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Does industry survey data improve GDP forecasting?

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Abstract

This study assesses the integration of industry survey data into Bayesian Vector Auto Regressive (BVAR) models for GDP forecasting in Sweden. Analyzing a combination of macro economic indicators, CPI and unemployment rates, with survey data from NIER, it explores the effects of different variable combinations on the forecasting ability of different models. The research concludes that some forward looking survey data boosts short term forecasting performance in BVAR models, especially expected sales price in the private sector and expected sales in the trade sector. Key findings include the superior predictive capability of certain variable combinations, most significantly the model consisting of expected sales price in the private sector, expected number of employees in the private sector and expected sales in the trade sector. The research offers insights for refining BVAR models and the incorporation of survey data to achieve more precise GDP forecasts.

Keywords: Bayesian, BVAR, Forecasting, GDP, survey data

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1 Introduction

The decision making of many institutions and firms is heavily reliant on the future development of the domestic economy, often measured in Gross Domestic Product (GDP). This data, despite its vital implications, is often published at a significant delay, creating uncertainties for market participants who depend on up-to-date economic information. This gap underscores the importance of developing effective nowcasting and forecasting methods. The central challenge lies in devising a model that accurately predicts future GDP trends, ensuring that decision-makers have reliable and current insights for their strategic planning.

Currently, various models with different levels of complexity and capabilities are employed for predicting future economic growth. One such model that has gained prominence is the Bayesian Vector Auto Regressive (BVAR) model. This model, developed by Christopher Sims and his colleagues at the university of Minnesota in the 1980s (see Sims 1980, Litterman et al. 1984, Litterman 1986, Doan et al. 1983), employs multivariate auto regression along with prior-distribution knowledge, in accordance with Bayesian principles, to model complex systems. A notable strength of the BVAR model is its resilience to overfitting partly due to the incorporation of priors. This also allows the model to be more parsimonious in parameter usage compared to traditional VAR models, as discussed by Itkonen and Juvonen in their research on Finnish GDP forecasting with large BVAR models (Itkonen and Juvonen 2017).

Due to the the multifaceted nature of GDP growth and macroeconomics, the question also arises as to which variables are useful when building forecast models. In economic research, different financial and monetary variables are used depending on what area is being studied. Quite commonly, a wide array of variables are used as seen in the research by Iyer and Gupta (2019) and Cimadomo et al. (2020). Research suggests that improvements could be made to forecast models by incorporating survey data in the model building. More specifically, for the case of GDP forecasting, either industry surveys or professional forecast surveys could be used as explored by Hansson et al. (2005), Silverstovs (2011), Banbura et al. (2021) and Ganics and Odendahl (2021) through different combinations of surveys and models. Industry surveys refer to surveys where the questions are answered by industry representatives, while professional surveys are answered by people with professional insights into forecasting. As exemplified in the literature, the characteristics that make BVAR models useful in regular econometrics is potentially amplified in the context of survey data. The potential here lies withing the building of the posterior distributions through sampling, which automatically weighs the different parameters within the model.

When examining contemporary literature, one finds a gap in knowledge where research have not been conducted into whether GDP forecasting BVAR models can be improved through industry survey data. This study aims to enrich the current literature by filling this research gap. Due to restrictions in computational power and time, this paper is restricted to a limited amount of variables. However, this is not considered a limitation to the conclusiveness of the findings due to the selection of variables. Instead of building large scale models which rely on self regulating of parameters, which is often seen in the cited literature above, a small sample of parameters was selected through the conducted literature study. This method is similar in character to the research of Raoufinia (2016) at the National institute of economic research (NIER) in Sweden. Raofinas paper examines the use of industry survey data, from the Economic tendency survey by NIER, and BVAR models to forecast unemployment rate through the use of different small scale models. The variables considered in this paper is listed in table 1 in section 3.1. The selection of survey data variables is partly based on the cited most effective variables in Raofinas paper (2016); in combination with other research where it was concluded that forward looking survey variables are the most effective at forecasting. The macroeconomic variables CPI and unemployment rate were selected due to its common occurrences in the literature, see Hansson et al. (2005), Iyer and Gupta (2019), Itkonen and Juvonen (2017) and Cimadomo et al. (2020). The variables were combined into 20 different four-variate models, 14 three-variate models and six two-variate models with GDP growth as dependent variable each time. These were then analyzed through their Bayesian posterior distributions and with Root Mean Square Deviation (RMSD).

Due to the nature of survey data the questions are directed to specific economic environments, which in turn shapes the research. The chosen environment for this paper is that of Sweden due to the readily available survey data through the Economic tendency survey conducted by NIER. The use of this survey also enabled the use of the variables which proved most effective in the aforementioned paper by Raofina (2016). The macro economic data for CPI and Unemployment rate was gathered through Statistics Sweden (SCB) and can be seen plotted in the figure below in their normalized form, as used in the analysis. The normalization is done through the standard score method.

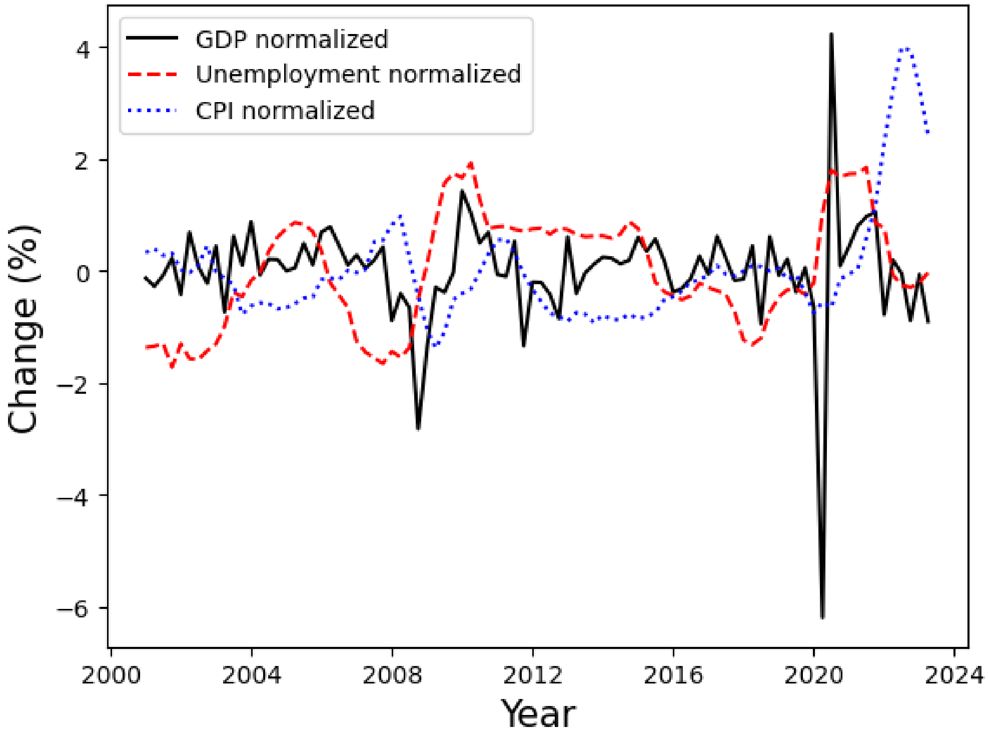


Figure 1: The figure shows quarterly change for GDP, Unemployment rate and CPI. The data displayed is the normalized data used in later analysis.

1.1 Research questions

To examine the impact of incorporating industry survey data into BVAR models for GDP forecasting, the following research questions have been formulated:

1. Does forward-looking industry survey data enhance the performance of BVAR models in forecasting GDP?

2. Which combination of variables demonstrates the most reliable performance in forecasting? The variables under consideration are listed in Table 1.

2 Theory and literature review

The following section lays the foundation for the forthcoming analysis. First the theory behind VAR models is covered together with the Bayesian theorem to get a basic understanding of the discussed models. Secondly a literature review was made with the purpose of investigating the current research environment within the fields of BVAR forecasting and inclusion of survey data in forecasting. The review resulted in necessary insights such as which variables are of highest relevance within macroeconomic forecasting, with focus on GDP forecasting. Lastly underlying economic theory is covered to underscore the importance of the chosen variables CPI and unemployment rate on GDP growth.

2.1 History of VAR analysis

Vector autoregression (VAR) models were proposed by Christopher Sims in 1980 as a way to evaluate alternative macroeconomic models using minimal identification assumptions and without relying on incredible exclusion restrictions (Sims 1980). VAR models are a class of time series models that allow for the joint analysis of multiple time series variables. They are widely used in macroeconomics, finance, and other fields to model the dynamic interactions between economic variables (Christiano 2012).

VAR models can be used for forecasting economic time series, designing and evaluating economic models, and evaluating the consequences of alternative policy actions. VAR models can produce accurate forecasts and by using Bayesian priors you are able to reduce the parameter space, as suggested by Sims and developed under his supervision by Robert B. Litterman and Thomas Doan (Litterman et al. 1984), (Litterman 1986), (Doan et al. 1983). The use of Bayesian prior models have only grown since and is a common staple in different economic forecast, mainly used by banks and similar institutions. BVAR models can also guide the construction of structural models by comparing the impulse response functions of different shocks to the data (Christiano 2012).

2.2 The AR, VAR and BVAR models

The main concept of Auto regressive (AR) models is the dependency of a time series on its own lags. The lags in this case is the values that comes chronologically before the current one. This model written mathematically, with lag p, would look like the equation below (Hyndman and Athanasopoulos 2021):

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + ... + \alpha_p y_{t-p} \tag{1}$$

The main takeaway here is that the lagged coefficients (alpha in the equation) are assumed independent of one another. One evolution of the AR models are the Vector Auto Regressive models. These models are multivariate in the sense that we assume several variables are to some extent dependent on each other, and thus can be estimated together. This model gets the shape of a vector at the target variables and matrixes at the lag coefficients. For a bivariate model, it would look like this with lag 1 (Hyndman and Athanasopoulos 2021):

$$\begin{bmatrix} y_{t,1} \\ y_{t,2} \end{bmatrix} = \begin{bmatrix} \alpha_{0,1} \\ \alpha_{0,2} \end{bmatrix} + \begin{bmatrix} \alpha_{11,1} & \alpha_{12,1} \\ \alpha_{21,1} & \alpha_{22,1} \end{bmatrix} \begin{bmatrix} y_{t-1,1} \\ y_{t-1,2} \end{bmatrix} \tag{2}$$

The VAR approach uses these lags and different estimation methods to evaluate and update its lag coefficients. To make this model Bayesian we use two things, Bayes theorem and Markov Chain Monte Carlo (MCMC) sampling. Bayes theorem describes the fundamental properties of the BVAR approach and is displayed below (Joyce 2023).

$$P(H|E) = \frac{P(E|H) \cdot P(H)}{P(E)} \tag{3}$$

H is the so called hypothesis whose probability may be affected by data. E is the evidence or in other words the data. $P(H)$ is then the *prior probability*, that is the estimated distribution of the data, before the data is observed. $P(E)$ is called the *marginal likelihood* and is essentially the probability of the observed data, here it acts as an normalizing constant. $P(H|E)$ is the *posterior probability*, that is the probability of H given E and is the sought after probability in the BVAR model. $P(E|H)$ is the *likelihood* and describes the probability of observing E given H. Now to make the step towards the BVAR model we incorporate MCMC sampling. The way a regular BVAR model is built is that we assume a prior distribution for our variables and coefficients, instead of letting them be purely random as in the case of non-bayesian statistics. This prior is then updated through chained random walk sampling (MCMC) in the data to a posterior distribution. What we get then on the output end of the model at a given time is not a variable value, but a likelihood distribution of the target variable (Haugh 2023).

