature of the generating process.

The stock indices forecast could be also predicted, according to volatility forecasts. Based on empirical observations, implied volatility measured by VIX Index, react asymmetrically up and down to stock market moves. Generally speaking, the volatility increases more when the level of stock prices drops compared to the stock price rise.

When stocks drop, the debt/equity ratios increase and stocks become more volatile with higher leverage ratios. Within the research community, GARCH models (first developed by Engle and Bollerslev, 1986, and Bollerslev, 1986) represent a typical technique used for volatility forecasts. Cai (2012) research paper compared three different GARCH-type Models in order to forecast the conditional variance process of major USA stock indices (DJIA, S&P 500 and NASDAQ) by using different kinds of distributions for the errors. The regression test results showed that different GARCH-type models forecast series can satisfy their expectations, while forecast series with shorter forecast horizons and longer in-sample sizes perform better than the opposite ones; errors with different distributions did not impact the forecast quality.

The most recent paper published by Sharma (2015) compared the daily conditional variance forecasts of seven GARCH-family models, using the daily price observations of 21 stock indices for the period January 1, 2000 to November 30, 2013. He found that the standard GARCH model outperforms more advanced GARCH models, and provides the best one-step-ahead forecasts of the daily conditional variance. The results are robust to the choice of performance evaluation criteria, different market conditions and the data-snooping bias.

2. Data and Methodology

To forecast the average stock return, we follow Kasuya and Tanemura (2000) and Bańbura, Giannone and Reichlin (2010) and estimate a small scale Bayesian VAR model. BVAR model as described in Litterman (1984) and Todd (1984) has become a widely popular approach used in time series forecasting. The results obtained in five years of forecasting with Bayesian vector autoregressions were published by Litterman (1986), considering the problem of economic forecasting, the justification for the Bayesian approach, its implementation, and the performance of BVAR model. One of its main advantages is that it deals with an over-parametrization (the dimensionality issue) of a standard VAR model by placing prior distributions over the parameters of the unrestricted VAR.[2] Over time it has also gained a widespread acceptance as a practical tool to provide reasonably accurate macroeconomic forecasts when compared to conventional macroeconomic models. Consider $y_t = (y_{1,t}, y_{2,t} \ldots y_{n,t})'$ to be a vector of random variables and VAR(p) model of the following form:

$$y_t = c + A_1 y_{t-1} + \ \ldots \ + A_p y_{t-p} + \varepsilon_t \tag{1}$$

where ε_t is an m-dimensional vector of Gaussian white noise with covariance matrix $E(\varepsilon_t \varepsilon'_t) = \sum_{\varepsilon}$ and $A_1, \ldots, A_p$ are n x n autoregressive matrices.

In setting the prior distributions, we follow standard practice and use Minnesota prior as suggested in Litterman (1986) in which all the equations are centered around the random walk process with drift. The prior mean can be linked to the following representation for y_t:

$$y_t = c + y_{t-1} + \varepsilon_t \tag{2}$$

which shrinks the diagonals of A_1 towards zero and the remaining coefficients in $A_1, \ldots, A_p$ towards one. This specification seems appropriate when dealing with stock market prices which are often considered to be strongly determined by the market's sentiment rather than macroeconomic factor development. The Minnesota prior also follows a belief that more recent lags provide the most reliable information rather than the more distant ones. Let us set the following moments for the prior distribution of the coefficients:

$$E\left[(A_k)_{ij}\right] = \begin{cases} \delta_i, \, j = i, \, k = 1 \\ 0, \ \ldots \ otherwise \end{cases} \quad K\left[(A_k)_{ij}\right] = \begin{cases} \dfrac{\lambda^2}{k^2}, \ \vartheta \dfrac{\lambda^2}{k^2} \dfrac{\sigma^2}{\sigma_j^2}, \, j = i, \, k = 1 \, otherwise \end{cases} \tag{3}$$

[2] In a standard VAR model, many parameters need to be estimated even though some of them might be insignificant. The BVAR model can impose restriction on these estimated coefficients and assume they are more likely to be near zero than the coefficients on a shorter lags.

