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Forecasting Goods and Services Inflation in Sweden

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Abstract

In this paper, we make use of a Bayesian VAR (BVAR) model to conduct an out-of-sample forecast exercise for goods and services inflation in Sweden. Our interest in goods and services prices stems from the fact that they make up over 70 per cent of the CPI index and that they are more directly affected by the macroeconomic development than other parts of the CPI. We find that the BVAR models generally outperform both univariate models for goods and services inflation, as well as forecasts made by the National Institute of Economic Research in Sweden. This might indicate that Faust and Wright's (2013) rather negative conclusion that inflation models cannot beat judgmental forecasts and inflation expectations might be wrong, at least in the case of Sweden.

JEL classification code: C53, E31

Keywords: Bayesian VAR, Inflation, Out-of-sample forecasting precision

Sammanfattning

I detta papper använder vi oss av en Bayesiansk VAR-modell (BVAR) i en out-of-sample prognosövning för varu- och tjänsteinflationen i Sverige. Vårt intresse för varu- och tjänstepriser kommer av det faktum att de utgör över 70 procent av KPI-index och att de mer direkt påverkas av den makroekonomiska utvecklingen än andra delar av KPI. Vi finner att BVAR-modellerna i allmänhet har högre prognosprecision för varu- och tjänsteinflationen än både univariata modeller och prognoser gjorda av Konjunkturinstitutet. Detta kan tyda på att Faust och Wrights (2013) ganska negativa slutsats att inflationsmodeller inte kan slå varken professionella prognoser eller inflationsförväntningar kan vara fel, åtminstone i Sverige.

Contents

1 Introduction

Expected future inflation is a key-variable that has to be taken into account in many decisions that are made in a modern economy. It affects borrowing costs, labor wage contracts, mortgage rates and so on. In a world with inflation targeting central banks the prominence of inflation forecasting has increased. According to New Keynesian theory the quality of inflation forecasts will affect the effectiveness of the monetary policy, see e.g. Woodford (2003) and Svensson (2005).

One of the main findings in the academic literature is that it is very difficult to model inflation. In a comprehensive study, Faust and Wright (2013) concludes that judgmental forecasts – measured by surveys of inflation expectations and the Fed Greenbook – often are more successful than forecasting models in predicting future inflation.[1] They even go as far as to conclude that an even simpler approach – a smooth path between a good nowcast of the current quarter and the long-run forecast – is a competitive benchmark.

In the academic literature, almost all of the evaluated forecasting models are models that aim to forecast headline inflation directly. This is somewhat surprising since there is no consensus whether headline inflation is best modelled by aggregating forecasts made for parts of the total consumer price index (CPI) or if it is better to forecast the headline inflation directly, see Hendry and Hubrich (2006, 2010) and Bermingham and D'Agostino (2011). Moreover, a disaggregate approach is common practice by professional forecasters around the world. For example, all major public sector forecasting institutions in Sweden – the Riksbank, the National Institute of Economic Research (NIER) and the Ministry of Finance – mainly use a bottom-up approach.

The main arguments for using disaggregated forecasting models are the following: (i) different parts of the CPI basket are affected by somewhat different economic forces, (ii) some parts are best (or most efficiently) forecasted by using market information,[2] (iii) the index design can have a huge impact on how actual price changes are measured in the CPI. Whether or not the disaggregate approach is superior is, however, an empirical question which we do not investigate in this paper.

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[1] It can, however, be noted that the forecasts published in the Fed Greenbook are partly influenced by model forecasts.

[2] For example, using futures prices for crude oil and electricity.

In this paper, we make use of the mean-adjusted Bayesian VAR model (BVAR) framework of Villani (2009) to conduct an out-of-sample forecast exercise for goods and services inflation in Sweden. One reason for our interest in goods and services is that they make up a large part (71 per cent in 2015) of the CPI index. Another reason is that goods and services are arguably more directly affected by the macroeconomic development (such as the business cycle and expectation formation) than other parts of the CPI.[3] The NIER divides the CPI into five main aggregates: goods, services, housing (excluding mortgage interest costs and energy), energy, and mortgage interest costs.[4] The most important goods and services of the Swedish CPI basket are shown in Table A1 in Appendix A.

The models include measures of resource utilization, labor costs, survey data of inflation and price expectations, the exchange rate and oil price. We find that the BVAR models generally outperform univariate models for inflation, especially at horizons up to 8 quarters, as well as forecasts made by the NIER, one of the best forecasting institutions in Sweden.[5]

The rest of this paper is organized as follows. Section 2 briefly presents the data used for our analysis. The BVAR models are discussed in Section 3. In Section 4, we present the results from our out-of-sample forecast exercise and Section 5 concludes.

2 Data

We use quarterly ex post, not real time, data between 1996Q2 and 2015Q3. Data are shown in Appendix B.[6]

Resource utilization is measured by either the seasonally adjusted[7] unemployment rate (Statistics Sweden's Labor Force Survey, ages 15−74 years) or the Riksbank's resource utilization indicator (see Nyman, 2010).

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[3] For example, energy prices are heavily affected by supply shocks and the index construction have a huge impact on how energy prices and mortage costs develop in the Swedish CPI.