2.3 The use of BVAR models and surveys in economic research

The use of BVAR models have been widespread since the research conducted by Sims, Litterman and Doan, see section 2.2, and is currently being employed in a wide variety of research being conducted in the modern day (Christiano 2012).

Juha Itkonen and Petteri Juvonen, wrote a paper in 2017 at the bank of Finland with the title "Now casting the Finnish economy with a large Bayesian vector auto regressive model" (Itkonen and Juvonen 2017). Their research aimed to build an accurate forecasting model for the Finnish GDP using a BVAR model. The motivation behind the use of the model is multifaceted but partly lies in the resilience to over fitting due to the priors being implemented. They describe the model as being more parsimonious in its parameter usage compared to the regular VAR model. The paper found that the BVAR model outperforms contemporary models, especially in short time span forecasting. This conclusion was derived after an analysis of the root mean square error of the different forecast methods.

Similarly with the paper above, a study was conducted by the Asian Development Bank by Iyer and Gupta (2019). This study aimed to construct a framework to forecast India's GDP based on quarterly data from 2004 to 2018. The predictive power of over 3000 BVAR models were researched with different variables from both real sector groups and monetary sector groups. The models were then compared with alternative econometric models such as VARs, SVARs and ARIMAS.

To compare, the study forecasted GDP growth four quarters aheads. It was found that the BVAR model outperformed the other econometrics models and showed good prediction power. They also found that the best performing BVAR models where those based on CPI, foreign direct investment (FDI) and portfolio flows.

Additionally a paper was published in 2016 by the Swedish National Institute of economic research by Raoufinia (2016). In this study several BVAR models was used to forecast employment growth with different variables. The aim of the paper was to research whether industry survey data from the Economic Tendency Survey would improve the predictive capability of the model. The study found significant improvement in the short term forecasts when the survey data was included. The survey data that saw the highest improvements were survey questions regarding employment expectations for the business sector in total and sales expectation in the trade sector.

The use of economic surveys in macroeconomic forecasts is a subject that is to an extent well analysed historically. In 2005 Hansson, Jansson and Löf published the paper "Business survey data: Do they help in forecasting GDP growth?" (2005). They used DFM-filtered survey (Dynamic Factor Modeling) data in bivatiate VAR models and compared them with different unfiltered models. The main findings of the paper according to the authors is that the DMF-procedure works well and outperforms other contemporary models. They also found the forward-looking survey data "striking" in its performance in short term forecasting, where it consistently outperformed other models. They also mention the use of Bayesian priors as a potential improvement for future research. This would, according to the authors, enable less parameter instability and avoid forecast errors at turning points. More recent papers by Ganics and Odendahl (2021), Banbura et al. (2021) and Silverstovs (2011) show similar promising results through different implementations. Ganics and Odendahl (2021) studied the effect of European Central Banks (ECB) survey of professional forecasters on the GDP forecasting ability of BVAR models. They found that the use of the professional survey increased the accuracy of the forecast with statistical significance. They also found that their baseline BVAR model without survey data had a slight upward tendency of GDP growth after the 2008 financial crisis. This tendency was mitigated when the survey data was introduced and the authors conclude that similar tendencies can be reduced in the same fashion. The same survey was studied by Banbura et al. (2021), they found the same improvements to forecasting ability but are more reserved in their assessment as to how the surveys should be implemented. They found that the respondents to the surveys tend to be overconfident, and provide too narrow forecast densities, which in turn result in poor calibration and low predictive scores (Banbura et al. 2021). They instead found improvements in forecasting when combining different models, both with and without survey data.

From the literature reveiw we conclude that the BVAR model is unanimously raised as a model of high relevance in macroeconomic forecasting. It varies from study to study which variables are considered and how large the Bayesian model is, but they agree that the Bayesian model seems to outperform or match contemporary models in short term forecasting. We also conclude that there exists research that has gone into whether survey data is useful or not in forecasting macroeconomic variables, such as GDP. The research seems to suggest that there is some contributing factor to forecasting ability when including industry survey data, but it is highly dependent on filtering data and weighing parameters within the non BVAR models. The same can be said for professional surveys where implementation leads to enhanced BVAR models, but some adjustments are needed in order to implement the data perfectly.

The gap found within the research is the combination of the two fields of industry survey data and BVAR models. The existing literature either handles industry survey data, but with non BVAR models, or use BVAR models but only professional survey data. This study aims to enrich the current body of literature by circumventing many of the problems encountered in the industry survey studies by using an Bayesian model; and further delve into the BVAR models through industry surveys.

2.4 Inflation and unemployment: The Philips curve

For economic policy makers, low unemployment and low inflation will always be a main goal. These two goals are however not always consistent with eachother, but rather display an inverse relationship in the short-term economy. This relationship was described by the New Zealand economist A. W. Philips in 1958. According to this perspective, as the economy grows, inflation tends to increase, leading to more job opportunities and reduced unemployment. The rationale is straightforward: when unemployment is high, the availability of workers is abundant, resulting in minimal or no upward pressure on average wages. Conversely, in periods of low unemployment, attracting workers becomes more challenging, necessitating wage increases. The pace at which wages rise is termed as wage inflation, a phenomenon that eventually translates into inflation in the prices of goods and services. Consequently, individuals, including the average worker, witness an increase in their monthly earnings, enabling them to afford a higher standard of living, reflected in their normal basket of goods and services (Mankiw 2010).

In this framework, low unemployment is often seen as indicative of a growing economy. Phillips contends that the coupling of economic growth with inflation is a natural consequence of the dynamics between wages, employment, and prices in the marketplace. It should be noted that this framework has been contested historically by many economists, and the framework has been revised into more modern iterations. One of the main critiques is the short time-frame applicability of the theory, and that the tradeoff only exists in the short run. More modern iterations of the Philips Curve, with contributions from among others Milton Friedman and Edmund Phelps, include expected inflation for more accurate use in monetary policy (Mankiw 2010).

2.5 Inflation, unemployment and GDP: Okun's law

To relate Phillips curve to GDP growth we take a look at Okun's law. If we consider the example of the Phillips curve above we conclude that lowering inflation requires a period of lowered output and subsequently higher unemployment. The cost of lowering inflation is thus able to be expressed through something called the sacrifice ratio. This ratio is expressed as the relation between the percentage sacrifice that must be made to the real GDP to reduce inflation by a set amount. This sacrifice ratio can then be formulated into terms of unemployment through Okun's law, which expresses a negative relationship between unemployment and changes in output, in terms of GDP (Mankiw 2010). Through these relationships we find a complex cyclical nature between the variables, which are highly codependent.

3 Data processing and methodology

The literature review concluded in the use of the BVAR model and the survey data variables. It also concluded in some specific choices of hyper parameters for the model building. The following section covers the methodology of how the model was applied, how data was processed and how the result was produced and analyzed.

3.1 Data gathering and processing

The empirical analysis started with the procurement of quarterly time-series data sets encapsulating GDP, CPI and the unemployment rate from statistics Sweden (SCB). Quarterly survey time-series data sets concerning the expected sales in the trade sector, expected numbers of employees in the private sector, expected sales price in the private sector and expected corporation inflation on a 12-moth horizon was collected from the Economics tendency survey which the Swedish National Institute of Economic Research provides to the public. The variables can be found in table 1 along with their abbreviations later used in the analysis.

Dependent variable	**Macroeconomic variables**	**Survey Data variables**
		Expected sales price* (S1)
	CPI (M1)	Expected number of employees* (S2)
GDP growth	Unemployment rate (M2)	Corporation inflation expectation, 12-month horizon* (S3)
		Expected sales** (S4)

Table 1: Variables considered in the analysis. *Regards the whole private sector, **regards the trade sector

The choice of variables stems from the literature review and the theory section. CPI and unemployment rate are mentioned in most of the reviews literature as variables of relevance when forecasting GDP. There also exists extensive literature which speaks to a connection between GDP, inflation and unemployment as seen in the Phillips curve and Okuns law. Despite the debatable nature of the relationships between the variables through these theories, there seems to exist a consensus that the variables are connected. This is deemed to be enough for the BVAR model to build upon and further emphasizes the choice of these variables. The choice of survey data variables stem from the paper by Raoufina at NIER (2016). They concluded that the variables that performed the best at predicting unemployment rate was the "Expected number of employees" and "Expected sales in the trade sector". Furthermore the paper by Hansson et. al (2005) found forward looking survey data most reliable in forecasting with BVAR models. Thus we also include two more forward looking variables; "corpotaion inflation expectation, 12-month horizon" was chosen to see the effects of a long-horizon variable and "expected sales price" was chosen due to its forward looking nature and its relation to CPI. The same relation can be expressed between the variables unemployment rate and "Expected number of employees". These relations are displayed through the plots in figure 2 and 3. In figure 2 we can see the forward looking nature of the survey data, as the trends precede the CPI data by some quarters. We see the same trend in figure 3, it should be noted that the expectation data for employees (S2) in this graph is inverted to convey the relationship between the two variables in a more informative way.

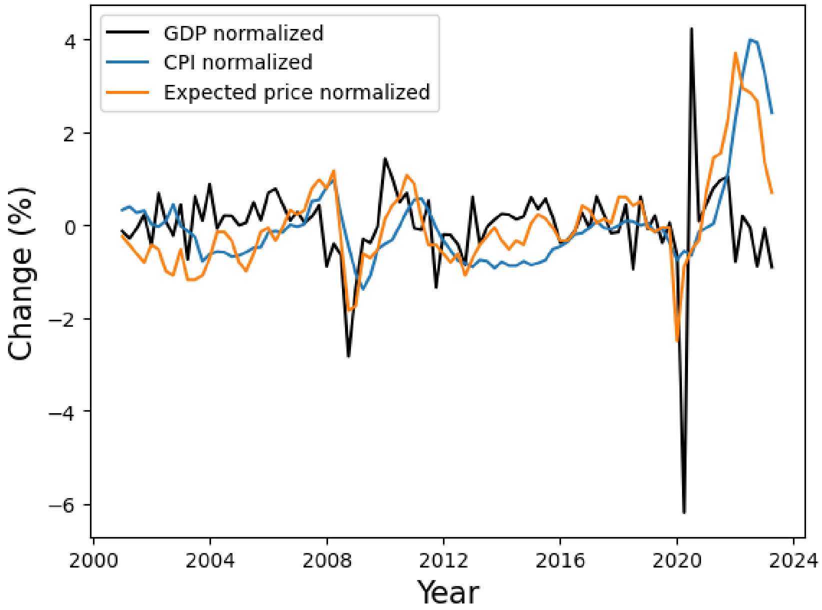


Figure 2: The figure shows quarterly change for GDP, expected price (S1) and CPI. The data displayed is the normalized data.