where δ_i is an informative prior, λ are set hyperparameters that control the overall tightness of the prior distribution around the random walk and set the relative importance of priority with respect to data information. $1/k^2$ is the factor showing at what rate prior variety decreases with increasing lag length and ϑ represents the relative tightness of the variance of other variables. Litterman (1986) sets the $\delta_i = 1$ but according to Bańbura, Giannone and Reichlin (2010) this priority is not appropriate for variables believed to be characterized by substantial mean reversion which is the case of international stock markets (Spierdijk, Bikker and Hoek van den, 2010). So we set this prior equal to $\delta_i = 0$.

The values for hyperparameters are crucial in BVAR framework as they determine how far estimated coefficients are allowed to deviate from their prior means, and how much is possible for the model to approach an unrestricted VAR. As shown by Mol, Giannone and Reichlin (2008), λ should be set with respect to the model size to avoid overfitting. We follow Bańbura, Giannone and Reichlin (2010) and set the overall tightness to yield a desired average in-sample mean squared forecast error (MSFE) for a number of key series included in the VAR specification, particularly production index, stock index and interest rate. The minimizing function takes on following notation:

$$\lambda(fit) = \arg\min_{\lambda} \left| fit - \frac{1}{3} \sum_{i \in 1} \frac{msfe_i^{(\lambda,m)}}{msfe_i^0} \right| \tag{4}$$

where $msfe_i^{(\lambda,\, m)} = \frac{1}{T-p-1} \sum_{t=p}^{T-2} \left(y_{i,\, t+1|t}^{(\lambda,\, m)} - y_{i,\, t+1} \right)^2$. It represents the in-sample one--step-ahead mean squared forecast error of a given model specification m and p is the lag-order of the model. We use the General-to-Specific approach to select the appropriate lag length for the case studies of Germany (p_1 = 13) and the United Kingdom (p_2 = 9). For the baseline estimation, we set λ_1 = 0.25 and λ_2 = 0.27 respectively. All estimations were computed using EViews or MATLAB software.

The focus of our analysis is on Germany and the United Kingdom. These two countries are selected because Germany and the United Kingdom are two largest economies in EU measured by the nominal GDP and account for almost half of the total value of the Eurozone economy. Therefore our estimation may be used to accumulate some general observations. Germany data covers the period from 1978M09 to 2015M12 and the United Kingdom from 1987M01 to 2015M12. All variables are seasonally adjusted and treated in a way that assures stationarity. Table 1 reports the data, mnemonics, descriptions, sources and specifications.

Table 1

Dataset Description

Mnemonic	Description	Source	Specification
IPI	Industrial production index	Eurostat	log, SA
CPI	Consumer price index	ECB	annualized, SA
BONDS	Government bonds yields	ECB	%, SA
DAX, FTSE	Stock indexes	Bloomberg	log, SA
IR	3M-EURIBOR and -LIBOR rates	ECB	%, SA
REER	Real effective exchange rate	ECB	%, SA

Note: SA = seasonally adjusted.

Source: Own estimation.

The baseline models comprise of all data, sorted from top to bottom using Cholesky ordering. We order variables in a way that captures real economy behavior, so production and prices are assumed not to react immediately to the monetary policy variable (the interest rate) but rather with a one-period lag. On the other hand, the interest rate takes into account both the current level of prices and production. To assure robustness of our results, we also experiment and order the stock indices last under the assumption that stock market shocks have no contemporaneous impact on the other variables in the model. However, this experiment did not change the estimation output.

3. Results and Discussion

In this section, we present our estimation results. First, we study the impulse response functions of stock market indices to simulated macroeconomic shocks and second, we conduct an out-of-sample forecasting experiment in order to simulate the behaviour of stock market indices in case of choosing scenario set-up (for example an 1% increase in the inter-bank interest rates). The purpose of this exercise is to answer the question what are the main macroeconomic determinants that drive the stock market indices dynamics in a short-run. The system we create for this purpose is then used to simulate the development of stock market indices together with computed uncertainty.