[4] Statistics Sweden publish a somewhat different division.

[5] See, The Riksbank, Account of monetary policy 2015, for an evaluation of ten private and public Swedish forecasting institutions.

[7] The seasonal adjustment is done using Tramo/Seats.

Labour costs, provided by the Swedish National Mediation Office, are measured by hourly earnings in the business sector according to the short-term wage and salary statistics which are measured as the year-on-year percentage change.

Expectations of future prices and inflation are provided by NIER's Economic Tendency Survey. The price expectations are measured using the first principal component estimated on the firms' expectation for the next quarter in three sectors (retail sale of non-durable goods, retail sale of other goods, and sale of motor vehicles).[8] Inflation expectations (1 year ahead) among firms are used since those have been found to have the best predictive power of future inflation of available survey data, see Stockhammar and Österholm (2016).

Goods and services inflation is provided by Statistics Sweden's CPI index. We use the NIER's classification of goods and services.[9] Inflation is measured as the seasonally adjusted quarter-on-quarter percentage change.[10]

The nominal *exchange rate* is the effective exchange rate according to NIER's KIX-index. The *oil price* variable is here the Brent oil prices. All three variables are measured as quarter-on-quarter percentage change. Oil prices are seasonally adjusted[11].

3 Methodology

3.1 The Bayesian VAR model

The general form of the BVAR-model is given by

$$\mathbf{G}(L)(\mathbf{x}_t - \boldsymbol{\mu}) = \boldsymbol{\eta}_t, \tag{1}$$

where $\mathbf{G}(L) = \mathbf{I} - \mathbf{G}_1 L - \ldots - \mathbf{G}_m L^m$ is a lag polynomial of order *m*, $\mathbf{x}_t$ is an *n*x1 vector of stationary variables, $\boldsymbol{\mu}$ is an *n*x1 vector describing the steady-state values of the variables in the system and $\boldsymbol{\eta}_t$ is an *n*x1 vector of *iid* error terms fulfilling $E(\boldsymbol{\eta}_t) = \mathbf{0}$ and $E(\boldsymbol{\eta}_t \boldsymbol{\eta}_t') = \boldsymbol{\Sigma}$. Equation (1) is somewhat unconventional as it is expressed in devia-

[8] The seasonal adjustment is done using the X-12-ARIMA algorithm.

[9] See Table A1 in Appendix A.

[10] The seasonal adjustment is done using the X-13-ARIMA-SEATS algorithm.

[11] The seasonal adjustment is done using the X-13-ARIMA-SEATS algorithm.

tions from the steady state. This specification of the BVAR – developed by Villani (2009) – has the benefit that an informative prior distribution for $\boldsymbol{\mu}$ often can be specified. Obviously, this can be particularly useful when forecasting Swedish inflation given that the Riksbank has an explicitly stated inflation target. Villani's specification of the BVAR has been proven useful in terms of improving forecast accuracy, see, for example, Beechey and Österholm (2010).

The priors on the parameters of the model used in this paper follow those in Villani (2009). The prior on $\boldsymbol{\Sigma}$ is given by $p(\boldsymbol{\Sigma}) \propto |\boldsymbol{\Sigma}|^{-(n+1)/2}$ and the prior on $vec(\mathbf{G})$, where $\mathbf{G} = (\mathbf{G}_1 \quad \ldots \quad \mathbf{G}_m)'$, is given by $vec(\mathbf{G}) \sim N_{mn^2}(\boldsymbol{\theta}_{\mathbf{G}}, \boldsymbol{\Omega}_{\mathbf{G}})$.[12] The prior on $\boldsymbol{\mu}$ is given by $\boldsymbol{\mu} \sim N_n(\boldsymbol{\theta}_{\boldsymbol{\mu}}, \boldsymbol{\Omega}_{\boldsymbol{\mu}})$ and is specified in detail in Table A2 and A3 in Appendix C. The hyperparameters of the model are uncontroversial and follow the literature.[13]

3.2 Model specification

In order to choose variables to include we have conducted a step-wise out-of-sample forecast exercise where we tested several different measures for, and combinations of, resource utilization, labour costs, exchange rates and as well as survey data, oil prices and the bond yield.

We focus on the RMSFE of the models and do not conduct any hypothesis tests regarding the forecast precision. We argue that this is a reasonable approach when evaluating the addition of a variable to a model. Methodologically, this study is thus close to other papers using out-of-sample forecast precision to assess Granger causality of various variables for inflation; see, for example, Bachmeier et al. (2007), Gavin and Kliesen (2008), Berger and Österholm (2009, 2011) and Scheufele (2011). When the purpose of the model purely is forecasting, the forecaster would – in the choice between two mod-

[12] The priors on the dynamics have been slightly modified relative to the traditional Minnesota prior. Instead of a prior mean on the first own lag equal to 1 and zero on all other lags (which is the traditional specification), the prior mean on the first own lag is here set equal to 0.9; all subsequent lags have a prior mean of zero. The reason for this is that the traditional specification is theoretically inconsistent with the mean-adjusted model, as it takes its starting point in a univariate random walk and such a process does not have a well-defined unconditional mean.

