Forecasting Inflation in Sweden*

Unn Lindholm[∀], Marcus Mossfeldt[#] and

Pär Stockhammar[♣]

November 2018

* We are grateful to Jakob Almerud, Erika Färnstrand Damsgaard, Erik Glans, Petter Hällberg, Pär Österholm and to seminar participants at the National Institute of Economic Research for valuable comments on this paper.

∀ National Institute of Economic Research, Box 3116, 103 62 Stockholm, Sweden.
Email: unn.lindholm@konj.se Phone: +46 8 453 59 23.

Ministry of Finance, 103 33 Stockholm, Sweden.
E-mail: marcus.mossfeldt@regeringskansliet.se Phone: +46 8 405 10 00.

♣ National Institute of Economic Research, Box 3116, 103 62 Stockholm, Sweden.
E-mail: par.stockhammar@konj.se Phone: +46 8 453 59 10.

WORKING PAPER NO 152

PUBLISHED BY THE NATIONAL INSTITUTE OF ECONOMIC RESEARCH (NIER)

ISSN 1100-7818

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Abstract

In this paper, we make use of Bayesian VAR (BVAR) models to conduct an out-of-sample forecasting exercise for CPIF inflation, as used as the inflation target by the Riksbank in Sweden. The proposed BVAR models generally outperform simple benchmark models, the BVAR model used by the Riksbank as presented in Iversen *et al.* (2016) and professional forecasts made by the National Institute of Economic Research in Sweden. Moreover, the BVAR models proposed in the present paper have better forecasting precision than both survey forecasts and the method suggested by Faust and Wright (2013).

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 (BVAR)-modell i en out-of-sample prognosövning för KPIF-inflationen i Sverige. KPIF är numera Riksbankens målvariabel för inflationsmålet. De föreslagna BVAR-modellerna har i allmänhet högre prognosprecision för KPIF-inflationen än både univariata benchmarkmodeller, Riksbankens BVAR-modell som den beskrivs i Iversen m.fl. (2016) och prognoser gjorda av Konjunkturinstitutet. Dessutom har de BVAR-modeller som föreslås i det här pappret högre prognosprecision än både inflationsförväntningar och den metod som Faust och Wright (2013) har föreslagit.

Contents

1 Introduction

Borrowing costs, labour wage contracts, mortgage rates etc. are substantially affected by the expected future inflation. Good inflation forecasts are therefore of crucial importance for the effectiveness of monetary policy decisions. In fact, according to the new Keynesian model, optimal policy depends on optimal forecasts, see e.g. Woodford (2003) and Svensson (2005). However, according to the academic literature, see e.g. Atkeson and Ohanian (2001) and Stock and Watson (2009), inflation is difficult to forecast compared to many other macroeconomic variables. It is also the case that model-based forecasts typically have a hard time beating survey forecasts[1], see e.g. Ang *et al.* (2007) and Croushore (2010).[2] The often-cited Faust and Wright (2013) made a comprehensive review of a wide range of forecasting methods in the US, Canada, Germany, Japan and United Kingdom. They make use of surveys of inflation expectations and the Fed Greenbook where the latter is partly influenced by model forecasts. Their conclusion is that the simple forecasting method of just taking an AR(1)-path (further described in Section 3.2.4) between the current quarter and the long-run survey forecast beat almost all model-based forecasts. To the authors best knowledge, this proposed method has not been evaluated on Swedish data before.

In practice though, central banks often publish forecasts supported by a rather wide range of forecasting models, e.g. indicator models (mainly used for short-term forecasting), VAR models and general equilibrium models such as DSGE models. The professional inflation forecaster typically has additional information, not captured by the models. These judgmental forecasts generally beat both model-based and survey forecasts, at least at very short forecasting horizons, see for example Lawrence *et al.* (1985) and Murphy and Winkler (1992). Mossfeldt and Stockhammar (2016) showed that judgmental forecasts improve on model-based forecasts at the shortest horizons; one quarter, also in the case of Swedish goods and services inflation.

This study builds on Iversen *et al.* (2016) who compared different models used by the central bank of Sweden (the Riksbank) and found that its Bayesian VAR (BVAR) and DSGE models had better forecasting precision than simple benchmark models and the Riksbank's own published forecasts. The BVAR model also proved to be superior to the

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[1] Survey forecasts is one source of inflation expectations where questions about predicted future inflation are asked to professional economists (from financial institutions or academia), to businesses or to consumers.

[2] Using the Survey of Professional Forecasters, Livingston Survey and Michigan Survey (Ang *et al.*, 2007) and the Survey of Professional Forecasters (Croushore, 2010).

DSGE model. However, compared to other forecasters of Swedish inflation, the Riksbank has among the lowest forecasting precision, see e.g. Sveriges Riksbank (2018). This makes it difficult to draw any conclusions from Iversen *et al.* (2016) regarding the relative forecasting precision of models and subjective forecasts for Swedish inflation.

In this paper we take an even broader perspective and evaluate model-based forecasts, survey forecasts, judgmental forecasts from the National Institute of Economic Research (NIER), the method suggested by Faust and Wright (2013) as well as basic benchmark models for CPIF inflation[3] which is the inflation target variable in Sweden. The BVAR models proposed in Iversen *et al.* (2016) and own refinements of them will also be included in this study.

We find that the new models presented in this paper generally outperform simple benchmark models, the BVAR model of Iversen *et al.*, the NIER's published forecasts as well as survey forecasts. The results also indicate that Faust and Wright's (2013) rather negative conclusion that inflation models cannot beat judgmental forecasts and inflation expectations does not hold in the case of Sweden.

The rest of this paper is organized as follows: Section 2 briefly presents the data used for our analysis. The forecasting 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 make use of quarterly data 1997Q1-2017Q3. The sample 1997Q1-2008Q4 will be used as training period and 2009Q1-2017Q3 as evaluation period. Data are shown in Figures A1 and A2 in Appendix A.

The reason for not using data prior to 1997 is that the inflation target was introduced in 1993 and it took several years before it had full effect on inflation. Also, the Cooperation Agreement on Industrial Development and Wage Formation (the Industrial Agreement) was introduced in Sweden 1997 which, since then, has been used as a benchmark for wage setting in the Swedish labour market. The evaluation period starts in 2009 since CPIF was revised in 2008 due to a measurement error in the production of the index. Starting after 2008 therefore provides a fairer evaluation between forecasters and models.

[3] CPIF inflation is the consumer price index with fixed interest rates.

2.1 Foreign variables

Foreign, i.e. trade-weighted, GDP growth, CPI inflation and *policy rate* are provided by the NIER.[4] GDP growth and inflation are measured as the quarter-on-quarter logarithmic (dlog) seasonally adjusted change.[5] The policy rate is measured by the average policy rate level in each quarter. *The oil price* is provided by Intercontinental Exchange (ICE) and is measured as the quarter-on-quarter percentage change (seasonally adjusted) in US dollars. *Foreign resource utilisation* is measured by the seasonally adjusted unemployment rate in the Euro Area according to Eurostat and by the first principal component from the five main sub-indices in the Economic Sentiment Indicator (ESI, published by the European Commission) for the Euro Area (own calculations).[6]

2.2 Domestic variables

Swedish resource utilisation is measured by the seasonally adjusted unemployment rate according to Statistics Sweden and the Riksbank's resource utilisation indicator.[7] The indicator is derived from calculating the first principal component from, among other sources, the NIER's business survey and unemployment and capacity utilisation in the manufacturing industry according to Statistics Sweden. *Hours worked* and *Swedish GDP growth* are seasonally adjusted dlog data from Statistics Sweden's national accounts. *Labour costs* are either measured by the hourly earnings in the business sector according to the short-term wage and salary statistics provided by the Swedish National Mediation Office (which are measured as the year-on-year percentage change), or by the dlog hourly earnings according to Statistics Sweden. As measure of domestic *inflation* we use the seasonally adjusted quarter-on-quarter percentage change CPIF index published by Statistics Sweden.[8] Data for the *policy rate* is provided by the Riksbank and is measured as the average quarterly repo rate level in each quarter. *The exchange rate* is real exchange rate level according to the KIX index published by the Riksbank.[9,10]

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[4] Trade-weighted using weighted averages of the euro area, Norway, Denmark, UK, US and Japan (before 1999 the policy rate in Japan is not included).