To assess the overall performance of our BVAR model, we first estimate one-step-ahead in-sample forecast to obtain the MSFE values for the minimization function (3) (graphical projections are available in the Appendix). We also compare our MSFE estimations for the BVAR model with the ones obtained from estimation the same model but by using only ordinary-least-squares (OLS) estimation that represents the standard VAR model. Table 2 suggests that MSFE of one-step ahead forecast by BVAR model is from 5% to 12% better than those of ordinary VAR models.

Table 2

MSFE Estimations

Variable	VAR		BVAR	
	Germany	UK	Germany	UK
IPI	1.591	1.007	1.402	0.949
CPI	0.234	0.306	0.209	0.289
DAX/FTSE	1.058	1.037	0.989	0.984

Note: Note that the estimation for RMSE and MSFE are often provided by the software, such is the case of EViews. The problem is that these estimates are often black boxes and therefore we are using our own code for estimation. The code is available upon request.

Source: Own estimation.

We pay our attention now to baseline model impulse response analysis of stock market indices to various macroeconomic shocks. We are interested in estimation of the impact of positive shocks to output (demand shock), inflation (supply shock), sovereign bond yields, inter-bank interest rates (monetary policy shock) and real effective exchange rates. The choice of variables is motivated by an influential publication of Fama (1983) and existing studies on macroeconomic shocks and stock markets (see for example Rapach, 2002; Bernanke and Kenneth, 2005; Bordo, Dueker and Wheelock, 2008; Hamed, Hussein and Tolba, 2012).

To estimate the demand shock, we use the industrial production index as a proxy to capture the economic activity and treat it as a combination of aggregate demand shock and productivity-affecting shock. We use the standard consumer price index to simulate price shock which can be viewed as a supply shock. Shock to sovereign bond yields can be interpreted as an increase in risk premium. The monetary policy shock which we also use in following forecast simulation is identified as a shock to 3-month inter-bank rates (EURIBOR and LIBOR) following excess literature on the topic (Bernanke, Boivin and Eliasz, 2005; Christiano, Eichenbaum and Evans, 1999; Makridakis, Wheelwright and Hyndman, 1998, etc.). Last, we use real effective exchange rate to identify exchange rate shock.

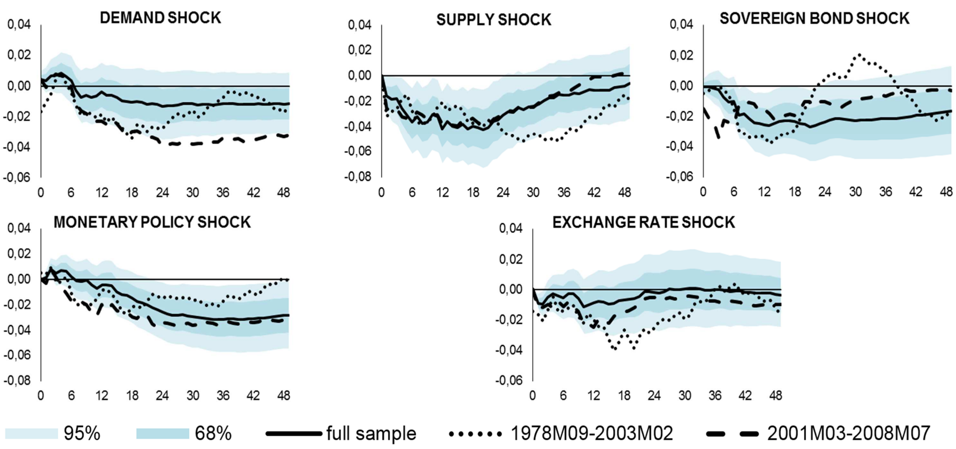
To assure robustness of our estimates over time, we divide our samples with respect to the economic cycle. We then compare these estimates with our baseline model. In case of Germany, we set the first cycle from September 1978 (beginning of the sample) to February 2003 and the second cycle from March 2001 to July 2007 to retain the degrees of freedom. In case of the United Kingdom, we set the first cycle similarly from January 1987 to February 2003 and the second cycle from March 2001 to July 2008. The results are robust with respect to time period used in the BVAR model as most of the IFRs lie inside the 95% confidence interval of the baseline full sample model.