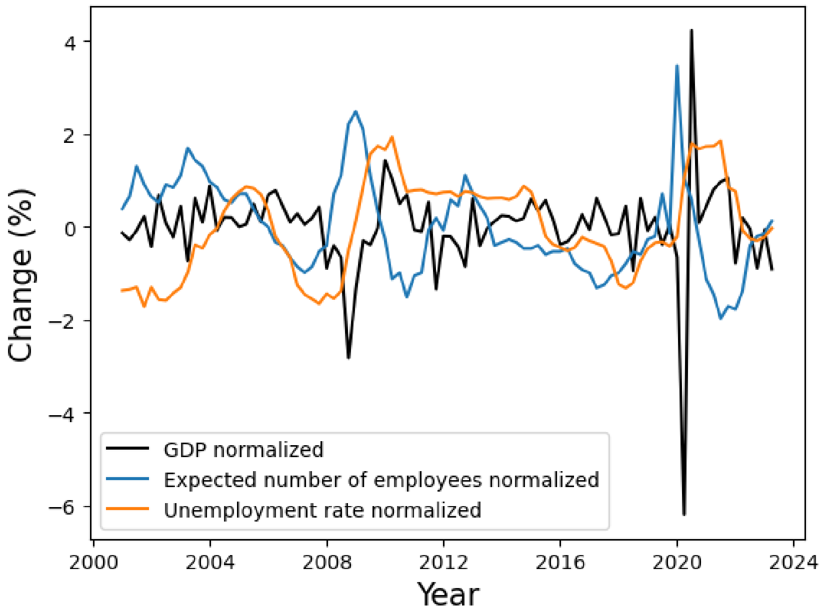


Figure 3: The figure shows quarterly change for GDP, expected number of employees (S2) and unemployment. The data displayed is the normalized data and the S2 data is inverted to better compare the relationship to the other graphs.

Prior to analysis, we subject the data to preprocessing to ensure normalization using the standard score method. The standard score method is shown in equation 4 where D_i is the transformed data point of index i, σ is the standard deviation of the data set, μ is the mean of the data set and x_i is the untransformed data point. The data were then split in to training and testing data where the testing data consisted of data from the last six quarters.

$$D_i = \frac{x_i - \mu}{\sigma} \tag{4}$$

3.2 Method and model description

In alignment with Bayesian methodology, we impose priors on the model parameters to inform the estimation process. Because the standard score method is used to normalize the data the priors is set as a Gaussian distribution with mean equal to zero and the standard deviation equal to one. With regards to the results of the literature study the lag was set to four, it was also tested to use a lag of two and three but no major difference in performance where found. A burn in of 4000 samples over four chains and a sampling of 8000 samples over four chains was used. The Bayesian estimation of model parameters is operationalized through the use of the python package pymc which is a python package specialized in Bayesian calculation.

Utilizing the estimated parameters, we project future values of GDP for six quarters. Unlike conventional point forecasts, the BVAR model yields a probabilistic forecast, delineating a posterior predictive distribution that quantifies the inherent uncertainty. The mean of the projected distribution is the calculated and compered to the real value using RMSD which is the the square root of the MSE.

To make the evaluation of the model more rigorous the model was trained and tested on data from twenty different time periods. Due to the effect that corona had on GDP growth the models where tested on data before corona to ensure that the models performance under normal economic circumstances where evaluated. The first time period the model where trained and tested on were from Q1 2001 to Q1 2020 and for the second time period the latest quarter were cut from the data and for the rest of the periods an additional quarter was cut until the last period used data from Q1 2001 to Q1 2015. Then the mean of the RMSD for all of the one quarter forecasts is calculated and the same is done for the rest of forecasts periods, see equation 5. Where $RMSFE_{m,i}$ is the root mean square forecast error of index m, which represent the model, q represent the forecast horizon and i represent the iteration. This is done for each model and the results is presented in a table where the models can be easily compared.

$$RMSFE_{m,q} = \sqrt{\frac{1}{20}\sum_{i=1}^{20} RMSD_{i,q}} \tag{5}$$

In order to be able to compare the different models, and especially see the effect of survey variables, a base model was selected. The selection process was conducted by comparing the performance of all models containing only macro variables. When the combination of variables that gives the best projection under normal economic circumstances is identified they will be tested on data from the corona period to see how the model perform under abnormal economic circumstances. Due too the nature of the predictions, RMSFE does not say much about their performance. The performance during the corona time period will instead be evaluated by their forecast graphs.

4 Results

4.1 Results from Pre-corona period

From table 2 it is possible to conclude that the uni variate model that only contains GDP changes is the best performing one and will be considered as the base model with which the rest of the models will be compared.

Models using only macro variables						
Models	Q1	Q2	Q3	Q4	Q5	Q6
M1, M2	0,4036	0,4356	0,4528	0,4908	0,5151	0,4829
M1	**0,345**	0,3805	0,3981	0,4097	0,4462	0,4443
M2	0,3939	0,4014	0,3698	0,4116	0,3986	0,3559
GDP	0,3695	**0,3323**	**0,3521**	**0,3291**	**0,3133**	**0,3295**

Table 2: The table showcases RMSFE for the three variate, two variate and single variate models using only macro variables. Bold lettering indicates the best performing model in the relevant quarter.

The results from the pre-corona period for the four-, three- and two variate models are presented in table 3, 4 and 5 below. The tables provides the aforementioned RMSFE values for each model, bold lettering indicates that the model beats the base model in the relevant quarter.

4.1.1 Four variate models

The following table showcases the RMSFE scores of each four variate model, compared too the base model. Bold lettering indicates that the model beats the base model in the relevant quarter.

Four variate models, pre corona						
Models	Q1	Q2	Q3	Q4	Q5	Q6
Base model	0,3695	0,3323	0,3521	0,3291	0,3133	0,3295
M1, M2, S4	0,4564	0,4187	0,4299	0,4951	0,5266	0,5065
M1, M2, S3	0,4278	0,4711	0,4403	0,5563	0,5114	0,5959
M2, S3, S4	0,4498	0,4545	0,3998	0,5412	0,4308	0,6002
M2, S2, S4	0,3869	0,38	0,3704	0,3624	0,4633	0,4303
M2, S1, S4	0,3989	0,4233	0,4772	0,4739	0,4778	0,5164
M2, S2, S3	0,412	0,3886	0,3995	0,5067	0,3921	0,3598
M2, S3, S1	0,4606	0,4715	0,579	0,5782	0,7385	0,5126
M2, S2, S1	0,377	0,3399	**0,3321**	0,3683	0,4393	0,3688
M1, S4, S3	0,4005	**0,3231**	0,39	0,4282	0,4641	0,4499
M1, S4, S2	0,3936	0,3486	0,405	0,4021	0,4712	0,4408
M1, S4, S1	**0,329**	**0,2719**	**0,3469**	0,3708	0,5029	0,5089
M1, S3, S2	0,414	0,345	0,3617	0,4557	0,4522	0,3708
M1, S3, S1	**0,3444**	**0,3129**	0,3681	0,3726	0,4403	0,4306
M1, S2, S1	0,4048	0,3402	0,3719	0,3743	0,4326	0,4016
S4, S3, S2	0,3707	0,3341	0,387	0,3936	0,3724	0,4032
S4, S3, S1	**0,3587**	**0,3172**	**0,3462**	0,3525	0,4317	0,3578
S4, S2, S1	**0,3055**	**0,2757**	**0,336**	0,3581	0,3997	0,3954
S3, S2, S1	0,4025	0,3825	0,4143	0,4453	0,4877	0,4589

Table 3: RMSFE of forecasted GDP for the different four variate models. For variable names see table 1. Bold lettering indicates that the model beats the base model in the relevant quarter.

4.1.2 Three variate models

The following table showcases the RMSFE scores of each three variate model, compared too the base model. Bold lettering indicates that the model beats the base model in the relevant quarter.

Three variate models, pre corona						
Modell	Q1	Q2	Q3	Q4	Q5	Q6
Base model	0,3695	0,3323	0,3521	0,3291	0,3133	0,3295
M2, S4	0,4275	0,3786	0,4309	0,4224	0,5134	0,4616
M2, S3	0,4138	0,4353	0,415	0,5617	0,4964	0,5145
M2, S2	0,4563	0,4085	0,4118	0,418	0,5599	0,3685
M2, S1	0,4222	0,4156	0,5216	0,5277	0,6783	0,5691
S4, S3	0,3956	**0,3139**	0,4032	0,4056	0,4026	0,3562
S4, S2	0,4166	**0,3129**	0,3682	0,4077	0,4521	0,4463
S4, S1	**0,3273**	**0,2941**	0,3555	0,4148	0,4761	0,3696
S3, S2	0,42	0,3344	0,4163	0,4285	0,3586	**0,3025**
S3, S1	0,3699	0,3699	0,4074	0,4441	0,4297	0,4509
S2, S1	**0,3684**	**0,3138**	0,3687	0,3863	0,4143	0,3384
M1, S4	**0,3579**	**0,3025**	0,4115	0,4197	0,4671	0,432
M1, S3	**0,3256**	0,3563	0,3917	0,4401	0,4152	0,4432
M1, S2	0,4318	0,4117	0,4338	0,4352	0,4784	0,4395
M1, S1	**0,3541**	**0,3215**	0,3964	0,4094	0,449	0,4623

Table 4: RMSFE of forecasted GDP for the different three variate models. For variable names see table 1. Bold lettering indicates that the model beats the base model in the relevant quarter.

4.1.3 Two variate models

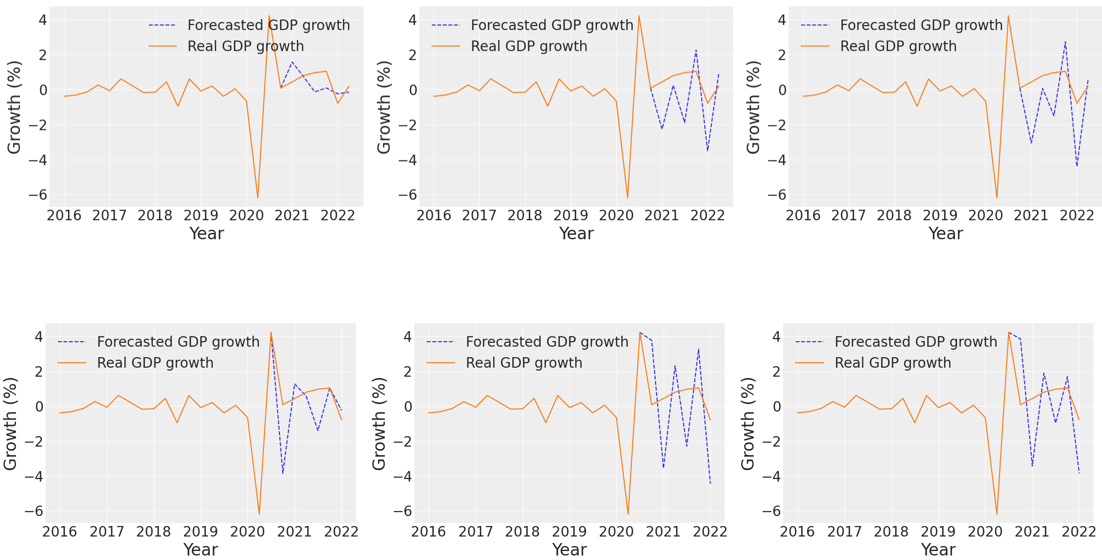
The following table showcases the RMSFE scores of each two variate model, compared too the base model. Bold lettering indicates that the model beats the base model in the relevant quarter.