[5] In order to replicate Iversen *et al.* (2016) we use the dlog transformation for some variables and quarter-on-quarter percentage changes for some. Of course, the differences between the two transformations are generally negligible.

[6] Industry, services, construction, retail trade and consumer confidence.

[7] See Nyman (2010).

[8] Dlogs are used instead of percentage changes in the Iversen *et al.* model.

[9] See Erlandsson and Markowski (2006) for information about the index.

[10] The nominal KIX index is published by the Riksbank, whereas the NIER transforms it into real terms.

3 Methodology

3.1 The Bayesian VAR model

The general form of the BVAR-model is given by

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

where $\boldsymbol{G}(L) = \boldsymbol{I} - \boldsymbol{G}_1 L - \boldsymbol{G}_2 L^2 - \cdots - \boldsymbol{G}_m L^m$ is a lag polynominal of order *m*, $\boldsymbol{x}_t$ is an *n*x1 vector of stationary variables, $\boldsymbol{\mu}$ is an nx1 vector describing the steady-state values of the variables in the system and $\boldsymbol{e}_t$ is an *n*x1 vector of *iid* error terms fulfilling $E(\boldsymbol{e}_t) = 0$ and $E(\boldsymbol{e}_t \boldsymbol{e}'_t) = \boldsymbol{\Sigma}$. 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). Also, in our study the BVAR-models generate lower root mean squared forecast errors (RMSFEs) than standard VAR-models, see Table A4 in Appendix C.

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 $vec(\boldsymbol{G})$, where $\boldsymbol{G} = (\boldsymbol{G}_1 \quad \dots \quad \boldsymbol{G}_m)'$, is given by $vec(\boldsymbol{G}) \sim N_{mn^2}(\boldsymbol{\theta}_{\boldsymbol{G}}, \boldsymbol{\Omega}_{\boldsymbol{G}})$.[11] The prior on $\boldsymbol{\mu}$ is given by $\boldsymbol{\mu} \sim N_n(\boldsymbol{\theta}_\mu, \boldsymbol{\Omega}_\mu)$ and is specified in detail in Table A1-A3 in Appendix B. The hyperparameters of the model are uncontroversial and follow the literature.[12]

[11] 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.

[12] 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).

3.2 Model specifications

3.2.1 THE IVERSEN ET AL. BVAR MODEL

The BVAR model presented in Iversen *et al.* (2016) contains three foreign and six domestic variables (see Table 1). The steady state prior intervals are shown in Table A1 in Appendix B. All prior intervals are not disclosed in Iversen *et al.* (2016), however, we received information from the authors about the priors used in 2009 and 2017. We therefore evaluate different versions of the model using the priors the Riksbank used in 2009 and 2017. Although the prior intervals differ, they only affect the forecasting ability to a very limited degree.[13]

3.2.2 REFINED VERSIONS OF THE IVERSEN ET AL. BVAR MODEL

Although Iversen *et al.* (2016) showed that their BVAR model had forecasting ability we believe that there are arguments for modifying its specification to see if it could be improved. From a theoretical standpoint one can argue that the business cycle best could be modelled using some measure of resource utilisation instead of using the change in GDP growth and hours worked. Furthermore, the results in Mossfeldt and Stockhammar (2016) indicated the possibility that forecasting performance might be improved by using a different measure for labour costs than the one used in the Iversen *et al.* model. Because of this we develop and evaluate two refined versions of the Iversen *et al.* model (see refined versions 1 and 2 of the Iversen *et al.* in Table 1).

To decide what measures to include in the refined Iversen *et al.* model we conducted an out-of-sample forecasting exercise where we tested several different measures for both foreign and domestic resource utilisation, as well as labour costs. The variables that proved to have the best predictive power when it came to foreign resource utilisation were unemployment for the Euro Area and the first principal component of the ESI for the Euro Area. In the case of domestic resource utilisation, the variables with the best predictive power were unemployment and the Riksbanks' utilisation indicator. In the case of labour costs, the exercise showed that hourly earnings measured by the short-term wage statistics had best predictive power (see the variables listed in Table A1-A3 in Appendix B for other tested measures). Table 1 shows the variables used in the two refined versions used in this paper.

[13] In Iversen *et al.* (2016) the authors state that the nominal exchange rate level is used in the "current version of the model" According to the Riksbank the real exchange rate level was used in 2017. We have therefore estimated the model using the real exchange level in both versions of the model we present here. However, we have made an estimation of the model using the nominal exchange rate level (not shown). The result (available from the authors upon request) is approximately the same as using the real exchange rate level.

Table 1 Variables used in the selected BVAR models[14]

Iversen et al. model	Refined version 1 of Iversen et al. model	Refined version 2 of Iversen et al. model	GFAPC model 1	GFAPC model 2
Foreign variables				
GDP[1]	EA unemployment	ES indicator	EA unemployment	Oil price
Inflation[1]	Inflation[1]	Inflation[1]	Inflation[1]	
Policy rate[1]	Policy rate[1]	Policy rate[1]		
Domestic variables				
Hours worked	Unemployment	Resource utilisation indicator		Resource utilisation indicator
GDP growth				
Hourly earnings[2]	Hourly earnings[3]	Hourly earnings[3]	Hourly earnings[3]	Hourly earnings[3]
CPIF inflation	CPIF inflation	CPIF inflation	CPIF inflation	CPIF inflation
Repo rate	Repo rate	Repo rate		
Exchange rate	Exchange rate	Exchange rate	Exchange rate	Exchange rate

Note. [1] Trade-weighted, see chapter 2. [2] National accounts. [3] Short-term wage statistics.

3.2.3 THE GLOBAL FACTORS AUGUMENTED PHILLIPS CURVE (GFAPC) MODELS

The fivevariate BVAR models used in Mossfeldt and Stockhammar (2016) in forecasting goods and services inflation in Sweden has proved to have good predictive power and typically beats judgmental forecast at horizons longer than one quarter. We therefore wanted to use the included variables in these models as a starting point when developing other similar forecasting models for CPIF inflation. Thus, to find the best models we conduct a step-wise out-of-sample forecast exercise where several different measures for, and combinations of, resource utilisation, labour costs, exchange rates, survey data and oil prices were tested.

The step-wise forecasting exercise was conducted as follows[15]:

Step 1: We evaluated the forecasting precision of bivariate models at 1-12 quarter horizons with different measures for the *resource utilisation* (and, naturally, CPIF inflation).

Step 2: Here, trivariate models were evaluated by adding measures for *labour costs* to the best bivariate models from step 1.[16]

Step 3: Fourvariate models were evaluated by adding measures for *exchange rate* and *import prices* to the best trivariate models from step 2.

[14] The variables in the x_t-vector of Equation (1) are ordered as in Table 1.

[15] Steps 1-3 in the procedure are based on the order in which the variables enter the BVAR-systems.

[16] Peneva and Rudd (2017) found little evidence that labour costs had a material effect on US inflation in recent years. However, Mossfeldt and Stockhammar (2016) found that labour costs had strong predictive power for Swedish goods and services inflation which motivates the evaluation of these measures in this study.