[13] The overall tightness is set to 0.2, the cross-variable tightness to 0.5 and the lag decay parameter to 1. See, for example, Doan (1992) and Villani (2009).

els that are considered equally likely a priori – generally choose the model with the smallest RMSFE. The impulse response functions are in this respect irrelevant.

The step-wise forecasting exercise was conducted as follows:

Step 1: We evaluated the forecasting precision of bivariate models at the 1-year, 2-year and 3-year horizons with different measures for the *exchange rate* (and, naturally, goods and services inflation).

Step 2: Here, trivariate models were evaluated by adding measures for *labour costs* to the best bivariate models from step 1.

Step 3: Fourvariate models were evaluated by adding measures for *resource utilization* to the best trivariate models from step 2.

Step 4: We evaluated fivevariate models by adding *survey data, oil prices and the bond yield* to the best fourvariate models from step 3.[14]

We also tested if forecasting precision could be improved by replacing one of the explanatory variables chosen in step 1-3 with another variable tested in step 4. Moreover, it was found that adding additional explanatory variables to the fivevariate model generally decreased forecasting precision.[15]

Following this procedure gave rise to the three models given in Table 1 where model 1 was found to generate the smallest RMSFEs at the 1-year horizon, model 2 generated the smallest RMSFEs at the 2-years horizon, and model 3 generated the smallest RMSFEs at the 3-year horizon.[16]

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[14] Oil prices are treated as exogenous in the BVAR model.

[15] We have tested different lag lengths, and found that m=4 generates the lowest RMSFEs. We also found that BVAR models generate lower RMSFEs than standard VAR models, see Table A4 and Table A8 in Appendix D.

[16] A list of tested, but not used, variables is provided in Table A3 in Appendix C.

Table 1 Variables used in each of the three selected models[17]

Type of variable	Model 1	Model 2	Model 3
Other	Oil prices (USD)	–	–
Resourse utilisation	–	Unemployment rate	Resource utilization indicator (Riksbank)
Labour costs	Hourly earnings	Hourly earnings	Hourly earnings
Expectations	Price expectations	Inflation expectations	Price expectations
Inflation	Goods and services inflation	Goods and services inflation	Goods and services inflation
Exchange rate	KIX index	KIX index	KIX index

4 Forecast comparisons

4.1 Models vs a univariate benchmark

In this section, we analyze the out-of-sample forecasting precision using quarterly data from 1996Q2 to 2015Q3. We compare the forecasting precision of the fivevariate models given in Table 1 above with the univariate BVAR model. Specifically, the out-of-sample forecast exercise is conducted as follows: All models are first estimated for a training period of nine years, using data from 1996Q2 to 2005Q1. Forecasts one to twelve quarters ahead, starting 2005Q2, are then generated and the forecast errors are recorded. The sample is then extended one quarter, the models are re-estimated and new forecasts twelve quarters ahead are generated. This procedure stops at the end of the sample; the last forecasts are generated based on data from 1996Q2 to 2015Q2. The forecast comparisons in this study are thus based on between 31 and 42 forecasts depending on the forecast horizon.

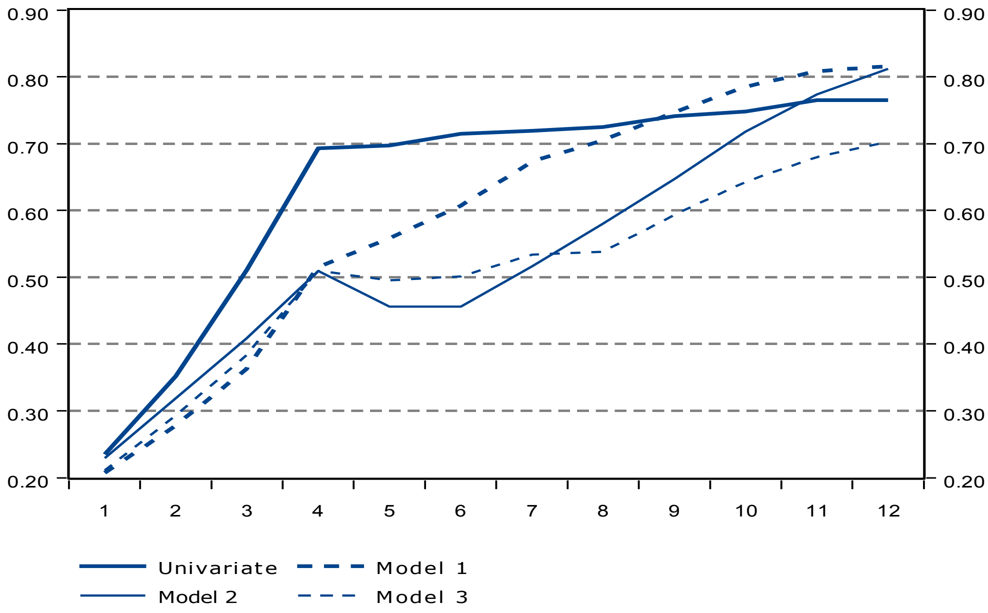
As described in section 3, goods and services inflation is modelled using seasonally adjusted quarter-on-quarter percentage changes. In this section, however, the forecasts of the more commonly used year-on-year percentage changes are evaluated.