Two variate models, pre corona						
Modell	Q1	Q2	Q3	Q4	Q5	Q6
Base model	0,3695	0,3323	0,3521	0,3291	0,3133	0,3295
M2	0,3939	0,4014	0,3698	0,4116	0,3986	0,3559
M1	**0,345**	0,3805	0,3981	0,4097	0,4462	0,4443
S4	0,3886	**0,3073**	0,4217	0,3853	0,5132	0,3649
S3	**0,3581**	0,3645	0,3809	0,4174	0,4305	0,4508
S2	0,4693	0,3755	0,3944	0,369	0,4914	**0,3237**
S1	0,4133	0,3813	0,4235	0,4749	0,485	0,4386

Table 5: RMSFE of forecasted GDP for the different two variate models. For variable names see table 1. Bold lettering indicates that the model beats the base model in the relevant quarter.

4.2 Results from corona period

The best performing four- and three-variate models were chosen from the tables above. They were then used for forecasting in quarters 2019 Q4 - 2020 Q4. The resulting graphs are shown in the figures below together with the forecasting of the base-model. The models are from left to right: Basemodel, threevariate (S4, S1) model, Fourvariate (S4, S2, S1) model.



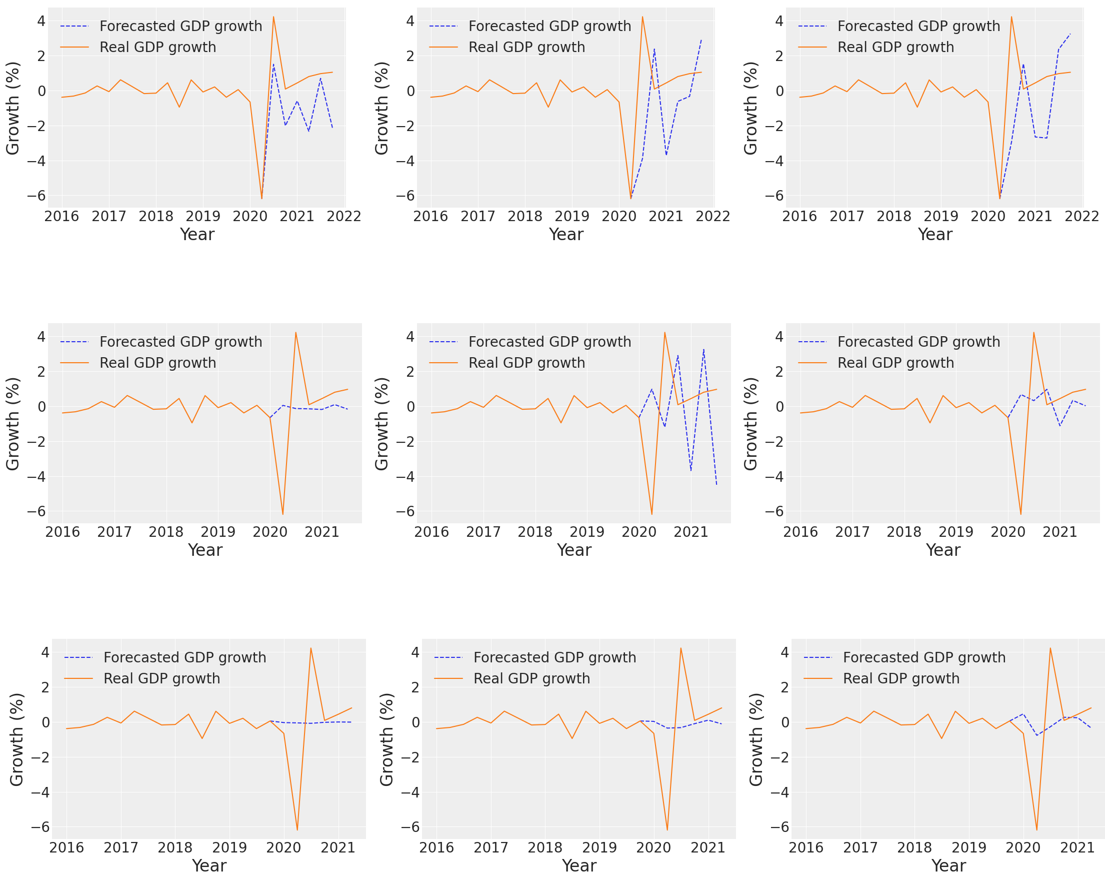


Figure 4: The figure displays the performance of different models during the corona period. From left to right: Basemodel, threevariate (S4, S1) model, Fourvariate (S4, S2, S1) model.

5 Analysis and discussion

The following section contains the analysis and discussion of all the results from section 4. This section is divided into multiple parts. First off the results from the pre-corona time period will be analyzed. Then follows an analysis of the corona period as well as analysis of some of the relevant graphs for both periods. The final part of the section covers a discussion which covers all the previous analysis.

5.1 Pre corona analyses

In the initial test to find the best performing model under normal economic circumstances it was concluded that some survey data has a positive impact on the models forecasting abilities and that the best model for short term forecast was a four variate model. Bellow is an in depth analysis on how the different models performed. The important parts for this section is which models beats the base model, in which quarter they beat the base model, as well as which variables regularly contribute to improving the forecasting.

To condense the information from the results, further tables were compiled with more in depth information. These tables contains the models that consistently performed the best and the models that consistently performed the worst. Green markings indicate the lowest RMSFE score, yellow the second lowest and red the highest.

5.1.1 Four variate models

From the table 3 we find some variance in the performance of the models, especially over what quarters they perform better than the base model. The cause of the variance is probably multifaceted, but it has its roots in what variables are included in the model. We also find that the models overall perform worse than the base model after Q3. The models that outperform the base model in the first three quarters are scarce, but the increase in performance is substantial.

Best performing four variate models, pre corona						
Models	Q1	Q2	Q3	Q4	Q5	Q6
Base model	0,3695	0,3323	0,3521	0,3291	0,3133	0,3295
M1, S3, S1	**0,3444**	**0,3129**	0,3681	0,3726	0,4403	0,4306
S4, S3, S1	**0,3587**	**0,3172**	**0,3462**	0,3525	0,4317	0,3578
S4, S2, S1	**0,3055**	**0,2757**	**0,336**	0,3581	0,3997	0,3954
M1, S4, S1	**0,329**	**0,2719**	**0,3469**	0,3708	0,5029	0,5089
Worst performing four variate models, pre corona						
M2, S3, S1	0,4606	0,4715	0,579	0,5782	0,7385	0,5126
M1, M2, S4	0,4564	0,4187	0,4299	0,4951	0,5266	0,5065
M1, M2, S3	0,4278	0,4711	0,4403	0,5563	0,5114	0,5959
M2, S4, S3	0,4498	0,4545	0,3998	0,5412	0,4308	0,6002

Table 6: The table shows the best performing four variate models, that is the models that beat the base model in at least two quarters and the words performing models, that is the model that dose not beat the base model in any quarter. The lowest RMSFE is shown in green each quarter, the second lowest is shown in yellow and the worst is shown in red.

Of the models that performed best, three contained macro economic variables, notably none of them contain more than one such variable. Furthermore the model that seems to perform best overall is the S4, S2, S1 model, which is a model with only survey variables. The performance difference here is notable, with substantial improvement in performance the first two quarters.

When we look at the worst models we find two models with both macro economic variables. However the worst performing model overall, by far, is the M2, S3, S1 model, which performs the worst in all but the last quarter. The absence and over representation of M2 in the best performing and worst performing models is also notable.

5.1.2 Three variate models

The variance in the performance of the three variate models is similar in character to the four variate models. However, the models only outperform the base model in the first two quarters instead of the first three. The best performing model in the short term seems to be the S4, S1 model. The worst performing models here are both models with the M2 variable, which contains the unemployment rate.

Best performing three variate models, pre corona						
Models	Q1	Q2	Q3	Q4	Q5	Q6
Base model	0,3695	0,3323	0,3521	0,3291	0,3133	0,3295
S4, S1	**0,3273**	**0,2941**	0,3555	0,4148	0,4761	0,3696
S2, S1	**0,3684**	**0,3138**	0,3687	0,3863	0,4143	0,3384
M1, S4	**0,3579**	**0,3025**	0,4115	0,4197	0,4671	0,432
M1, S1	**0,3541**	**0,3215**	0,3964	0,4094	0,449	0,4623
Worst performing three variate models, pre corona						
M2, S1	0,4222	0,4156	0,5216	0,5277	0,6783	0,5691
M2, S3	0,4138	0,4353	0,415	0,5617	0,4964	0,5145

Table 7: The table shows the best performing three variate models, that is the models that beat the base model in at least two quarters and the worst performing models, that is the model that dose not beat the base model in any quarter. The lowest RMSFE is shown in green each quarter, the second lowest is shown in yellow and the worst is shown in red.

5.1.3 Two variate models

The two variable models are overall similar to the three varaite models. The best performing models only outperform the base model in one quarter each, with these distributed within the first two quarters.

Best performing two variate models, pre corona						
Base model	0,3695	0,3323	0,3521	0,3291	0,3133	0,3295
M1	**0,345**	0,3805	0,3981	0,4097	0,4462	0,4443
S4	0,3886	**0,3073**	0,4217	0,3853	0,5132	0,3649
S3	**0,3581**	0,3645	0,3809	0,4174	0,4305	0,4508
Worst performing two variate models, pre corona						
S1	0,4133	0,3813	0,4235	0,4749	0,485	0,4386
M2	0,3939	0,4014	0,3698	0,4116	0,3986	0,3559

Table 8: The table shows the best performing two variate models, that is the models that beat the base model in at least one of the first three quarters and the worst performing models, that is the model that dose not beat the base model in any of the first three quarters. The lowest RMSFE is shown in green each quarter, the second lowest is shown in yellow and the worst is shown in red.

5.1.4 Overarching results

From the pre-corona period it was concluded that the four variable model using expected sales in the trade sector, expected numbers of employees in the whole private sector and expected sales price in the whole private sector performed the best for short term forecasts up to three quarters. It was also concluded that the uni variate model, the base model, performed best for forecast of more than three quarters. The models that saw increases in performance when including survey variables, only saw improvements in the short term. The best four variate models outperformed the base model in up to three quarters, the three and two variate models however only performed better in up to two quarters. This result is not entirely surprising, we should expect the models with more variables to be more volatile. This volatility seemingly allows them to capture the short term trends, since the volatility of the model is more similar to the real GDP movements. However in the long term, the inevitable bad predictions of the model make the errors more noticeable with the increased volatility.