Step 4: We evaluated fivevariate models by adding *survey data, foreign inflation, oil* and *electricity prices, the bond yield* and *trend inflation* to the best fourvariate models from step 3.[17,18,19]

3.2.4 THE FAUST AND WRIGHT MODEL

The "fixed ρ forecast" was used as a benchmark by Faust and Wright (2013) and it was shown that it had better forecast precision than a vast majority of competing models. Its starting point is at the current inflation rate at the outset and models the path that the inflation rate will take towards what they call the local mean inflation rate.[20] In the "fixed ρ" forecast of Faust and Wright (2013) it is assumed that the inflation gap, g_t, is an AR(1) with a fixed slope coefficient, ρ. Thus, the model is $g_t = \rho g_{t-1} + \varepsilon_t$, where $g_t = \pi_t - \tau_t$ is assumed stationary and τ_t is assumed to follow a random walk. This can in turn be used to obtain a forecast of g_{T+h} and, by adding τ_T back to the forecast, a forecast of inflation.

Since Sweden's Riksbank uses an inflation target of 2 per cent, CPIF-inflation and the 5-year inflation expectations according to the Prospera survey have been relatively stable around this level during the evaluated period, see Figure A3 (with year-on-year CPIF inflation in Figure A4 for comparison) in Appendix A.[21] We have used 2 per cent as equivalent for the local mean inflation rate. The estimated AR(1)-coefficient for the CPIF inflation, ρ, is 0.59 between 1997Q1 and 2008Q4.

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

[18] We have also evaluated six- and sevenvariate models, though adding more variables to the fivevariate models did not increase the forecast accuracy. We have tested different lag lengths and found that m=4 generates the lowest RMSFEs.

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

[20] To capture the varying local mean inflation rate, Faust and Wright (2013) measure the trend level of inflation, τ_t, using the most recent five-to-ten-year inflation forecast from Blue Chip (Blue Chip has asked respondents to predict the average inflation levels from five to ten years' hence twice a year, since 1979).

[21] Until September 2017 the inflation target was formally expressed using CPI inflation. However in practice, as mortgage rates are included in CPI, CPIF inflation has been the main focus for the Riksbank for a long time. From September 2017 the CPIF inflation is also formally the Riksbank's inflation target variable.

4 Forecast comparisons

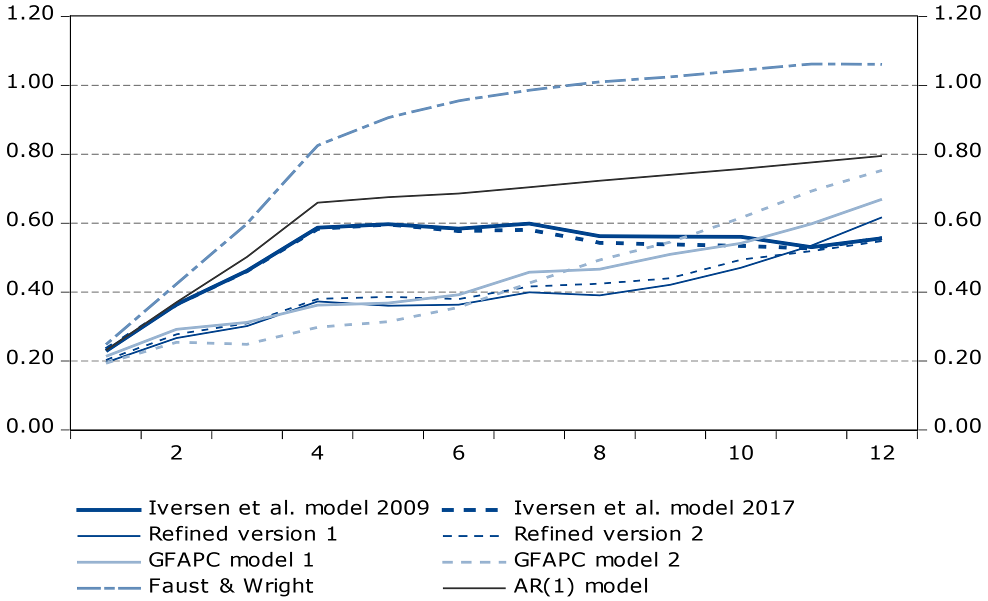
4.1 Models vs a simple benchmark

In this section, we analyse the out-of-sample forecasting precision using quarterly data from 1997Q1 to 2017Q3. We compare the forecasting precision of the BVAR models given in Table 1 above with a benchmark AR(1) 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 1997Q1 to 2008Q4. Forecasts one to twelve quarters ahead, starting 2009Q1, 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 1997Q1 to 2017Q2. The forecast comparisons in this study are thus based on between 24 and 35 forecasts depending on the forecast horizon.

As described in section 3, CPIF inflation is modelled using seasonally adjusted quarter-on-quarter percentage changes. However, most people think about inflation in annual rates which is a reason why year-on-year percentage changes are more commonly used when evaluating the forecasts, see among many others: Iversen *et al.* (2016), Mossfeldt and Stockhammar (2016) and Faust and Wright (2013). In order to facilitate comparisons, year-on-year percentage changes is also used in this section.

The RMSFE of all models and the benchmark AR(1) model are shown in Figure 1. As can be seen, all BVAR models have superior forecasting precision over the AR(1) on all horizons. One of the smaller models (GFAPC model 2) has the lowest RMSFE on the 1-6 quarter horizon, while the larger refined models are better on the 7-10 quarters horizons – clearly outperforming the original Iversen *et al.* model(s) on all but the very longest horizons. Interestingly, the Faust and Wright model has the largest RMSFE of all models, and also larger than the AR(1) model.

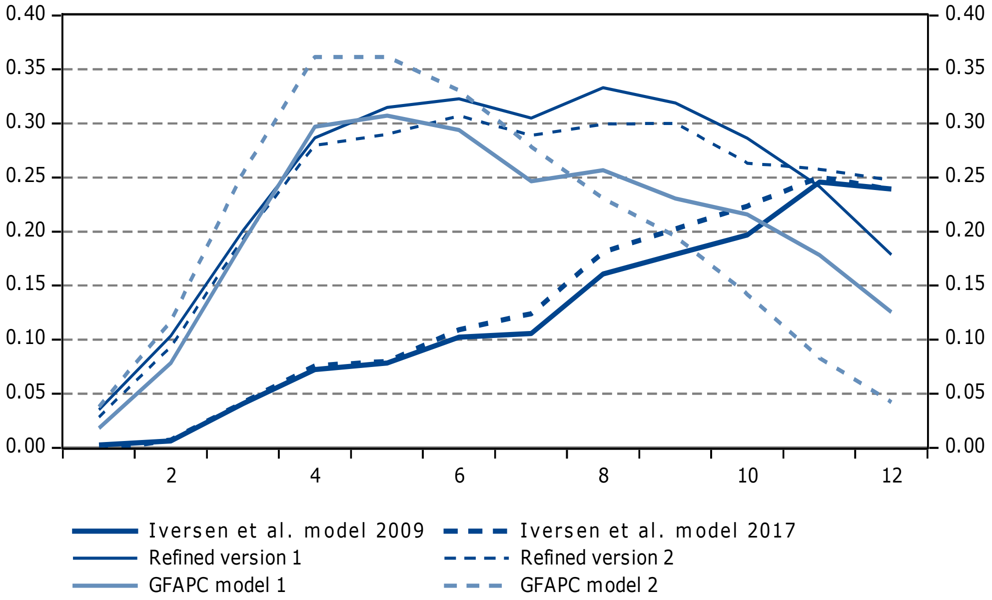
Figure 1 RMSFEs, 2009Q1-2017Q3



The differences in RMSFE between the AR(1) model and the BVAR models are shown in Figure 2. A positive RMSFE difference indicates that the BVAR model has better out-of-sample forecasts than the benchmark model. The models' improvement compared to the AR(1) model is at most 0.36 percentage points in reduction in RMSFE (GFAPC model 2 at the 4 and 5 quarters horizon), which translates into a reduction of the RMSFE by a maximum of 55 per cent.[22] 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).