In this Section we present the results for the three models that were found to have smallest RMSFEs at the 1-year, 2-years and 3-years horizons respectively. Model 1 was the model with best forecasting precision at the 1–3 quarters horizons. Models 2 and 3 were found to have smallest RMSFEs at the 5–7 quarters and 8–12 quarter horizon respectively, see

[17] The variables in the $\mathbf{X}_t$ -vector of Equation (1) are ordered as in Table 1.

Figure 1. All the three models outperforms the univariate BVAR model at the 1−8 quarters forecast horizon. At the longest horizon, 12 quarters, only model 3 outperforms the univariate model.

Figure 1 RMSFEs, 2005Q2−2015Q3



Note. See Section 2 and Table 1 in Section 3 for a description of variables used in each model.

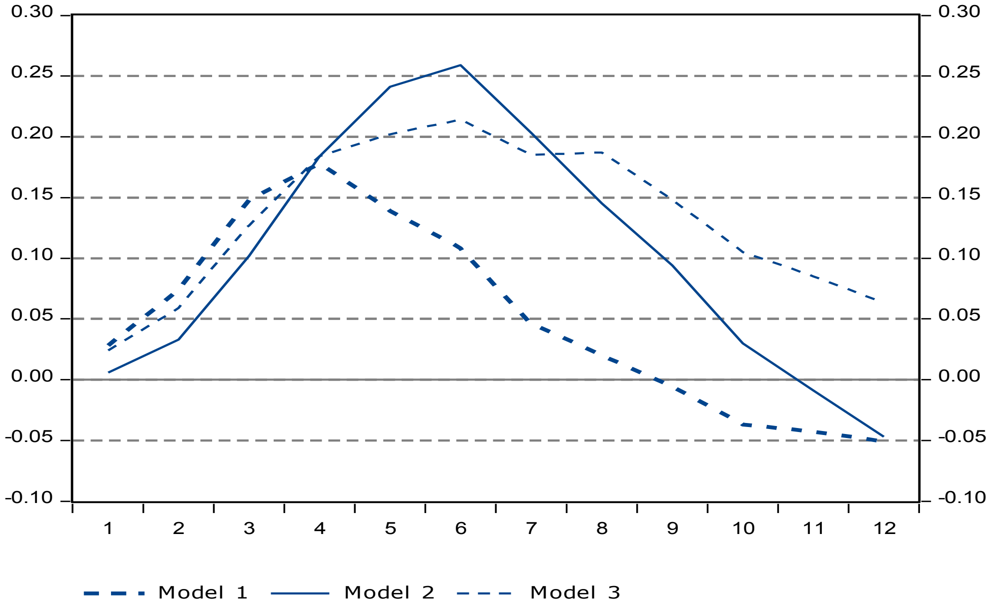
The differences in RMSFE for goods and services inflation between the univariate model and the fivevariate models are shown in Figure 2.[18] A positive RMSFE difference indicates that the particular fivevariate model has better out-of-sample forecasts than the benchmark model. The models' improvement compared to the univariate model is at most 0.26 percentage points in reduction RMSFE (model 2, horizon 6 quarters), which translates into a reduction of the RMSFE by 37 per cent.[19] This is considered to be an economically significant improvement in forecasting precision and is generally bigger than the improvements found in Faust and Wright (2013).[20]

[18] See also Appendix D for tables showing (i) the RMSFEs of each model (Table A4), and (ii) the reduction in RMSFE compared to the univariate model (Table A5). See also Figure A2 in Appendix D for a version of Figure 2 that also includes other models that were good, but not as good as model 1, 2 and 3.

[19] 100*(0,26/0,72)=37 per cent. The reduction in RMSFE is expressed as per cent of the RMSFE of the univariate models.

[20] The results are, however, not directly comparable. Faust and Wright (2013) make use of a AR(1) with fixed slope coefficient as a benchmark and they use other measures of inflation (CPI, core CPI, GDP deflator and the PCE deflator).

Figure 2 Reduction in RMSFEs compared to the univariate model, 2005Q2–2015Q3



Note: Reduction in RMSFE:s is given in percentage points on the vertical axis. Forecasting horizon in quarters on the horizontal axis. A positive number indicates that the model has a lower RMSFE than the univariate model. See Section 2 and Table 1 in Section 3 for a description of variables used in each model.