In table 3, 4 and 5 it seems as the four variable models have the largest variance between themselves which is made clear when comparing with table 6, 7 and 8; where the worst performing four variable model is significant worse then the worst performing three and two variable models. When comparing the above mentioned tables it is also possible to conclude that the best three variable model outperforms the best two variable model and that the worst three variable model is worse then the worst two variable model. This result is anticipated when considering the compounding effect that variables with bad predicting power will induce over longer time periods.

In the graphs below it is possible to see that the base model and the best performing four variate model tend to move in the same directions but that the four variate model tend to have larger movements. This is believed to make the four variate model better at predicting the corrects amplitude of the movements in the short therm. This could be an indicator to why the four variate model outperforms the base model in the short term while performing worse in the long term.

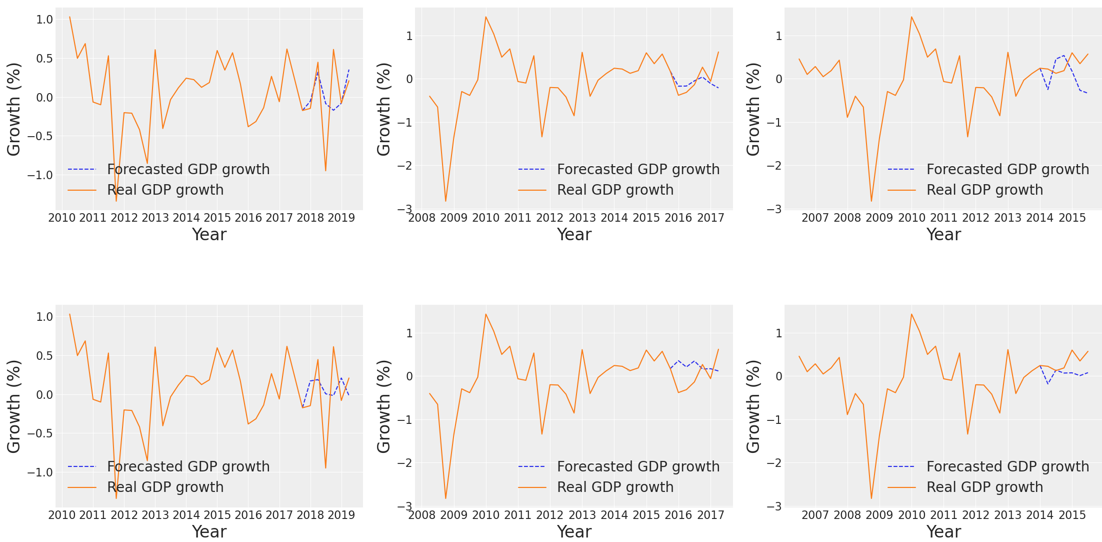


Figure 5: The top row is the Fourvariate S4, S2, S1 model for three different itterations/ time-periods and the bottom row is Basemodel for the same time period.

5.2 Corona period

To evaluate the corona time period result we look at the graphs in figure 4. The method to evaluate the models here is more subjective since the RMSFE does not tell us much. The reason for this is the large deviances that occur when the real values for the GDP growth has large variances and few data points. Instead we take the approach of evaluating the graphs from a reason standpoint.

The findings, however, are not as conclusive as in the pre corona time period. The result here vary quite a bit, despite the chosen models being the ones that performed the best on the short term forecasting. Here the base model seems most reliable in finding trends during the volatile periods, as it captures a majority of the characteristic spikes in the short term. Notably, none of the models predict the initial drop in growth at the start of corona. This is not necessarily strange, considering the abrupt emergence of the corona crisis itself. For the models to predict this drop there would have to exist some foresight in the survey data, which probably does not exist. The models with the survey variables also seem to under exaggerate the volatility in the short term and overexaggerate the volatility in the long term. The base model on the other hand showcases some restraint in the forecasting of the later quarters. This makes the base model more reliable in the long term forecasting of this period.

5.3 Error analysis and possible improvements

The largest improvement is believed to be to use a larger data set. This study used data from 2001 Q1 to 2022 Q4, expanding the data set would reduce the risk of over fitting the model while also giving the model more data to optimize its parameter towards. This would be especially beneficial to make the model better at adapting to rare economic circumstances, like economic crashes. This is because the data set used only involves two such crashes, the financial crisis in 2008 and the corona crisis in 2020. Incorporating data that includes more crashes would inform the model of how the GDP acts in such economic environment and give the model a chance to optimise its parameters to better handle it. To reduce the risk of the results being influenced by randomness it would also be beneficial to average the performance of the different models over more iterations, in this study the performance of each model was average over 20 iterations. The influence of randomness on the results i believed to be relative small but increasing the numbers of iterations to would still lead to a more rigorous results. The reason that more iterations where not used is due to limitations in computational power and time.

The model could also be improved by using different priors and normalisation method. Better priors could led to a improvement in performance and a reduction in the number of samplings required to make the posterior distributions converge, which would lead to a decrease in the required computational time.

6 Conclusions

The study presented a comprehensive analysis of Bayesian Vector Autoregression (BVAR) models, focusing on the impact of incorporating industry survey data into these models and their forecasting performance. The investigation was segmented into pre-Corona and Corona periods, each offering distinct insights into the models' effectiveness.

In the pre-Corona period, the univariate model, using GDP growth, was established as the most effective baseline for comparison. The inclusion of survey data in the models improved short-term forecasting accuracy for some combinations of the considered variables. This improvement was particularly noticeable in four-variate models during the first three quarters, where they occasionally surpassed the baseline model in performance. Here the S4, S2, S1 model saw the greatest performance. The study observed similar trends in three-variate models, with the S4, S1 model being particularly effective in the short term. Two-variate models also followed this pattern, predominantly outperforming the baseline in the initial quarters. These findings are similar in character to the findings of Raoufinia (2016), the uni variate model is outperformed in the short term in both papers, but is more stable in the long term. However, a notable observation across models with multiple variables in this paper, was their increased volatility, seen trough the graphs. This characteristic helps to explain the capture of short-term trends, but seems to lead to an over-exaggeration in long-term forecasting, suggesting potential overfitting issues.

During the volatile Corona period, the models, including those that performed well in short-term pre-Corona forecasting, showed increased variability and less conclusive results. The univariate base model proved more reliable, particularly in long-term forecasting, as it demonstrated a capacity to capture major trends without overreacting to short-term fluctuations. The sudden onset of the Corona crisis posed a significant challenge, as none of the models effectively predicted the initial economic downturn. This limitation highlighted the constraints in the foresight of survey data and the inherent unpredictability of such economic crises.

The study underscores a crucial trade-off between short-term accuracy and long-term reliability in economic forecasting models, which correlates with the papers Raoufinia (2016) and Itkonen and Juvonen (2017). Models incorporating survey data enhanced short-term forecasts but encountered challenges with longer-term predictions due to overfitting and limited data. The variability in model performance based on the included variables and the forecasting horizon was particularly pronounced in periods of economic uncertainty like the Corona crisis.

Our findings are limited to the selecting of variables that we deemed relevant in forecasting. The selection itself however was based on the limitations in computing power. The models that saw greatest increase in short term forecasting were the models that included the Expected sales price (S1) and Expected sales in the trade sector (S4). The largest increase in performance was experienced in the models where the survey variables were not combined with the macro variables. Notably the S1 variable got the worst performance when combined alone with GDP in a two variate model. Of the macro variables CPI (M1) greatly outperformed unemployment rate (M2) when combined with survey data. These findings seem to highlight the importance of selecting appropriate model variables, even with BVAR models. This problem is deemed to be enhanced through the limited available data, where more training data would correct the non-reliable coefficients more.

Conclusively, this study have contributed to the understanding of how survey data can be incorporated in to BVAR models and to which survey variables has a positive effect on how the models perform. The previous research on this was limited and our finding provides valuable insights, especially in the context of the Swedish economy, but can also be generalised and provide insight in how survey data can be used in other countries as well.

6.1 Future research

Our research opens up some debate regarding the use of BVAR models and industry survey data. Extensions of our research could be conducted with larger data sets and more computing power. This would enable better estimations of model parameters, as well as more periods to average the forecasting errors. It would also enable the use of larger models with more survey data, if this would increase or decrease the volatility of the models is hard to tell from our limited review. Further extensions of our research is also needed to arrive at more defining conclusions regarding the usefulness of such models. Future research could delve into the use of different prior distributions of the survey data sets as seen in the research by Iyer and Gupta (2019) and Doh and Smith (2020). There is also some interest in seeing the pooling effect of combining different BVAR model, as seen in Banbura et al. (2021) or averaging the results from different models to improve prediction. One could also modify the individual hyper parameteres, such as lag, for the individual variables and examine the different effects at greater depth than done here. Implementations of these changes could provide better performing models.

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Appendices

Appendix A Code

The code below is the one used in the four variate analysis in the pre-corona period for this thesis. The code for the other models and corona period is the same, except for the change of some variables and time periods. These changes are deemed intuitive and thus only the code for the four variate model is displayed.