[22] 100*((0,66-0,30)/0,66)=55 per cent for the GFAPC model 2 at the four quarters horizon, see Table A4 and A5 in Appendix C.

Figure 2 Reduction in RMSFEs compared to an AR(1) model, 2009Q1–2017Q3



Note: Reduction in RMSFEs 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 AR(1) model.

Furthermore, the comparison of the models shows that the GFAPC model 2 is better and the GFAPC model 1 is about as good as the larger models at shorter horizons. However, at longer horizons the larger models outperform the smaller ones. The comparison also shows that the refined versions of the Iversen *et al.* models, by taking the resource utilization explicitly into account, improves the forecasting performance substantially. On average, the reductions in RMSFE are twice as high for the refined Iversen *et al.* models compared to the original models (see Table 2). The differences in forecasting precision are also statistically significant at some horizons.[23]

Table 2 Average reduction in RMSFE compared to an AR(1) model

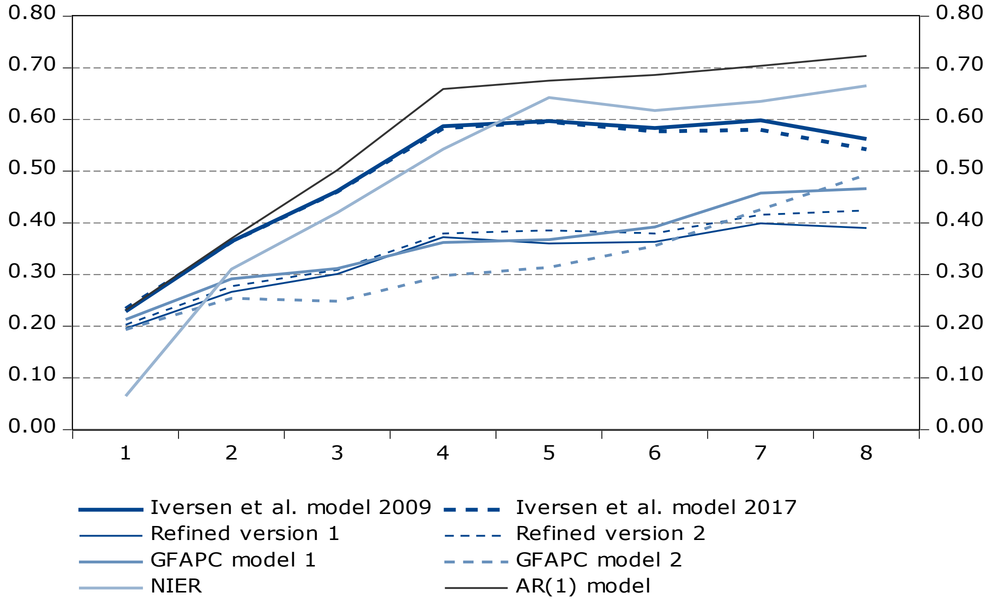
Horizon	Iversen *et al.* 2009	Iversen *et al.* 2017	Refined version 1	Refined version 2	GFAPC model 1	GFAPC model 2
1-4Q	0.03	0.03	0.16	0.15	0.15	0.19
5-8Q	0.11	0.12	0.32	0.30	0.28	0.30
9-12Q	0.22	0.23	0.26	0.27	0.19	0.12
1-12Q	**0.12**	**0.13**	**0.24**	**0.24**	**0.20**	**0.20**

[23] For instance, both the Refined version 1 and GFAPC model 1 have significantly smaller absolute forecast errors than the Iversen *et al.* 2017 model at the 2-8 quarters horizons (Refined version 1) and 3-6 quarters (GFAPC model 1) according to the Diebold-Mariano (1995) test with HAC standard errors. Between the Refined version 1 and GFAPC model 1 there is no significant difference on any horizon. Nor is the Iversen *et al.* 2017 model significantly better at the 11 and 12 quarters horizon.

4.2 Models vs a professional forecaster

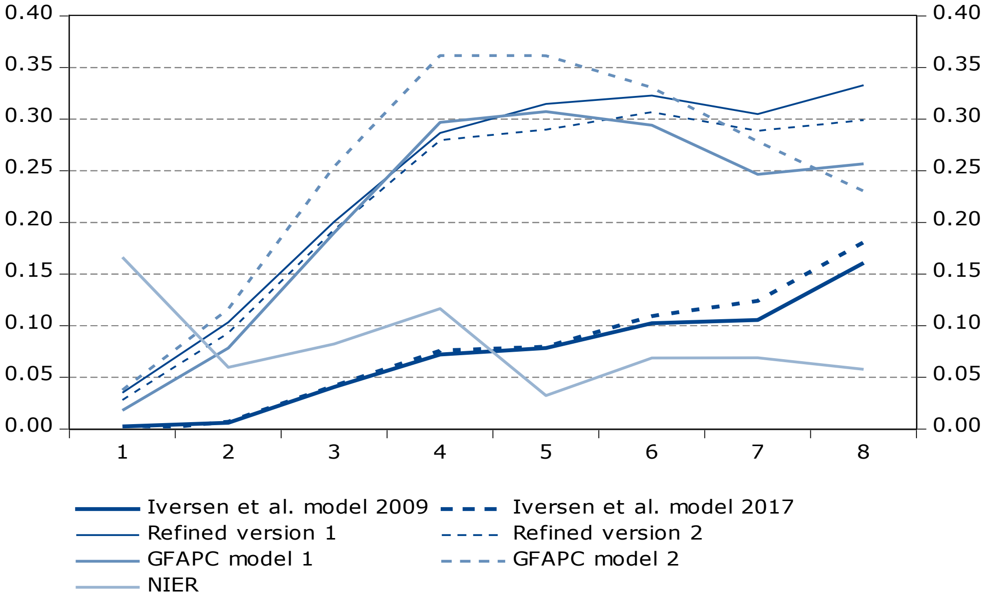
The comparison between the models and a professional forecaster is limited to the 1-8 quarter horizons since the NIER does not publish forecasts at longer horizons.[24] We find that the forecasts made by the NIER outperform the simple benchmark AR(1) model at all horizons, see Figure 3. We can also note that the NIER clearly outperforms the models at the very short term (1 quarter ahead), but has a hard time beating the models at longer horizons. The NIER's RMSFEs are higher than all BVAR models at the 2 to 8 quarters horizons. The notable exception being the original Iversen *et al.* BVAR models, whose RMSFEs are higher than the NIER's at the 1 to 4 quarters horizon.

Figure 3 RMSFEs 2009Q1-2017Q3



[24] The NIER do, however, publish scenarios for longer horizons than 1-8 quarters. The NIER's estimation of developments over the next two years is a forecast while the description of the development thereafter is defined as a scenario. Forecasting refers to an attempt to predict the most likely development of a number of variables, including cyclical variations. Scenarios are thought of as consistent descriptions of macroeconomic developments expected given a number of central, but simplified, assumptions.

Figure 4 Reduction in RMSFEs compared to an AR(1) model, 2009Q1-2017Q3



Note: Reduction in RMSFEs 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 AR(1) model.