The impulse response functions are shown in Figure 1 and Figure 2. Simulated shocks are equal to one standard deviation in terms of magnitude meaning they are not of the same value but of the same probability. The data treatment, however, allows us to interpret the strength of response in percentage changes after multiplying them by one hundred.

Figure 1 presents impulse responses of the DAX stock index on particular macroeconomic shocks. The figure shows point estimates with one and two standard deviation bounds.

Figure 1

DAX Index Response Functions to Various Macroeconomic Shocks



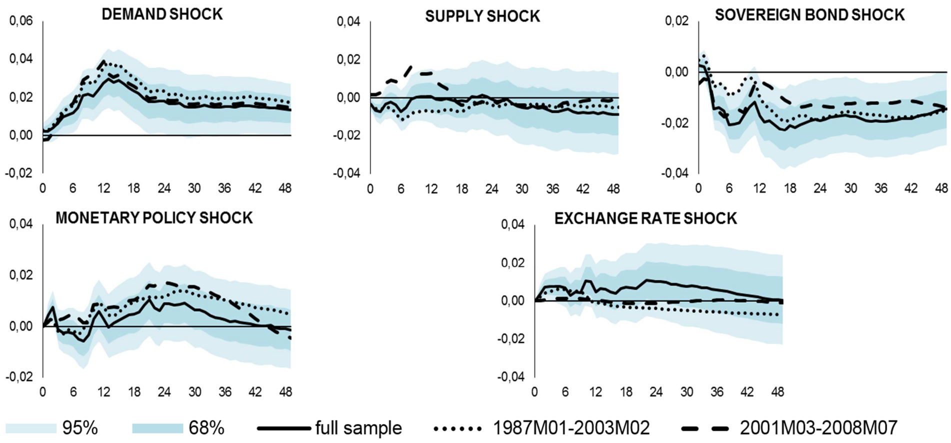
Notes: Months after shock are put on the horizontal axis, vertical axis describes the strength of the response with 95% and 68% bootstrapped confidence bounds.

Source: Own estimation.

The initial impact of the demand shock on the DAX stock price index is positive but quickly disappears and is not statistically significant at 95% bounds. By contrast, the supply shock derived from rises in prices is strongly negative and the effect is persistent as the DAX index drops by about 3% at impact. Positive inflation shock, therefore reduces the stock prices and might indicate a change in market conditions toward bust. A positive sovereign bonds shock also negatively influences stock index. As the risk premium rises the market participants are selling off their stock supplies in a fear of a bear market. When focusing on the effects of the monetary policy, we find similar evidence as Bordo, Dueker and Wheelock (2008). They found that the initial impact of short-term interest rate is positive at first but over a long-run it raises the rate at which investors discount future earnings and negatively affects stock market growth. Opposed to Bordo, Dueker and Wheelock (2008), we have found no evidence of estimation sensitivity to ordering of the short-term interest rate in BVAR model. The exchange rate appreciation shock temporarily lowers DAX, due to the negative effect on exporters, but the effect quickly fades out.

Figure 2

FTSE Index Response Functions to Various Macroeconomic Shocks



Notes: months after shock are put on the horizontal axis, vertical axis describes the strength of the response with 95% and 68 % bootstrapped confidence bounds.

Source: Own estimation.