Listing 1: Code for the four variate model

```
import os

import arviz as az
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import pymc as pm
import arviz as az
import matplotlib.pyplot as plt
import numpy as np
import time

from matplotlib.colors import ColorConverter
colors = ("C0", "C1")

dark = {
    "C0": tuple(c * .35 for c in (ColorConverter.to_rgb("C0"))),
    "C1": tuple(c * .35 for c in (ColorConverter.to_rgb("C1"))),
}


az.style.use("arviz-darkgrid")
seed = sum(map(ord, "PyMC LABS - BVAR"))
rng = np.random.default_rng(seed=seed)

df = pd.read_excel("\\Users\lforn\OneDrive\Skrivbord\data_bas.xlsx", index_col↩
    =0)

res = np.zeros(6)
res_std = np.zeros(6)

variabler = ["GDP_norm", 'arb_norm','KPI_norm', 'EXP_price_norm']
df = df[variabler][:-(13)]
for i in range(20):
```

```
data = df[variabler][:-(6)]
test_data = df[variabler][-(6-i):df.shape[0]]


lags = 4

coords={
    "lags": reversed(range(-lags, 0)),
    "vars": (variabler ),
    "cross_vars": (variabler),
    "time": range(len(data) - lags),
}

with pm.Model(coords=coords) as BVAR_model:

    intercept = pm.Normal("intercept", mu=0, sigma=1, dims=("vars",))
    lag_coefs = pm.Normal("lag_coefs", mu=0, sigma=1, dims=("lags", "vars",↩
         "cross_vars"))
    noise = (pm.HalfNormal("noise", dims=("vars",)))/2

    ar_BNP = pm.math.sum([
        pm.math.sum(lag_coefs[i, 0] * data.values[lags-(i+1): -(i+1)], axis↩
            =-1)
        for i in range(lags)
    ], axis=0)

    ar_arb = pm.math.sum([
        pm.math.sum(lag_coefs[i, 1] * data.values[lags-(i+1): -(i+1)], axis↩
            =-1)
        for i in range(lags)
    ], axis=0)

    ar_kpi = pm.math.sum([
    pm.math.sum(lag_coefs[i, 2] * data.values[lags-(i+1): -(i+1)], axis=-1)
     for i in range(lags)
 ], axis=0)

    ar_exp = pm.math.sum([
    pm.math.sum(lag_coefs[i, 3] * data.values[lags-(i+1): -(i+1)], axis=-1)
     for i in range(lags)
 ], axis=0)

    mean = intercept + pm.math.stack([ar_BNP, ar_arb, ar_kpi, ar_exp], axis↩
        =-1)

    obs = pm.Normal("obs", mu=mean, sigma=noise, observed=data[lags:], dims↩
        =("time", "vars"))

x = 0
if __name__ == '__main__':
    with BVAR_model:
        trace = pm.sample(chains=4, random_seed=rng, cores = 4, draws=2000,↩
             tune=1000)
```

```
        x=1
if x==1:
    def _forecast(intercept, lag_coefs, noise, forecast=6):
        len_data = len(data)
        new_draws = np.zeros((data.shape[0]+forecast, data.shape[1]))

        new_draws[:len_data] = data[:]
        for i in range(forecast):
            ar_BNP = np.sum(lag_coefs[:, 0] * new_draws[len_data+i-lags:len_data+i])
            ar_arb = np.sum(lag_coefs[:, 1] * new_draws[len_data+i-lags:len_data+i])
            ar_kpi = np.sum(lag_coefs[:, 2] * new_draws[len_data+i-lags:len_data+i])
            ar_exp = np.sum(lag_coefs[:, 3] * new_draws[len_data+i-lags:len_data+i])
            mean = intercept + np.stack([ar_BNP, ar_arb,ar_kpi, ar_exp])
            new_draws[len_data+i] = rng.normal(mean, noise)

        new_draws[:-forecast-1] = np.nan
        return new_draws

    forecast = np.vectorize(
        _forecast,
        signature=("(v),(l,v,v),(v)->(o,v)"),
        excluded=("forecast",),
    )

    draws = rng.integers(6000, size=500)

    post = trace.posterior.stack(sample=("chain", "draw"))
    intercept_draws = post["intercept"].values.T[draws]

    lag_coefs_draws = post["lag_coefs"].values.T[draws].T
    lag_coefs_draws = np.moveaxis(lag_coefs_draws, -1, 0)

    noise_draws = post["noise"].values.T[draws]


    ppc_draws = forecast(intercept_draws, lag_coefs_draws, noise_draws, forecast=6)
    ppc_draws = np.swapaxes(ppc_draws, 0, 1)


    _, ax = plt.subplots(4, 1, sharex=True)

    ax[0].set_title(variabler[0])
    ax[0].plot(df.index, ppc_draws[..., 0], color="C0", alpha=0.05)
    ax[0].plot(df[variabler[0]], color="k", label="observed")
    ax[0].plot([], color="C0", label="forecast")

    ax[1].set_title(variabler[1])
    ax[1].plot(df.index, ppc_draws[..., 1], color="C1", alpha=0.05)
```

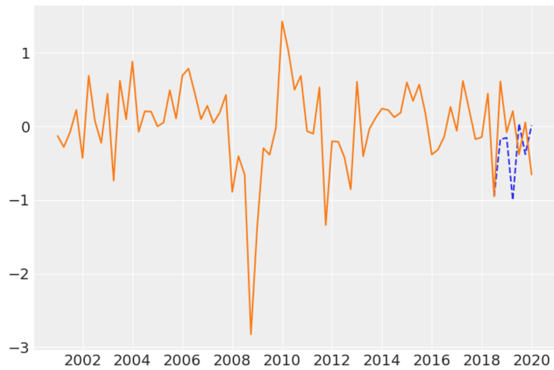
```
        ax[1].plot(df[variabler[1]], color="k", label="observed")
        ax[1].plot([], color="C1", label="forecast")

        ax[2].set_title(variabler[2])
        ax[2].plot(df.index, ppc_draws[..., 2], color="C1", alpha=0.05)
        ax[2].plot(df[variabler[2]], color="k", label="observed")
        ax[2].plot([], color="C1", label="forecast")

        ax[3].set_title(variabler[3])
        ax[3].plot(df.index, ppc_draws[..., 2], color="C1", alpha=0.05)
        ax[3].plot(df[variabler[3]], color="k", label="observed")
        ax[3].plot([], color="C1", label="forecast")

        for axi in ax:
            axi.axvline(test_data.index[0], ls="--", color="k")
            axi.legend(fontsize=10, loc=(1, .4))
            axi.set_ylabel("quartely change", fontsize=12)
        plt.savefig('grafer_gu/kandiad_graf_' + str(i))
        plt.clf()
        mean_BNP = np.zeros(len(ppc_draws[..., 0]))

        for j in range(len(ppc_draws[..., 0])):
            mean_BNP[j] = np.mean(ppc_draws[..., 0][j])


        plt.plot(df.index, mean_BNP, linestyle='--')
        plt.plot(df["GDP_norm"])

        plt.savefig('grafer_gu/kandiad_graf_mean_' + str(i))
        plt.clf()
        MSE = np.zeros(6)
        BNP =np.array(df["GDP_norm"])
        for k in range(6):
            MSE[5-k] = np.sqrt((mean_BNP[-(k+1)] - BNP[-(k+1)])**2)

        res = np.vstack((res, MSE))


        STD_BNP = np.zeros(6)

        for j in range(6):
            STD_BNP[5-j] = np.std(ppc_draws[..., 0][-(j+1)])

        res_std = np.vstack((res_std, STD_BNP))
        print(i)
        df = df[:-1]

filepath = ('grafer_gu/resultat_RMSD_lag_4_' + variabler[1] + '_' + variabler↩
    [2] + '_' + variabler[3] +  '.xlsx')
res = pd.DataFrame(res)
res.to_excel(filepath, index=False)
```

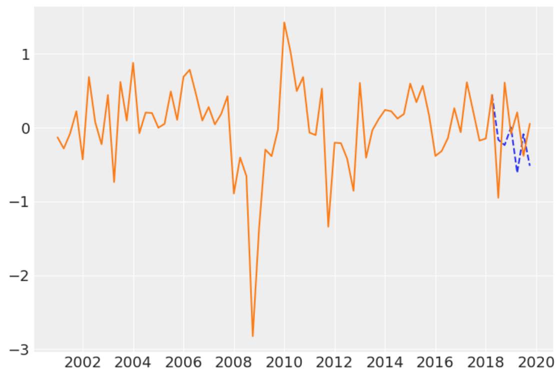
```
filepath_std = ('grafer_gu/STD_lag_4_' + variabler[1] + '_' + variabler[2] + '_' + variabler[3] + '.xlsx')
res_std = pd.DataFrame(res_std)
res_std.to_excel(filepath_std, index=False)
```

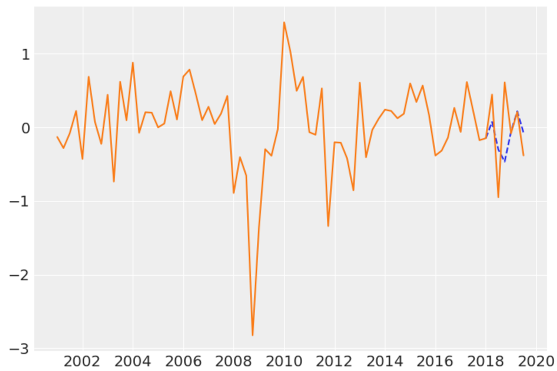
Appendix B Further results

Too showcase the performances further we include the graphs from the best performing model and base model here. This is for the reader to get further insights into how the models perform. The graphs display all the 20 periods over which the average was analyzed in the thesis. The graphs themselves display the percentage change of GDP in orange with the forecasts of the models in blue with dashed line style.