When the NIER makes its inflation forecast it generally has an information advantage since one monthly outcome is typically known when the quarterly forecast is made. This information advantage should not, however, be overstated since the volatility of the monthly CPIF data is very high. The NIER's better forecasting precision at the shortest forecast horizon is probably better explained by the use of short-term information such as energy spot prices (which are published daily) and the "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.

That the NIER's forecasts are inferior to the BVAR models at horizons longer than one quarter can probably partly be explained by an inaccurate assessment of how quickly inflation should reach its target (in the absence of disturbances), i.e. there is an inflation target bias. That NIER's forecasts are biased is also shown in Sveriges Riksbank (2018).

4.3 Survey forecasts

Table A6 and A7 in Appendix C show RMSFEs of the main Swedish inflation expectations, namely the 6 different categories of the TNS Sifo Prospera Survey (each at horizons one, two and five years) and the inflation expectations of businesses and households from the NIER survey (both are one-year expectations). The RMSFEs have been calculated by comparing the expectation with the actual value at each horizon (regardless of the intended horizon of the inflation expectations). A selection of inflation expectations data is shown in Figure A3 in Appendix A. Even the survey with the best forecasting precision, the NIER businesses, has far higher RMSFEs than most of the models. This is contrary to the findings of e.g. Ang *et al.* (2007) and Croushore (2010).

4.4 Discussion of model variables

A conclusion from our work in finding out which out of a long list of possible variables that has actual forecasting power is that one does not have to make things complicated. Our chosen models include standard macroeconomic variables such as wages, exchange rate and resource utilization.

Interestingly enough – both foreign and domestic resource utilization shows predictive power for Swedish inflation. This might not, however, be that surprising, since the business cycle in different countries to a large extent tend to move in tandem (which makes the movements of the time series rather similar) and the fact that a large part of the Swedish CPI basket constitutes of imported goods (and services). Our evaluation shows that including a measure of domestic resource utilisation gives about the same increase in forecasting precision as including a measure of foreign resource utilisation, compare the performance of GFAPC model 1 (including foreign resource utilisation) and GFAPC model 2 (domestic). What is also notable is that the employment rate (or survey indicators) shows better predictive power than different types of judgmental measures of the output gap.[25] The fact that foreign inflation often improves the models predictive power can be interpreted as a sign that this variable, to some extent, captures price pressures that is not captured in the already included measures of resource utilisation. That foreign and domestic inflation tend to correlate can be explained not only by the fact that the business cycles tend to correlate, but also because supply shocks to, for example, energy and food prices tend to affect both. That the foreign headline inflation has better predictive power than foreign core inflation might be explained by the fact that energy prices (that is included in headline inflation) are important in explaining variations in (Swedish) inflation.

Given the fact that a nonnegligible part of the CPIF basket is made up of imported goods (and services), it is not surprising that the exchange rate matters. Our finding that the exchange rate has better predictive power than producer prices may be due to the (lower) quality of the producer prices data. The fact that inflation and price expectations did not prove to add predictive power is not at all that surprising since Swedish inflation expectations by their own have limited

[25] See Table A3 in Appendix B. RMSFEs are available from the authors upon request.

predictive power, see Table A6 and A7 in Appendix C. This is also in line with findings in Stockhammar and Österholm (2018), albeit for CPI inflation. One possible interpretation is that (Swedish) inflation expectations are hard to measure and/or that expectations are captured by the other included variables.

5 Conclusions

The results presented in this paper strongly indicate that BVAR models can be useful in forecasting Swedish inflation. The presented BVAR models do not only reduce the RMSFE's compared to an AR(1) model benchmark by on average 34 per cent[26], as well as compared to survey forecasts (as advocated by e.g. Ang *et al.* (2007) and Croushore (2010)), they also clearly outperform one of the best professional inflation forecasters in Sweden on all (but the shortest) forecasting horizons.[27] The presented BVAR models also clearly outperform the best forecasting models used by the Riksbank as presented in Iversen *et al.* (2016) .

Small models containing only five standard macroeconomic variables - such as resource utilisation, labour costs and the exchange rate – have significantly higher forecasting precision at the 3-6 quarters horizons than the BVAR models presented in Iversen *et al.* (2016). Larger models perform better at longer forecasting horizons than the smaller ones and have a better forecasting precision on average (1-12 quarters) than both the smaller models and, especially, the Iversen *et al.* model for which the differences in forecasting precision are statistically significant at the 2-8 quarters horizons. Previous research has shown that the inflation forecasting performance of Phillips curve models have been rather mixed (see, for example, Faust and Wright (2013), Stock and Watson (2009)). The results in this paper indicate that including resource utilization increases forecasting performance for Swedish inflation. For example, the refined versions of the Iversen *et al.* model that explicitly takes resource utilization into account, prove to have a much better forecasting precision than the original Iversen *et al.* model. Our result thus supports the conclusion in Karlsson and Österholm (2018) that the Phillips curve is alive and well in Sweden.

[26] The average refers to the average RMSFE (1-12 quarters) of the refined Iversen *et al.* models and the smaller BVAR models, i.e. the RMSFEs of the original Iversen *et al.* models are not included in the calculation.

[27] The NIER belongs to the forecast institutions with highest forecasting precision 2007-2017 according to Sveriges Riksbank (2018).

Furthermore, the results show that foreign resource utilization – as well as foreign inflation – are important predictors in forecasting Swedish inflation, indicating that global factors can be just as important as domestic ones. Whether global factors have become an important factor in explaining domestic inflation is debated in the literature. For example, Borio and Filardo (2007) found that global resource utilisation added considerable explanatory power to benchmark Phillips curve models that did not include this dimension. Most recent studies, tend to find the effects to be less eye-caching. For example, Mikolajun and Lodge (2016) found that foreign resource utilisation had no effects on domestic inflation for most of the advance countries in their study (curiously enough, in the case of Sweden, the estimated coefficient was positive, but insignificant). Another example is ECB (2017) that found that foreign slack was significant in about a third of the more than 100 estimated specifications containing both domestic and foreign resource utilisation.

The fact the best models have better forecasting precision than the NIER, which is one of Sweden's best professional inflation forecasters, indicates that one should be pragmatic when forecasting inflation. To this end, BVAR models can be a useful tool; allowing the user to use his or her knowledge to set reasonable priors, and at the same time letting the actual data to have a say. As Yellen argued in a famous speech in 2017 it might be the case that we know less about inflation dynamics than we might like to think we do.[28] One case in point is that the NIER's forecasts have been biased, indicating a systematic belief that the inflation would be higher (closer to the target) than what proved to be the case.[29]

Furthermore, the presented results strongly indicate that Faust and Wright's (2013) conclusion that inflation models cannot beat judgmental forecasts is not valid in the case of Sweden. The results also show that that their conclusion that the very simple forecasting method of just taking a simple glide path between the current quarter and the long-run survey forecasts can beat almost all model-based forecasts is also not correct for Sweden. In fact, all presented models outperform the Faust and Wright "fixed ρ model" model. This might, however, not be so surprising given the fact that CPIF inflation has systematically been lower than the inflation target for a long time (and that their model is based on inflation going back to the target over time). However, Faust and Wright (2013) did not evaluate any BVAR models of the kind presented in this paper.

In this paper we have proposed BVAR models that, compared to the state-of-the-art academic literature and prior empirical findings, improve the inflation forecasting

[28] See Yellen (2017).

[29] See e.g. Sveriges Riksbank (2018).

precision in Sweden. The improvements are typically quantitatively meningful and sometimes statistically significant. The findings in this paper might be beneficial to all analysts and forecasters of Swedish inflation.