4.2 Models vs a professional forecaster

In this section, we compare the forecasting precision of the models presented in the previous section with the judgmental forecasts from a professional forecasting institution, the NIER.[21] The evaluation period and forecasting horizon are different from the previous section due to lack of data. We evaluate forecasts 1–6 quarters ahead for the period 2008Q4–2015Q3.[22]

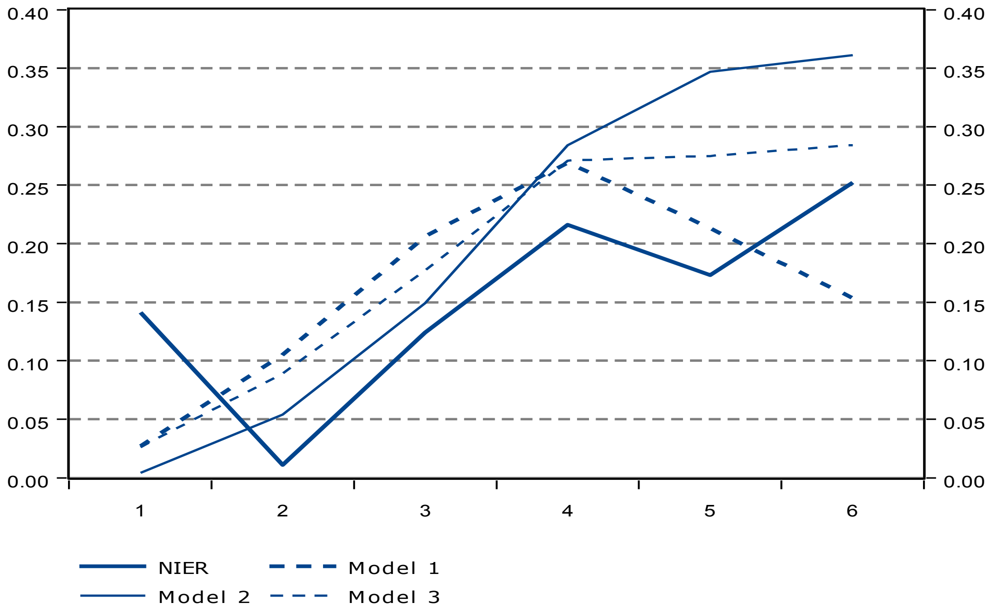
The differences in RMSFEs between the univariate model and the three fivevariate models and the NIER forecasts are shown in Figure 3.[23] As mentioned before, a positive RMSFE difference signals that the particular model generates better out-of-sample forecasts than the univariate model.

[21] No other forecasting institution in Sweden publishes their forecasts for goods and services inflation.

[22] We have data from NIER from 2008Q1 but have chosen to start the evaluation three quarters later due to the fact that the CPI index was revised in september 2008 (due to an error in the calculation of the goods and services inflation).

[23] See also Appendix D for tables showing (i) the RMSFEs of each model, and (ii) the reduction in RMSFEs compared to the univariate model.

Figure 3 Reduction in RMSFEs compared to the univariate model, 2008Q4–2015Q3



Note: Reduction in RMSFE:s is given in percentage points on the vertical axis. Forecasting horizon in quarters on the horizontal axis. A positive number indicates that the model has a lower RMSFE than the univariate model. See Section 2 and Table 1 in Section 3 for a description of variables used in each model.

We find that the forecasts made by the NIER outperform the univariate model at all horizons. We can also note that the NIER clearly outperforms the models at the very short term (1 quarter ahead), but has a hard time beating the models at other evaluated horizons. NIER's RMSFEs are higher than all three BVAR models at the 2–5 quarters horizons.

When the NIER makes its forecast it generally has an information advantage since the institute knows one monthly outcome when the quarterly forecast is made. However, the volatility of the monthly data is very high which makes this information advantage of limited value. The NIERs better forecasting precision at the shortest forecast horizon is probably better explained by a "technical information advantage" of the forecaster, knowing e.g. current changes in the seasonal components, tax changes or changes in the way Statistics Sweden calculates the different sub-indices.

5 Conclusions

The results presented in this paper indicate that BVAR models for goods and services inflation in Sweden can be useful in improving forecasting precision at horizons longer than one quarter. The fact that none of the models could beat a professional forecaster at the shortest forecasting horizon points to the necessity of conditioning inflation forecasting models on a good nowcast in line with Faust and Wright's (2013) suggestion. The fact that the models could beat a professional forecaster at longer horizons might indicate that Faust and Wright's (2013) conclusion that inflation models cannot beat judgmental forecasts and inflation expectations might be wrong, at least in the case of Sweden. We should however note the fact that we have not evaluated forecasts for headline inflation in this paper. An interesting avenue for further research is to combine the models presented in this paper with disaggregated models for the other parts that makes up the CPI. Their forecasting precision for headline inflation can then be compared with those of one or several models that forecast headline inflation directly.