B.1 Results best model



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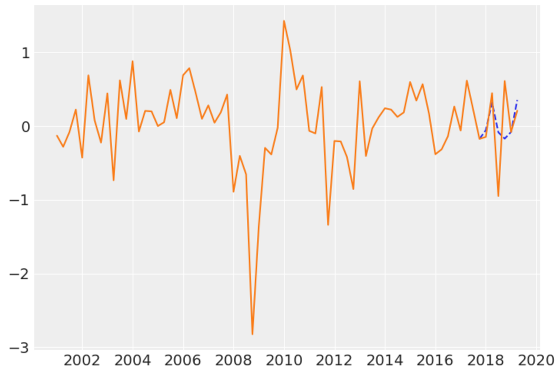
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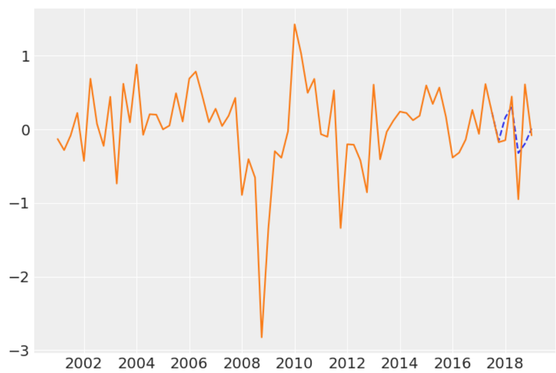
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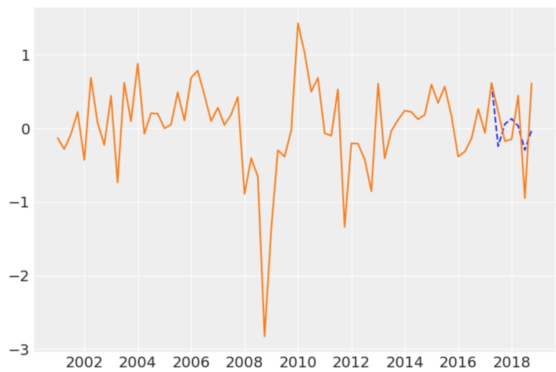
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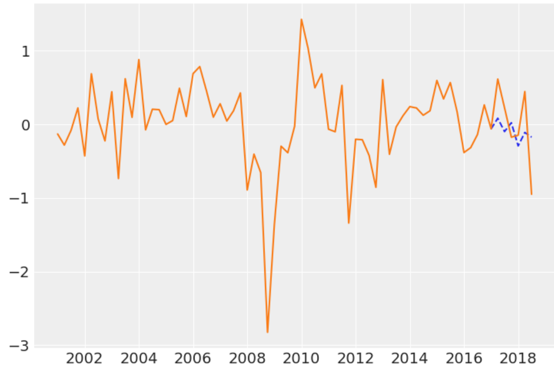
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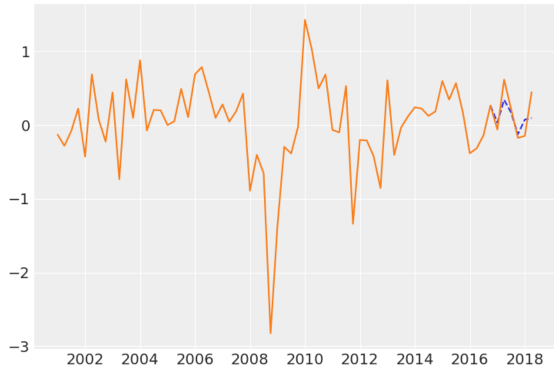
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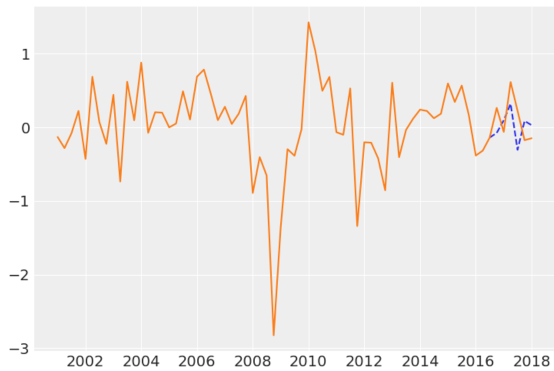
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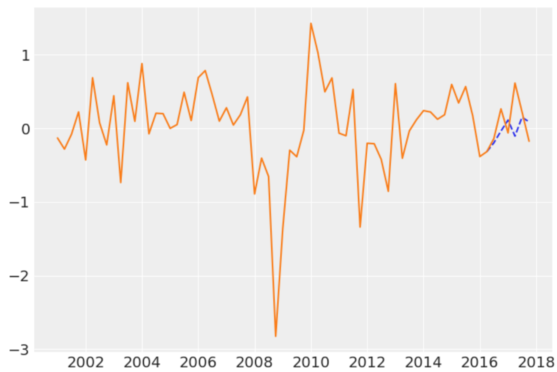
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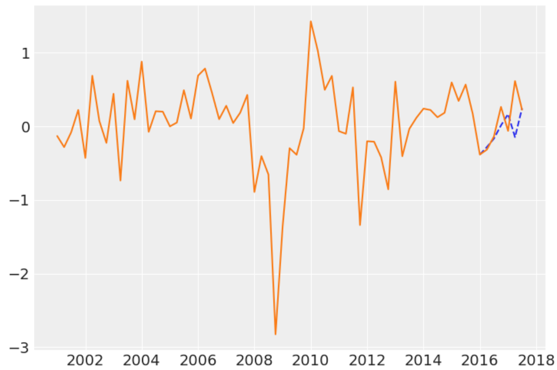
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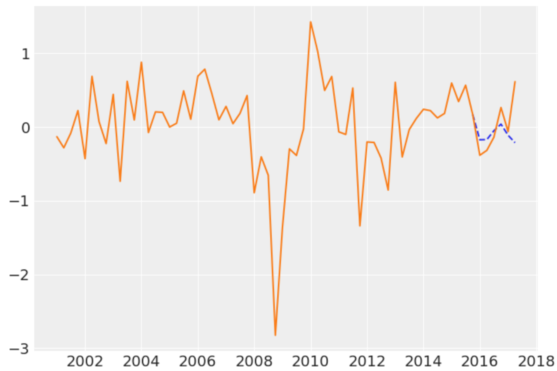
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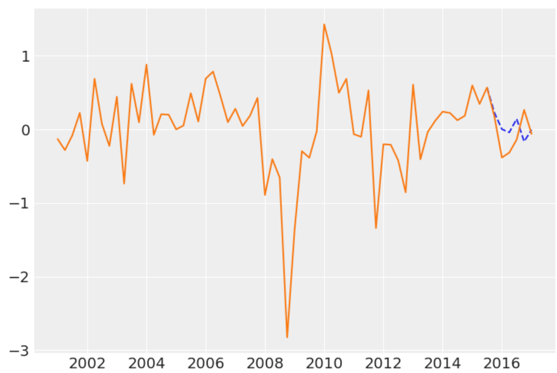
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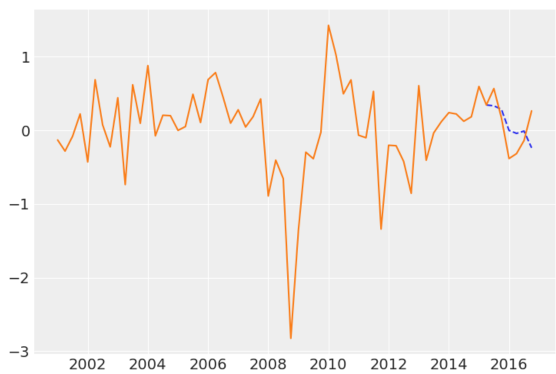
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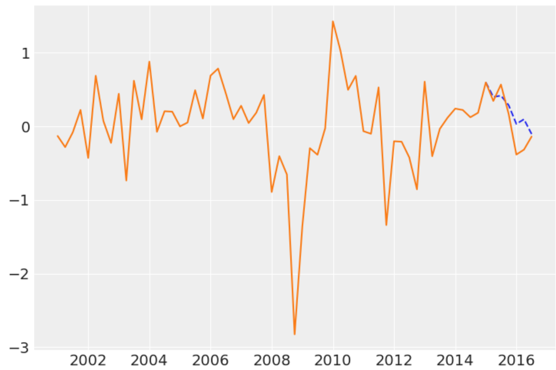
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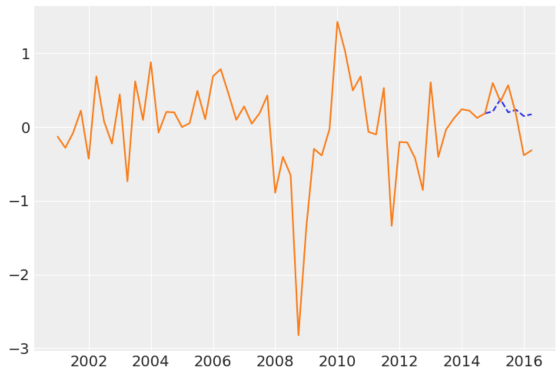
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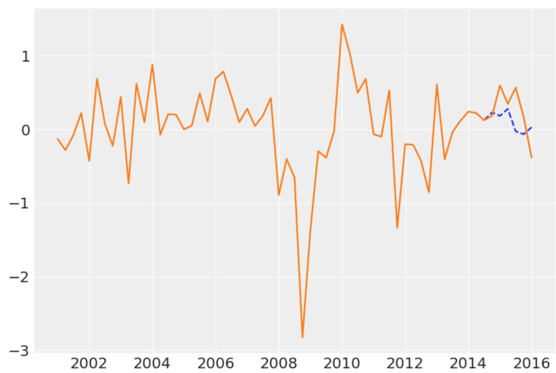
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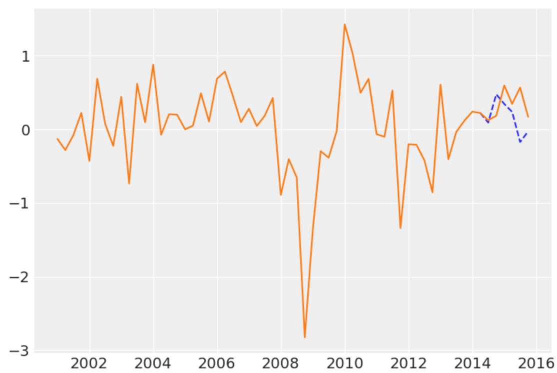
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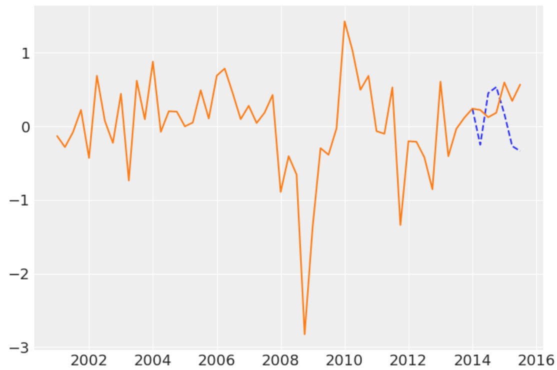
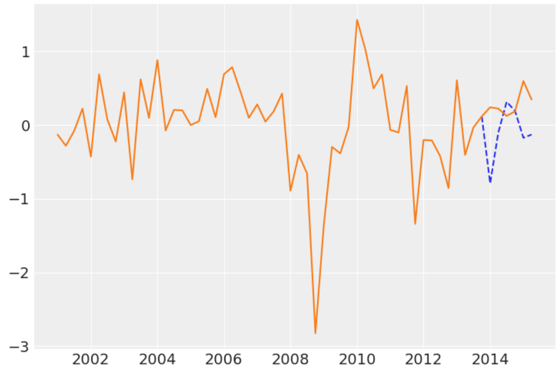
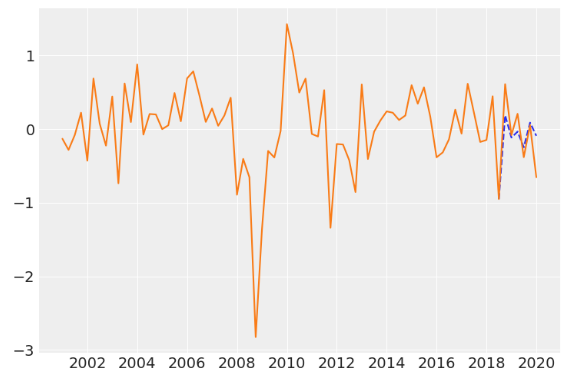
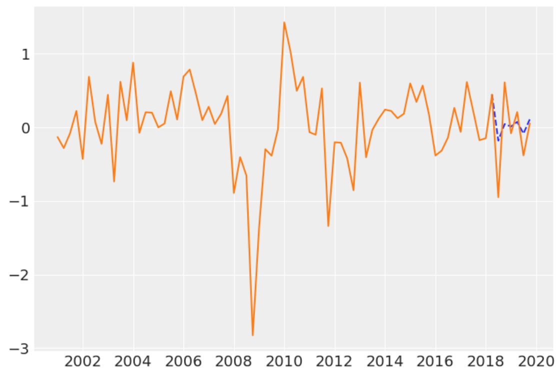
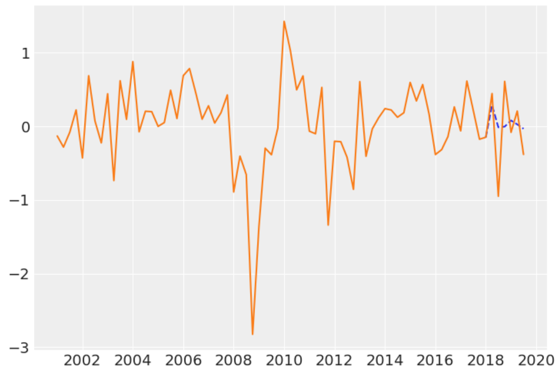