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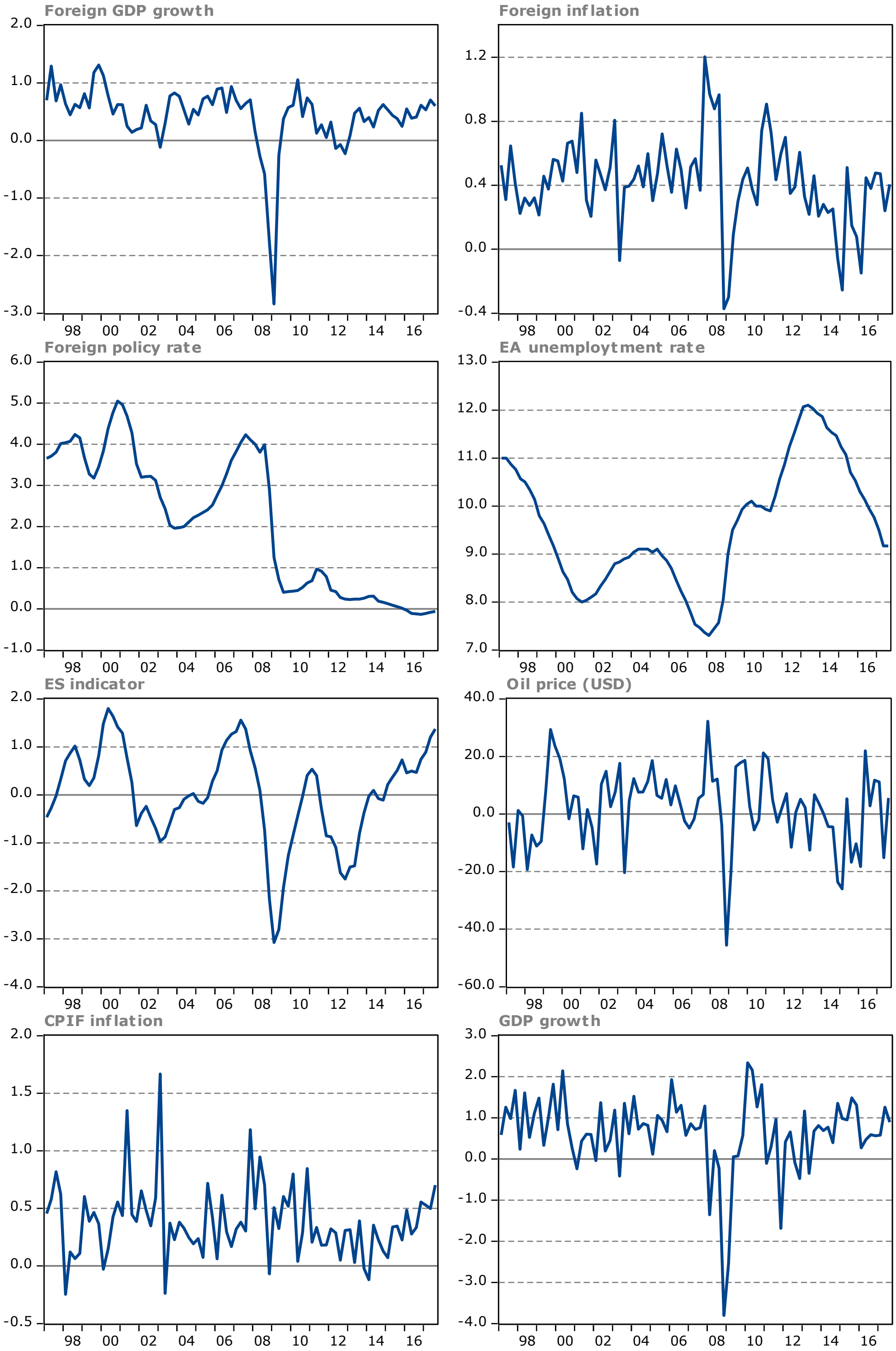
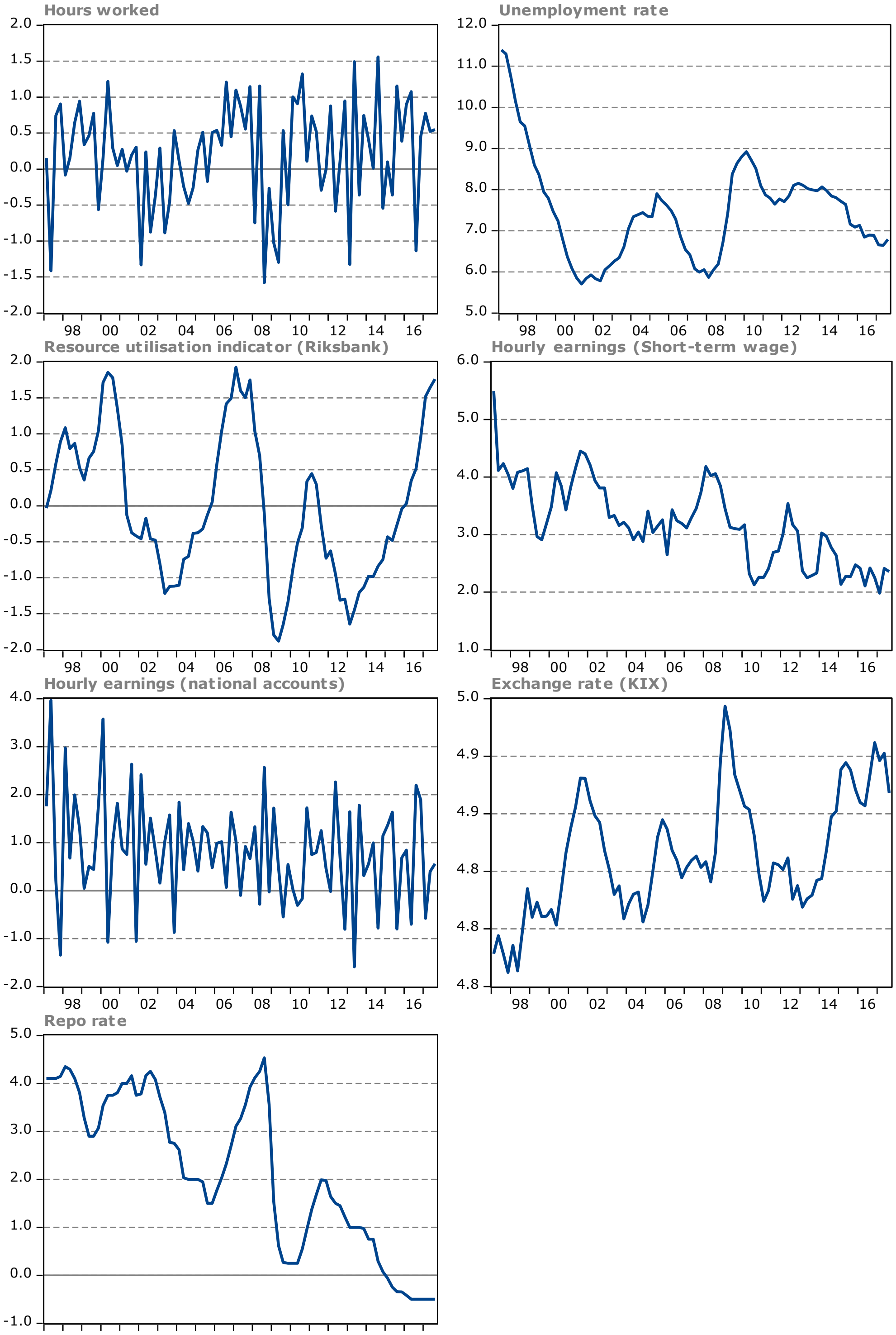
Appendix A – Data

Figure A1. The Data



Note. Foreign and Swedish GDP growth and foreign inflation is given as the quarter-on-quarter logarithmic change (dlog). Foreign policy is the average policy rate level in each quarter. The oil price and domestic inflation (CPIF) is measured as the quarter-on-quarter percentage change. The EA unemployment rate and the ES indicator are measured in per cent. See Section 2 for more information.