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Appendix A – CPI-weights

Table A1 Weights for different goods and services

Per cent of CPI basket 2015

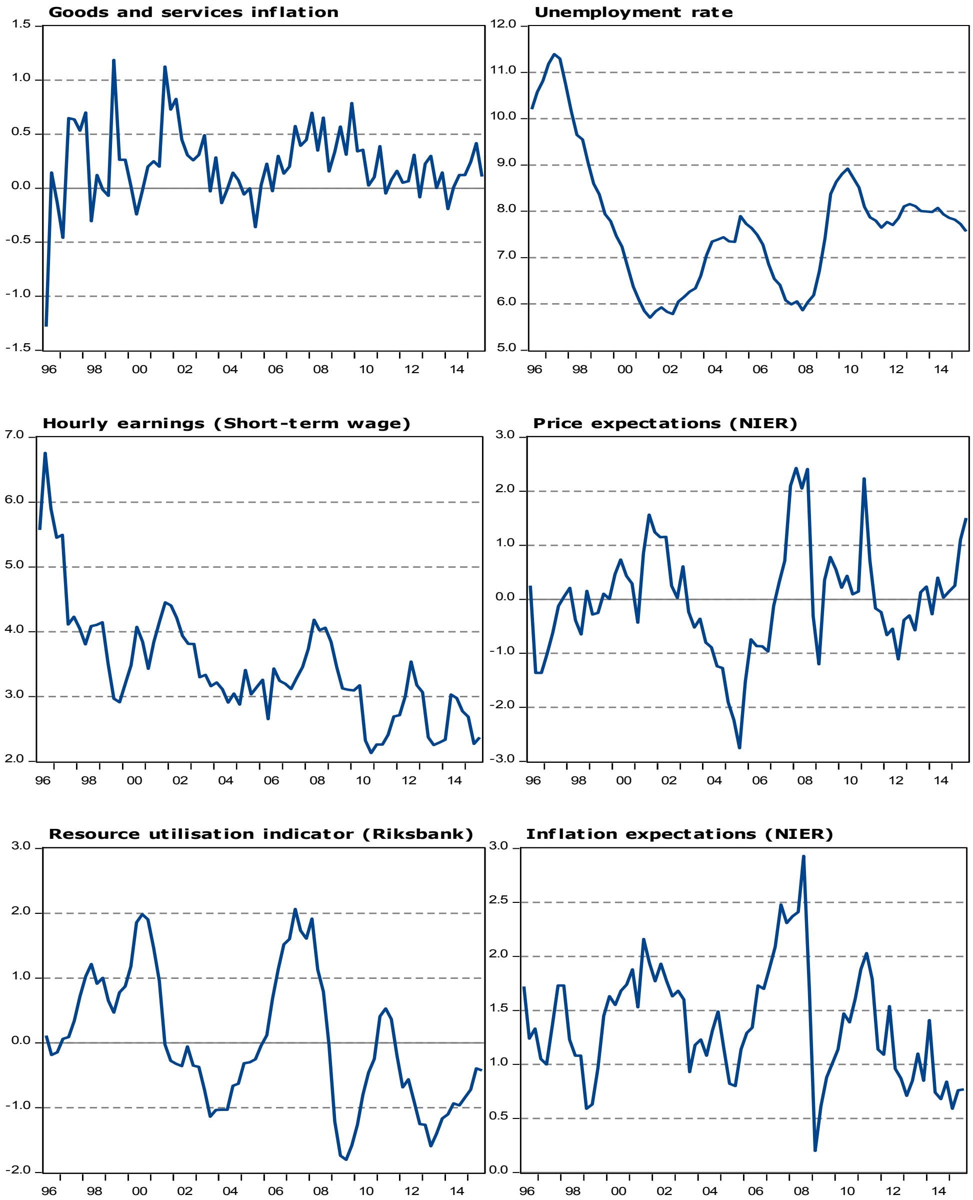
	Weight
Goods	**41,4**
Food	13,7
Clothes and shoes	5,1
Alcohol and tobacco	3,9
Purchase of vehicles	3,7
Other	14,9
Services	**29,4**
Restaurants, cafés and the like	4,8
Transport services	4,6
Leisure and recreation	3,2
Communication	3,3
Other	13,5
Goods and services (total)	**70,8**

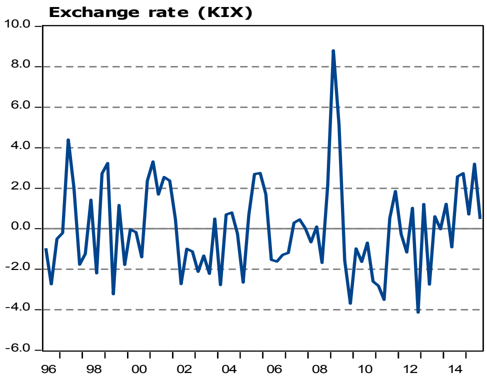
Sources: Statistics Sweden and NIER.

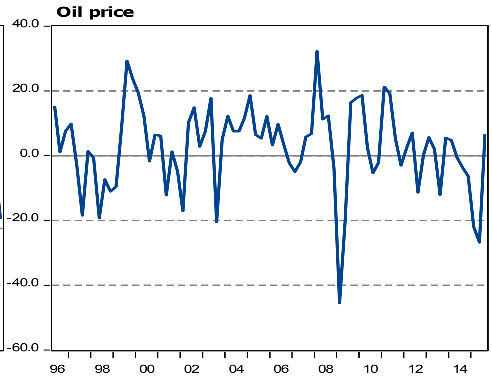
Appendix B – Data

Goods and services inflation, the exchange rate and oil price given as the quarter-on-quarter percentage change. The unemployment rate, resource utilization and inflation expectations are measured in per cent. Hourly earnings are given as the yearly percentage change. Price expectations are measured as an index. See Section 2 for more information.