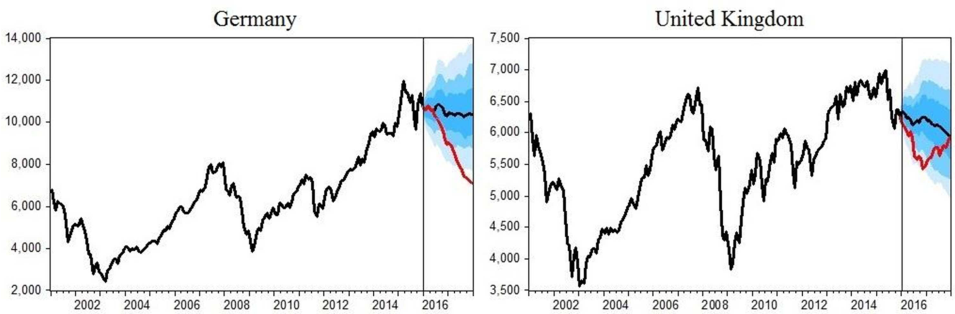
Next, we focus on FTSE index response to chosen macroeconomic shocks. While we have found some similar responses to the DAX index case, others behave quite differently. London is one of the world's largest financial centre and except of the strong domestic financial services demand, take advantage of the global opportunities that arise by pursuing new listings from abroad or enable other foreign companies to finance their mergers, acquisitions and strategic alliances. On the other hand, Germany with the strong industry contribution to the total GDP and a long-term high trade surplus belongs to the biggest capital exporters globally.

Apart from DAX index, the production shock (rise in demand) has a positive and statistically significant impact on FTSE up to 2%. By contrast, inflation shock has no sound effect on stock market index in the United Kingdom, as the significant part of the UK stock market participant are represented by global investors, who do not follow the local inflation. A positive sovereign bonds shock behaves in the same way as in Germany and has negative persistent impact. Results of the stock market response to restrictive monetary policy are a bit confusing. While it initially lowers the stock market value, it bounds back after approximately 10-months and we can detect a positive effect for a few horizons. This could confirm some historical evidence that the interest rate increase immediately transfer investors towards higher yields from government bonds, but does not necessarily mean the stock market decline in the near future. The exchange rate appreciation shows the similar effect as in DAX case.

Next, we estimate the out-of-sample 24-months forecast of both stock market indices and use the specified model with macroeconomic variables to define some basic simulations. Figure 3 shows the results of simulated Bayesian dynamic 24-months ahead forecast of both analysed stock indices with 90%, 70% and 50% confidence bounds.

F i g u r e 3

DAX and FTSE Indexes 24-month ahead Forecast with Interest Rates Development



Source: Own estimation.

Note that the actual forecast starts in January 2016. The dark line represents a baseline scenario forecast and the red thick line represents a simulated scenario of permanent one percentage point increase in the 3-month inter-bank rates (EURIBOR, LIBOR).

The motivation for this exercise was not to predict the stock market development (wide confidence bounds suggest a great portion of uncertainty in the out-of-sample prediction) but to show the relative importance of macroeconomic development to stock market returns. Due to the non-standard monetary policies, mainly quantitative easing and applied almost zero interest rate, major world stock indices reached maximum values in 2015, as investors were not able to find an alternative investment opportunities and contribute to stock price rallies. The expected normalized interest rate policy may cause changes in a part of institutional investors toward bond markets. The lower demand upon stocks may also raise from less buybacks realized directly by companies itself.

Conclusion

This article investigates the behaviour and responses of stock market indexes to various macroeconomic determinants. In particular, we focus on the German DAX 30 and British FTSE 100 indices as they can serve as the indicators for the development of the German and British economy as well as the illustration for the evaluation of the model performance. We relied on a small scale Bayesian VAR model and used it to simulate the development of stock market indices. We examined both forecasting accuracy and structural analysis of the effects of various macroeconomic shocks. The setting of the prior follows standard recommendations in the Bayesian literature.

Our main findings can be summarized as follows: first, we have assessed the performance of Bayesian VAR model for the analysis of macroeconomic environment influence on stock market indices in Germany and the United Kingdom. We have confirmed the general view that BVAR model outperforms a standard VAR model when the forecasting accuracy improved from 5% to 12% with respective variables. Second, we have found that both indices behave in the same way (increase) when are hit by a positive production shock, but they differ in case of a supply shock. The supply shock derived from the rise in prices has no sound effect on stock market index in the UK. It is in contrast to Germany where the inflation increase is stronger and quite persistently connected to fall in stock market prices. The positive sovereign bonds shock, as well as currency appreciation are reflected in a declined trends of stock indices by both analysed cases. Last, the baseline and simulated scenario confirmed the downturn reaction of both indices to interest rate shocks which is a reaction on higher demand upon sovereign bonds and partial transfer of funds from stock markets.