Figure A2. The Data (cont.)



Note. Hours worked is given as the quarter-on-quarter logarithmic change (dlog). Hourly earnings (short-term wage) is measured as the year-on-year percentage change and hourly earnings (national accounts) is given as the quarter-on-quarter logarithmic change (dlog). The unemployment rate and the resource utilisation indicator (by the Riksbank) are measured in per cent. The exchange rate is measured in level. The Swedish policy rate (the repo rate) is the average policy rate level in each quarter. See Section 2 for more information.

Figure A3. A selection of inflation expectations

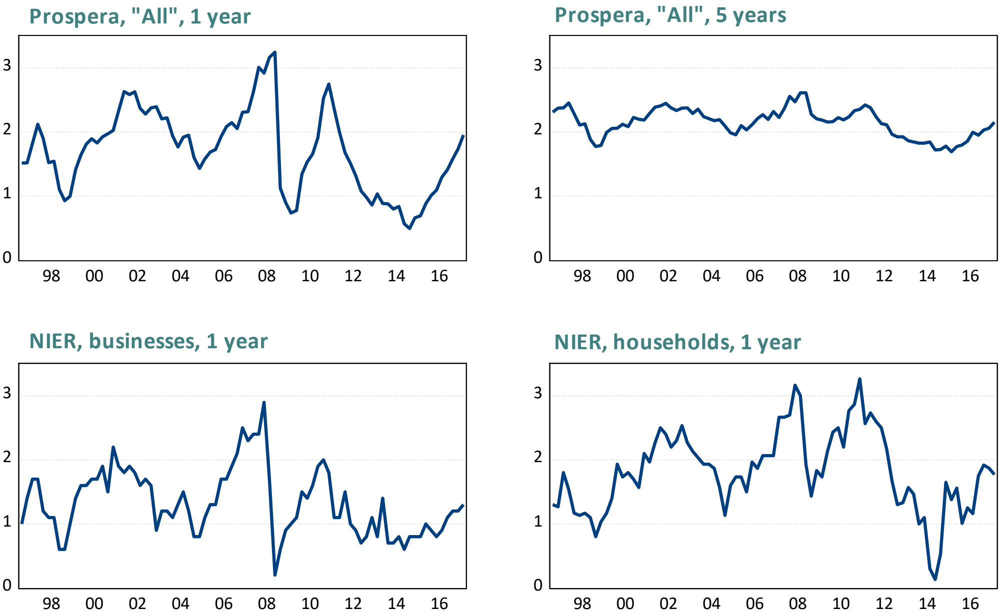
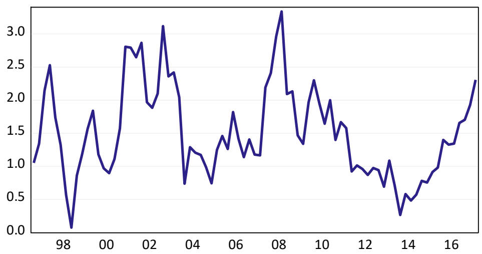


Figure A4. CPIF inflation (year-on-year)



Appendix B – Steady state priors

Table A1 Steady state priors for variables included in the Iversen et al. model

Type of variable	The Iversen et al. model	Prior interval 2009	Prior interval 2017
Foreign	GDP growth[1]	(2.0; 3.0)	(2.0; 3.0)
	Inflation[1]	(1.5; 2.5)	(2.0; 3.0)
	Policy rate[1]	(4.5; 5.5)	(4.5; 5.5)
Business cycle	Hours worked	(0.0; 0.5)	(0.0; 0.5)
	GDP growth	(2.0; 2.5)	(1.9; 2.1)
Labour costs	Hourly earnings[2]	(3.5; 4.5)	(3.5; 4.5)
Inflation	CPIF inflation	(1.95; 2.05)	(1.99; 2.01)
Policy rate	Repo rate	(4.2; 4.4)	(4.2; 4.3)
Exchange rate	Real KIX	(4.75; 4.85)	(4.8; 5.0)

Note. 1 Trade-weighted. 2. National accounts. Ninety-five percent prior probability intervals for parameters determining the unconditional means. Prior distributions are all assumed to be normal.

Table A2 Included variables and steady-state priors for the refined versions of the Iversen et al. model and the GFAPC models

Type of variable		Prior interval
Foreign	Inflation[1]	(2.0; 3.0)
	Policy rate[1]	(4.5; 5.5)
	EA unemployment	(−1.0; 1.0)
	ES indicator	(−1.0; 1.0)
	Oil price (USD)	(−2.0; 3.5)
Business cycle	Unemployment	(5.0; 9.0)
	Resource utilisation indicator	(−1.0; 1.0)
Labour costs	Hourly earnings[2]	(2.6; 4.6)
Inflation	CPIF inflation	(1.0; 3.0)
Policy rate	Repo rate	(4.2; 4.4)
Exchange rate	Real KIX	(4.8; 5.0)

Note. 1 Trade-weighted. 2. Short-term wage statistics. The model from 2009 have different values for the mean on first lag for the variables, whereas in 2017 this is set to 0 for all variables. Ninety-five percent prior probability intervals for parameters determining the unconditional means. Prior distributions are all assumed to be normal.

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

Type of variable	Prior interval
Foreign resource utilisation	
US output gap (OECD)	(−1.0; 1.0)
OECD output gap (OECD/NIER)	(−1.0; 1.0)
Euro Area (19) output gap (OECD)	(−1.0; 1.0)
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)
Unemployment rate	(5.0; 9.0)
Short-term unemployment rate	(3.5; 6.0)
Labour costs	
Labour costs (per hour)	(0.5; 1.3)
Unit labour cost	(0.0; 0.8)
Exchange rates and prices	
KIX16	(−1.0; 1.0)
Euro/SEK	(−1.0; 1.0)
USD/SEK	(−1.0; 1.0)
Import prices, manufactured goods	(−0.7; 1.7)
Import prices, food	(−0.7; 1.7)
Producer prices, goods, imported+domestic	(−2.0; 3.5)
Producer prices, food, imported+domestic	(−2.0; 3.5)
Oil price (SEK)	(−2.0; 2.0)
Electricity, spot price	(−10.0; 11.0)
Survey	
Inflation expectations, the Economic Tendency Survey	(1.0; 3.0)
Price expectations, principal component	(-1.0; 1.0)
Price expectations, food	(1.0; 3.0)
Price expectations, specialized trade	(1.0; 3.0)
The Economic Tendency Indicator	(90; 110)
Consumer confidence indicator	(90; 110)
Other	
EA HICP excl. energy, food, alkohol, tobacco	(1.0; 3.0)
Government bond yield (3 months maturity)	(3.0; 5.0)
CPIF, 3 quarters moving average	(0.25; 0.75)
CPIF, 9 quarters moving average	(0.25; 0.75)
CPIF trend, principal component of all price groups	(-1.0; 1.0)
CPIF, 3 quarters moving average, principal component	(-1.0; 1.0)
Trim75, underlying inflation[1]	(1.0; 3.0)

Note. Labour costs, unit labour 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. Survey data are measured as an index. Ninety-five percent prior probability intervals for parameters determining the unconditional means. Prior distributions are all assumed to be normal.