Figure A1




Exchange rate (KIX)
10.0
8.0
6.0
4.0
2.0
0.0
-2.0
-4.0
-6.0
96
98
00
02
04
06
08
10
12
14


Oil price
40.0
20.0
0.0
-20.0
-40.0
-60.0
96
98
00
02
04
06
08
10
12
14

Appendix C – Steady state priors

Table A2 Steady-state priors for variables chosen to be included in models

	Prior interval
Unemployment	(5.0; 9.0)
Resource utilization indicator (Riksbank)	(–1.0; 1.0)
Hourly earnings in the business sector (short-term wage and salary statistics)	(3.1; 4.1)
Inflation expectations	(1.0; 3.0)
Price expectations	(–1.0; 1.0)
Inflation (goods and services)	(1.1; 2.1)
Exchange rate (KIX)	(–1.0; 1.0)
Oil price (USD)	(–2.0; 2.0)

Note. Goods and services inflation, the exchange rate and oil prices are measured in quarter-on-quarter percentage change. The unemployment rate, the resource utilization indicator, inflation expectations are measured in per cent. Hourly earnings are measured in yearly percentage change. Price expectations are measured as an index. Prior intervals refer to a 95% confidence interval. See Section 2 for more information. As described in Section 2 goods and services inflation is modelled using seasonally adjusted quarter-on-quarter percentage changes. In the forecast evalutation the more commonly used year-on-year percentage changes are evaluated.

Table A3 Steady-state priors for variables not chosen to be included in models

	Prior interval
Resource utilisation	
Labour market gap (NIER)	(-1.0; 1.0)
Output gap (NIER)	(-1.0; 1.0)
Resource utilization indicator (NIER)	(-1.0; 1.0)
Short-term unemployment rate	(3.5; 6.0)
Labour costs	
Hourly earnings in the business sector (national accounts)	(3.1; 4.1)
Labour costs (per hour)	(0.75; 1.05)
Unit labour cost	(0.0; 0.8)
Exchange rates and import prices	
KIX16	(−1.0; 1.0)
Euro/SEK	(−1.0; 1.0)
USD/SEK	(−1.0; 1.0)
Import prices, consumer goods	(0.25; 0.5)
Import prices, manufactured goods	(0.25; 0.5)
Import prices, food	(0.25; 0.5)
Survey	
Consumer confidence indicator	(95; 105)
New orders (expectations), Manufacturing	(5; 25)
Number of employees (expectations), Total industry	(−10; 10)
Number of employees (expectations), Trade[1]	(−10; 10)
Sales situation (assessment), Trade[1]	(−10; 10)
Selling volume (outcome), Trade[1]	(15; 35)
Selling volume (expectations), Trade[1]	(30; 50)
Goods in stock (assessment), Trade[1]	(15; 35)
Profitability (assessment), Trade[1]	(−15; 5)
Labour shortage (assessment), Trade[1]	(0; 20)
Shortage of labour (assessment), Total industry	(0; 20)
Other	
Producer prices, goods, imported+domestic	(0.25; 0.5)
Producer prices, food, imported+domestic	(0.25; 0.5)
Oil price (SEK)	(−2.0; 2.0)
Profit share	(30; 40)
Government bond yield (3 months maturity)	(3; 5)

Note. Labor costs, unit labor costs, exchange rates, import and producer prices and oil price measured in quarter-on-quarter percentage change. The output and labour market gaps, unemployment rate, profit share and government bond yield are measured in per cent. Hourly earnings are measured in yearly percentage change. Survey data are measured as an index. Prior intervals refer to a 95% confidence interval.

[1] Retail and wholesale trade.

Appendix D – RMSFEs

Table A4 RMSFEs of the BVAR-models evaluated 2005Q2−2015Q3

Percentage points

Horizon	Univariate	Model 1	Model 2	Model 3
1Q	0.24	0.21	0.23	0.21
2Q	0.35	0.28	0.32	0.29
3Q	0.51	0.36	0.41	0.38
4Q	0.69	0.52	0.51	0.51
5Q	0.70	0.56	0.46	0.50
6Q	0.72	0.61	0.46	0.50
7Q	0.72	0.67	0.52	0.53
8Q	0.73	0.71	0.58	0.54
9Q	0.74	0.75	0.65	0.59
10Q	0.75	0.79	0.72	0.64
11Q	0.77	0.81	0.77	0.68
12Q	0.77	0.82	0.81	0.70

Note. As described in Section 2 goods and services inflation is modelled using seasonally adjusted quarter-on-quarter percentage changes. In the forecast evalutation, and in this table, the more commonly used year-on-year percentage changes are evaluated.

Tabell A5 Reduction in RMSFE compared to the univariate model 2005Q2−2015Q3

Percentage points

Horizon	Model 1	Model 2	Model 3
1Q	0.03	0.01	0.02
2Q	0.07	0.03	0.06
3Q	0.15	0.10	0.13
4Q	0.18	0.18	0.18
5Q	0.14	0.24	0.20
6Q	0.11	0.26	0.21
7Q	0.05	0.20	0.19
8Q	0.02	0.15	0.19
9Q	−0.01	0.09	0.15
10Q	−0.04	0.03	0.11
11Q	−0.04	−0.01	0.09
12Q	−0.05	−0.05	0.06

Note. A positive RMSFE difference shows that the particular fivevariate model contributes to better out-of-sample forecasts than the benchmark model. As described in Section 2 goods and services inflation is modelled using seasonally adjusted quarter-on-quarter percentage changes. In the forecast evalutation, and in this table, the more commonly used year-on-year percentage changes are evaluated.