In the near future the stock markets, except the standard corporate results and macroeconomic developments, will still be heavily dependent on the monetary policy changes and central bank statements. The economy environment with a long duration of negative interest rates would negatively influence an appropriate investment decisions. The normalization of monetary policies would lead to a stabilization of the asset price development and healthy allocation of available resources. This would significantly lower stock market volatility, currency fluctuations, risk and potential creation of market bubbles.

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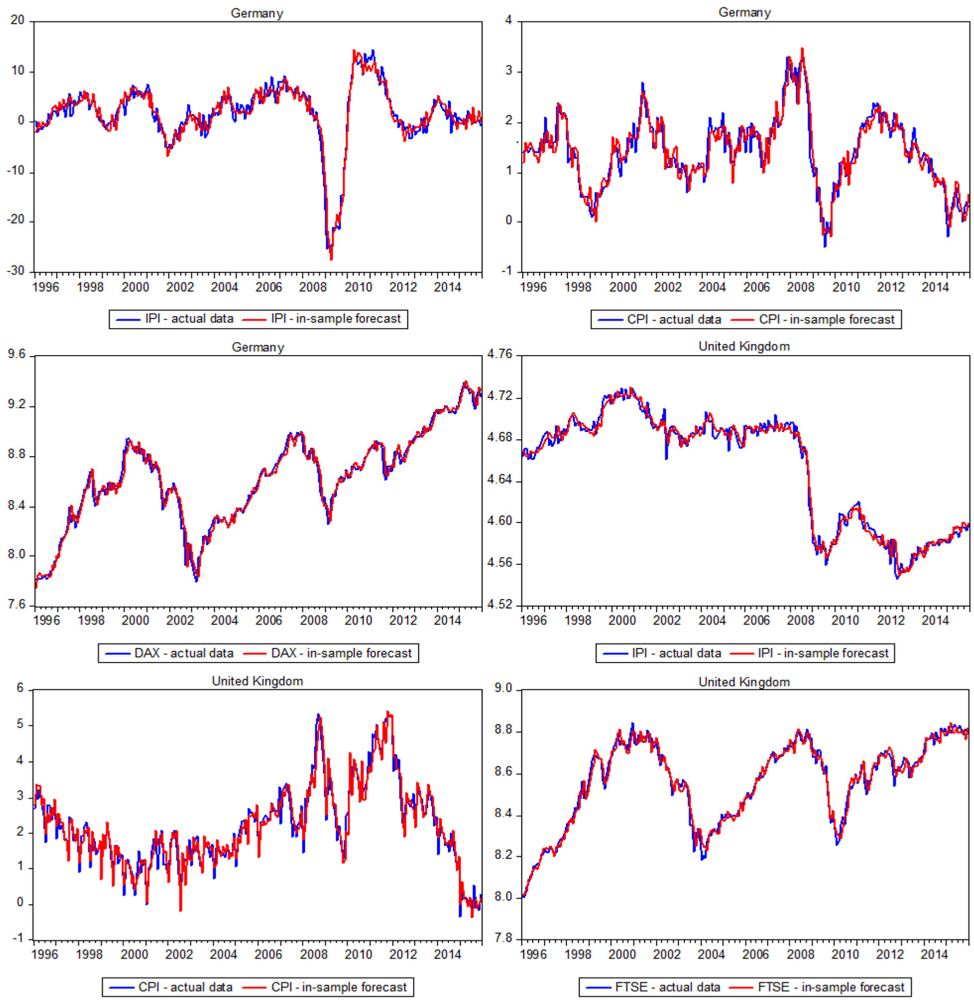
Appendix

Figure 1A

Inter-sample Forecasts by Bayesian VAR Model for Germany and United Kingdom Key Variables



Source: Own estimation.