B.2 Results base model



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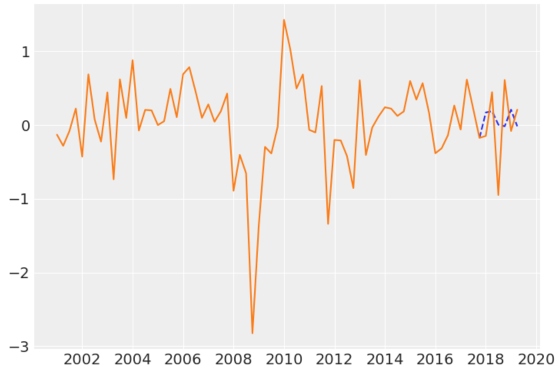
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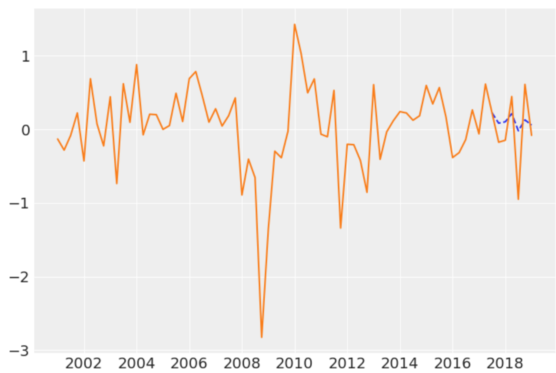
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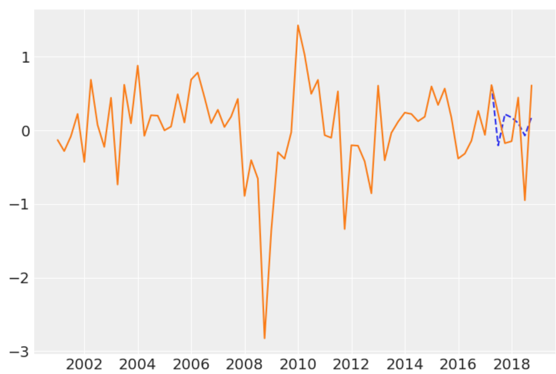
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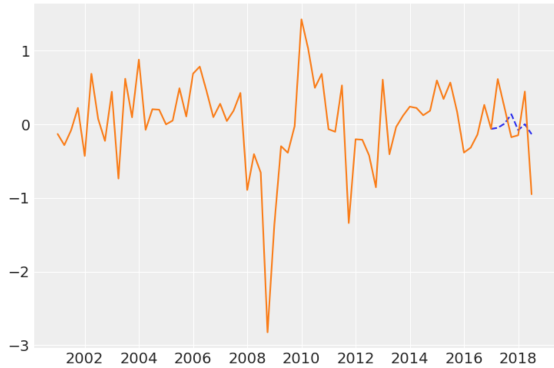
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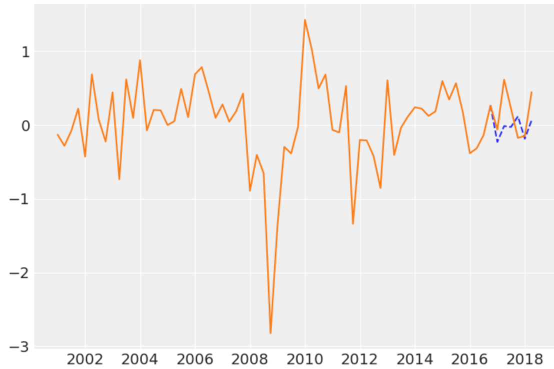
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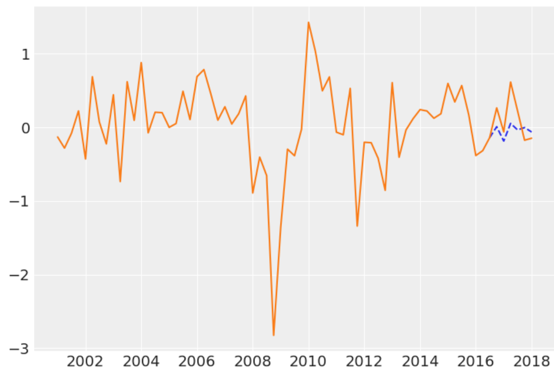
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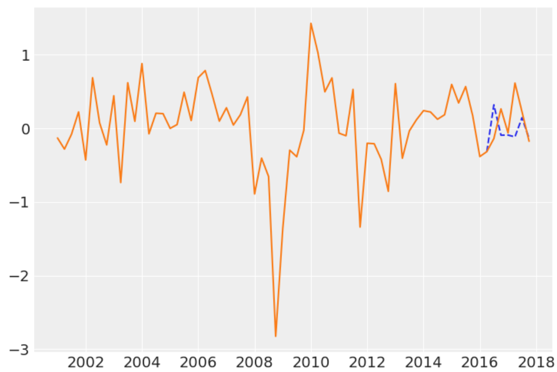
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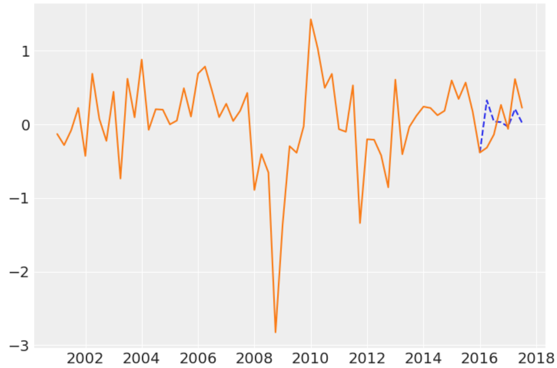
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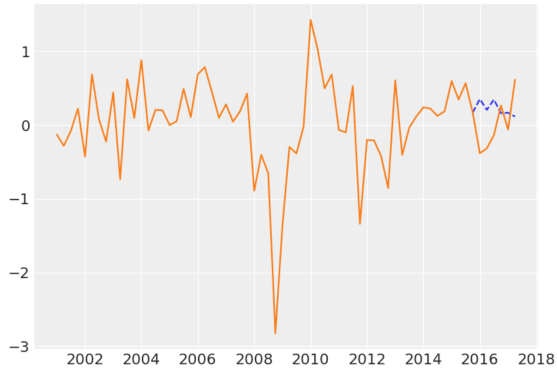
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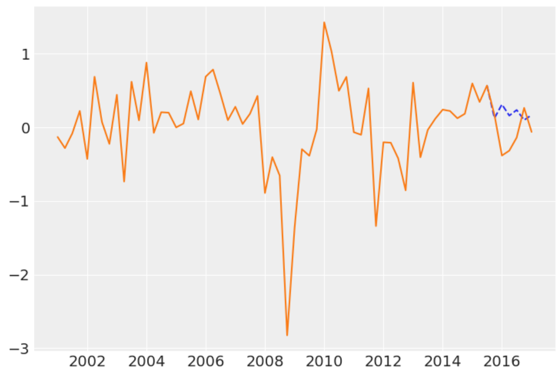
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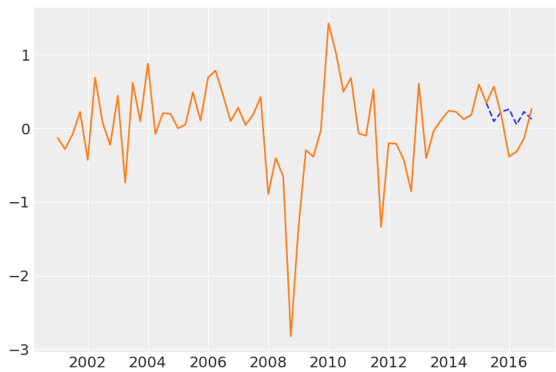
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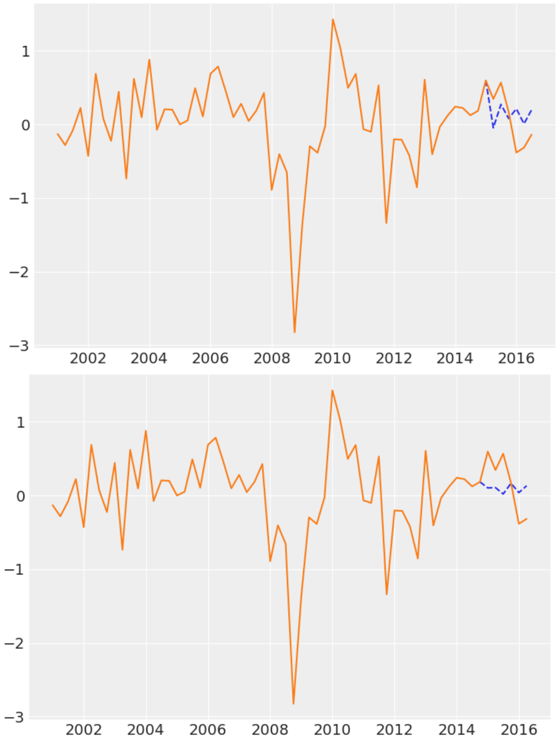
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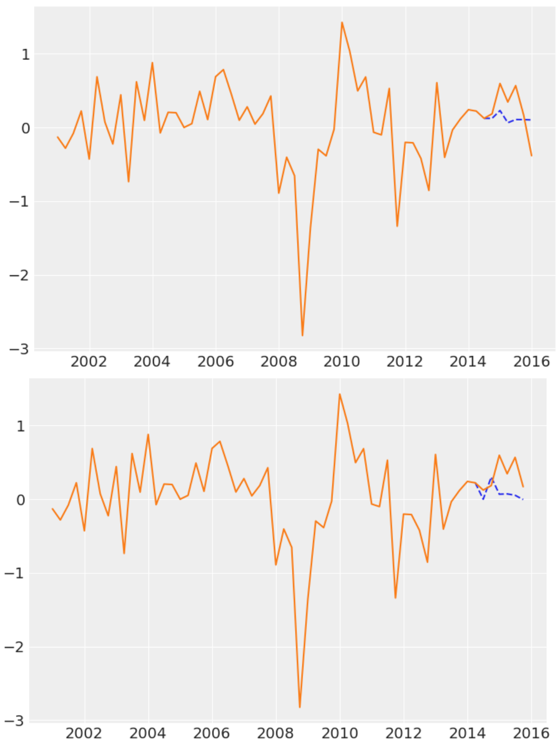
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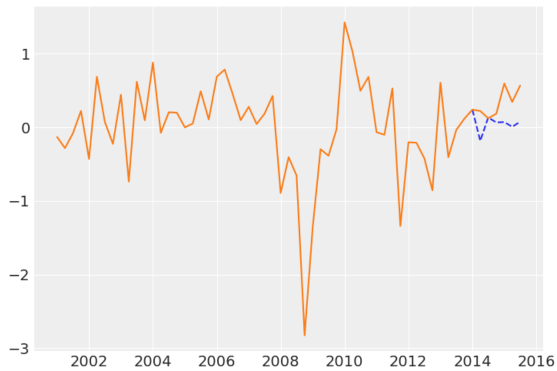
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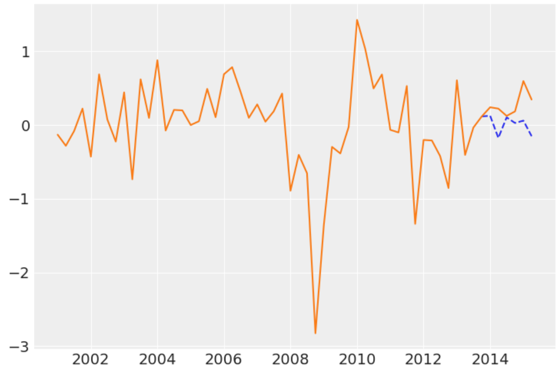
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