Table A6 RMSFEs of BVAR models evaluated 2008Q4−2015Q3

Percentage points

Horizon	Univariate	Model 1	Model 2	Model 3	NIER
1Q	0.22	0.20	0.22	0.20	0.08
2Q	0.35	0.24	0.29	0.26	0.34
3Q	0.53	0.32	0.38	0.35	0.41
4Q	0.73	0.46	0.45	0.46	0.52
5Q	0.77	0.56	0.43	0.50	0.60
6Q	0.80	0.64	0.44	0.51	0.54

Note. As described in Section 2 goods and services inflation is modelled using seasonally adjusted quarter-on-quarter percentage changes. In the forecast evalutation, and in this table, the more commonly used year-on-year percentage changes are evaluated.

Table A7 Reduction in RMSFE compared to the univariate model 2008Q4−2015Q3

Percentage points

Horizon	Model 1	Model 2	Model 3	NIER
1Q	0.03	0.00	0.03	0.14
2Q	0.11	0.05	0.09	0.01
3Q	0.21	0.15	0.18	0.12
4Q	0.27	0.28	0.27	0.22
5Q	0.21	0.35	0.28	0.17
6Q	0.15	0.36	0.28	0.25

Note. A positive RMSFE difference shows that the particular fivevariate model contributes to better out-of-sample forecasts than the benchmark model. As described in Section 2 goods and services inflation is modelled using seasonally adjusted quarter-on-quarter percentage changes. In the forecast evalutation, and in this table, the more commonly used year-on-year percentage changes are evaluated.

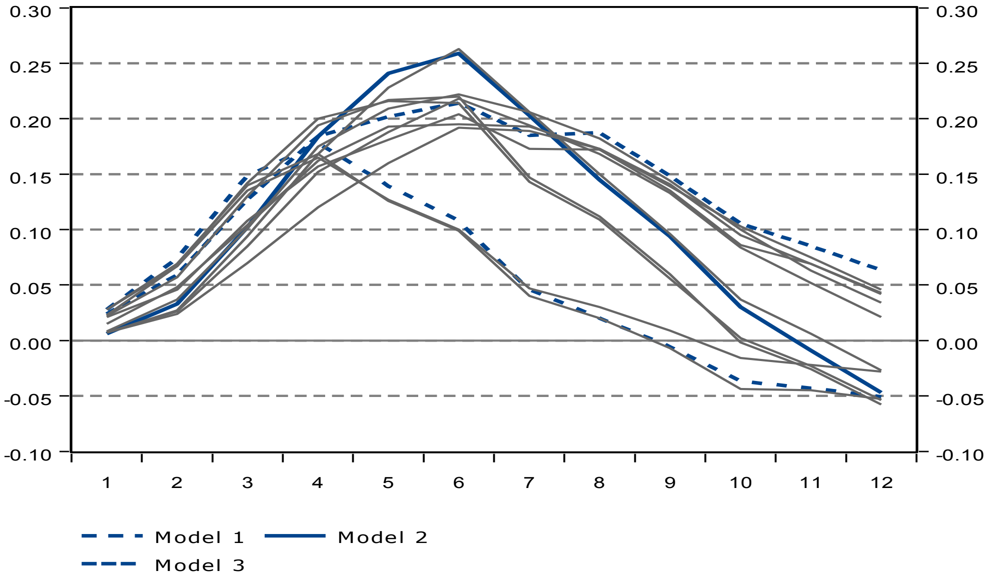
Table A8 RMSFEs of standard VAR models evaluated 2005Q2−2015Q3

Percentage points

Horizon	Univariate	Model 1	Model 2	Model 3
1Q	0.22	0.34	0.36	0.30
2Q	0.36	0.50	0.58	0.52
3Q	0.55	0.73	0.82	0.75
4Q	0.76	0.99	1,07	0.99
5Q	0.78	1.13	0,98	0.98
6Q	0.80	1.13	0,93	0.91
7Q	0.78	1.21	0,84	0.88
8Q	0.76	1.30	0,87	0.93
9Q	0.77	1.50	0,86	0.97
10Q	0.77	1.79	0,83	0.95
11Q	0.77	2.04	0,83	0.90
12Q	0.73	2.27	0.74	0.81

Note. As described in Section 2 goods and services inflation is modelled using seasonally adjusted quarter-on-quarter percentage changes. In the forecast evalutation the more commonly used year-on-year percentage changes are evaluated.

Figure A2 Reduction in RMSFEs compared to the univariate model, 2005Q2–2015Q3



Note: Reduction in RMSFE:s is given in percentage points on the vertical axis. Forecasting horizon in quarters on the horizontal axis. A positive number indicates that the model has a lower RMSFE than the univariate model. The thin grey lines shows RMSFEs for models which were good, but not as good as model 1, 2 and 3.

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