[1] Similar to the Trim85 measure by the Riksbank, read more at https://www.riksbank.se/en-gb/statistics/macro-indicators/underlying-inflation/

Appendix C – RMSFEs

Table A4 RMSFEs of all models

Percentage points

Horizon	AR(1)	Recent mean	No change	Iversen et al. 2009	Iversen et al. 2017	Refined version 1	Refined version 2	GFAPC model 1	GFAPC model 2	F&W	NIER	VAR Refined 1	VAR Refined 2	VAR GFAPC 1	VAR GFAPC 2
1Q	0.23	0.22	0.29	0.23	0.23	0.20	0.20	0.21	0.19	0.25	0.06	0.51	0.43	0.34	0.25
2Q	0.37	0.36	0.51	0.36	0.36	0.27	0.28	0.29	0.25	0.42	0.31	0.59	0.53	0.43	0.36
3Q	0.50	0.49	0.69	0.46	0.46	0.30	0.31	0.31	0.25	0.60	0.42	0.70	0.66	0.57	0.41
4Q	0.66	0.65	0.94	0.59	0.58	0.37	0.38	0.36	0.30	0.83	0.54	0.86	0.83	0.72	0.53
5Q	0.68	0.71	0.93	0.60	0.60	0.36	0.39	0.37	0.31	0.91	0.64	1.01	1.10	0.76	0.49
6Q	0.69	0.76	0.90	0.58	0.58	0.36	0.38	0.39	0.36	0.95	0.62	1.36	1.00	0.87	0.55
7Q	0.70	0.82	1.00	0.60	0.58	0.40	0.42	0.46	0.43	0.99	0.64	1.49	0.78	1.01	0.65
8Q	0.72	0.87	1.06	0.56	0.54	0.39	0.42	0.47	0.49	1.01	0.67	1.24	0.47	1.08	0.70
9Q	0.74	0.91	1.08	0.56	0.54	0.42	0.44	0.51	0.55	1.02	na	0.97	0.76	0.83	0.69
10Q	0.76	0.93	1.17	0.56	0.53	0.47	0.49	0.54	0.62	1.04	na	0.83	1.10	0.70	0.77
11Q	0.78	0.97	1.17	0.53	0.53	0.54	0.52	0.60	0.69	1.06	na	1.43	1.55	0.84	0.87
12Q	0.80	1.00	1.15	0.56	0.56	0.62	0.55	0.67	0.75	1.06	na	3.08	1.46	1.12	0.98

Table A5 Reduction in RMFSE compared to an AR(1) model

Percentage points

Horizon	Iversen et al. 2009	Iversen et al. 2017	Refined version 1	Refined version 2	GFAPC model 1	GFAPC model 2	F&W	NIER
1Q	0.00	0.00	0.04	0.03	0.02	0.04	−0.02	0.17
2Q	0.01	0.01	0.10	0.09	0.08	0.12	−0.05	0.06
3Q	0.04	0.04	0.20	0.19	0.19	0.25	−0.10	0.08
4Q	0.07	0.08	0.29	0.28	0.30	0.36	−0.17	0.12
5Q	0.08	0.08	0.32	0.29	0.31	0.36	−0.23	0.03
6Q	0.10	0.11	0.32	0.31	0.29	0.33	−0.27	0.07
7Q	0.11	0.12	0.31	0.29	0.25	0.28	−0.28	0.07
8Q	0.16	0.18	0.33	0.30	0.26	0.23	−0.29	0.06
9Q	0.18	0.20	0.32	0.30	0.23	0.20	−0.28	na
10Q	0.20	0.22	0.29	0.26	0.22	0.14	−0.29	na
11Q	0.25	0.25	0.24	0.26	0.18	0.08	−0.29	na
12Q	0.24	0.24	0.18	0.25	0.13	0.04	−0.27	na
Average reduction								
1–4Q	0.03	0.03	0.16	0.15	0.15	0.19	−0.08	0.11
5–8Q	0.11	0.12	0.32	0.30	0.28	0.30	−0.27	0.06
9–12Q	0.22	0.23	0.26	0.27	0.19	0.12	−0.28	na
1–12Q	**0.12**	**0.13**	**0.24**	**0.24**	**0.20**	**0.20**	**−0.21**	**na**

Table A6. RMSFEs of inflation expectations

Horizon	Prospera, All, 1 year	Prospera, All, 2 years	Prospera, All, 5 years	Prospera, Employees, 1 year	Prospera, Employees, 2 years	Prospera, Employees, 5 years	Prospera, Employers, 1 year	Prospera, Employers, 2 years	Prospera, Employers, 5 years
1Q	0,63	0,65	0,91	0,67	0,66	0,93	0,66	0,63	0,96
2Q	0,72	0,72	0,93	0,76	0,72	0,94	0,77	0,71	0,99
3Q	0,79	0,77	0,96	0,83	0,78	0,96	0,83	0,76	1,00
4Q	0,84	0,82	0,99	0,89	0,83	0,99	0,89	0,81	1,03
5Q	0,86	0,86	1,02	0,91	0,86	1,01	0,92	0,86	1,07
6Q	0,90	0,90	1,06	0,95	0,90	1,04	0,95	0,89	1,10
7Q	0,94	0,95	1,09	0,99	0,94	1,07	0,99	0,94	1,13
8Q	0,96	0,98	1,14	1,00	0,97	1,10	1,02	0,97	1,16
9Q	0,98	1,01	1,16	1,03	1,00	1,13	1,03	1,00	1,18
10Q	1,01	1,04	1,20	1,06	1,04	1,17	1,04	1,02	1,22
11Q	1,03	1,08	1,24	1,07	1,06	1,19	1,06	1,05	1,25
12Q	1,04	1,09	1,25	1,07	1,06	1,19	1,06	1,05	1,24

Note: The RMSFEs have been calculated by comparing the expectation with the actual value at each horizon (regardless of the intended horizon of the inflation expectations).

Table A7. RMSFEs of inflation expectations. cont.

Horizon	Prospera PMM, 1 year	Prospera PMM, 2 years	Prospera PMM, 5 years	Prospera PMT, 1 year	Prospera PMT, 2 years	Prospera PMM, 5 years	Prospera MMP, 1 year	Prospera MMP, 2 years	Prospera MMP, 5 years	NIER busi-nesses	NIER house-holds
1Q	0,69	0,68	0,90	0,63	0,67	0,94	0,54	0,67	0,88	0,52	0,87
2Q	0,78	0,75	0,93	0,73	0,74	0,96	0,63	0,71	0,90	0,58	0,94
3Q	0,85	0,81	0,96	0,79	0,80	0,99	0,71	0,76	0,91	0,66	1,01
4Q	0,89	0,86	1,00	0,84	0,84	1,01	0,75	0,80	0,94	0,70	1,09
5Q	0,92	0,91	1,05	0,87	0,88	1,05	0,76	0,82	0,97	0,69	1,15
6Q	0,96	0,95	1,09	0,91	0,92	1,09	0,78	0,85	1,00	0,68	1,21
7Q	1,00	1,00	1,14	0,95	0,97	1,11	0,82	0,90	1,03	0,72	1,26
8Q	1,03	1,04	1,19	0,98	1,00	1,15	0,84	0,93	1,07	0,74	1,33
9Q	1,04	1,06	1,22	1,01	1,03	1,18	0,87	0,96	1,09	0,74	1,39
10Q	1,07	1,11	1,27	1,03	1,06	1,22	0,89	0,99	1,12	0,76	1,46
11Q	1,10	1,14	1,31	1,05	1,10	1,25	0,90	1,01	1,15	0,77	1,49
12Q	1,11	1,15	1,32	1,07	1,11	1,26	0,92	1,02	1,16	0,78	1,48

Note: The RMSFEs have been calculated by comparing the expectation with the actual value at each horizon (regardless of the intended horizon of the inflation expectations). PMM=purchasing managers, manufacturing, PMT=purchasing managers, trading and MMP=money market players