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National Institute of Economic Research

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June 2016

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# Abstract

In this paper, Bayesian VAR models are used to forecast employment growth in Sweden. Using quarterly data from 1996 to 2015, we conduct an out-of-sample forecast exercise. Results indicate that the forecasting performance at short horizons can be improved when survey data is included, such as employment expectations in the business sector and forward-looking variables from the trade sector.

# Sammanfattning

I denna studie används bayesianska VAR-modeller för att prognostisera svensk sysselsättningstillväxt. Resultaten från en prognosutvärdering med kvartalsdata för perioden 1996–2015 visar att data från Konjunkturbarometern kan användas för att förbättra sysselsättningsprognoser på kort sikt. Det gäller exempelvis anställningsplanerna i hela näringslivet och olika förväntningar i handeln.

**JEL classification code**: E24, C11

Keywords: Bayesian VAR model, employment forecasting

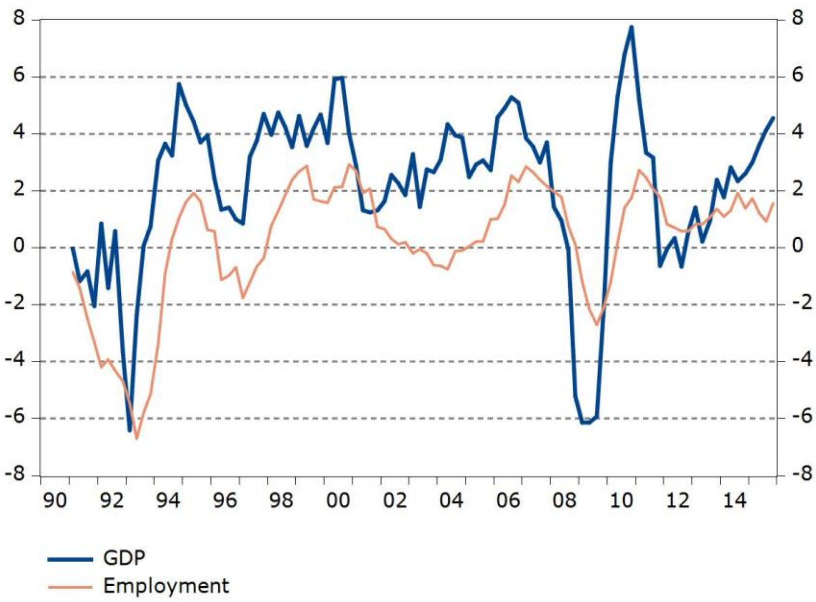
# Contents

# 1 Introduction

Since employment growth is a variable of fundamental interest to many economic agents, there is a great interest in employment forecasts. Over the last years, employment growth in Sweden has been surprisingly strong given the growth in GDP (see Figure 1).[1]

When it comes to forecasting employment growth in the short run, it could be beneficial to rely on models that employ survey data. Survey data is supposed to serve as coinciding or leading indicators, see, for example, Carroll et al. (1994), Ludvigson (2004), Dreger and Schumacher (2005), Hansson et al. (2005), Kwan and Cotsomitis (2006), Banbura et al. (2011) and Siliverstovs (2013).

**Figure 1. Real GDP and employment**
Annual percentage change




Source: Statistics Sweden.

In this paper, Bayesian VAR models are used to forecast employment growth in Sweden. The models include employment growth, GDP growth and survey data provided

[1] Österholm (2016) points out that the GDP growth required to keep the unemployment rate in Sweden constant appears to have fallen the last ten years.

by the National Institute of Economic Research's (NIER) *Economic Tendency Survey*. We conduct an out-of-sample forecast exercise and find that Bayesian VAR models including survey data outperform a univariate Bayesian VAR model for employment growth.

# 2 Empirical analysis

Using seasonally adjusted quarterly data from 1996Q1 to 2015Q2, we estimate Bayesian VAR models of the type:

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

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 $n \times 1$ vector of stationary variables, $\boldsymbol{\mu}$ is an $n \times 1$ vector describing the steady-state values (unconditional means) of the variables in the system and $\boldsymbol{\eta}_t$ is an $n \times 1$ vector of iid error terms fulfilling $E(\boldsymbol{\eta}_t) = \mathbf{0}$ and $E(\boldsymbol{\eta}_t \boldsymbol{\eta}_t') = \boldsymbol{\Sigma}$.[2] We estimate four different model specifications:

$$\mathbf{x}_t = (e_t)' \tag{2}$$

$$\mathbf{x}_t = (e_t, y_t)' \tag{3}$$

$$\mathbf{x}_t = (e_t, y_t, S_{1t})' \tag{4}$$

$$\mathbf{x}_t = (e_t, y_t, S_{1t}, S_{2t})', \tag{5}$$

where $e_t$ is the percentage change in seasonally adjusted employment, $y_t$ is the percentage change in seasonally adjusted real GDP and $S_t$ are survey data from the quarterly *Economic Tendency Survey* (ETS) conducted by the NIER.

The number of variables in the ETS is large and conducting an out-of-sample forecast exercise in a BVAR framework for every possible combination of variables in the ETS would be very time consuming. In order to narrow down the number of potential

[2] This mean-adjusted specification was developed by Villani (2009). This specification has been proven useful when it comes to forecasting; see for example Beechey and Österhom (2010).

variables of interest, we initially conducted a nowcasting exercise in which one survey data variable was tested at a time.[3] The results are shown in Table A1 in the Appendix. Four variables in the survey were identified as particularly interesting, due to their, compared to the alternatives, low root mean squared forecast errors, namely employment expectations in the total business sector (henceforth denoted $STOTNEE_t$ ), purchases of goods expectations in the trade sector (question 202, henceforth denoted $STR202_t$ ), business activity (sales) expectations in the trade sector (question 201, henceforth denoted $STR201_t$ ), and new orders from the domestic market in the manufacturing industry (question 107, henceforth denoted $SIND107_t$ ), Data are shown in Figure A1 in the Appendix.

Turning to the priors of the models, the prior on $\mathbf{\Sigma}$ is given by $p(\mathbf{\Sigma}) \propto |\mathbf{\Sigma}|^{-(n+1)/2}$ and the prior on $vec(\mathbf{G})$, where $\mathbf{G} = (\mathbf{G}_1 \quad \ldots \quad \mathbf{G}_m)'$, is given by $vec(\mathbf{G}) \sim N_{mn^2}(\mathbf{\theta_G}, \mathbf{\Omega_G})$.[4] The prior on $\mathbf{\mu}$ is given by $\mathbf{\mu} \sim N_n(\mathbf{\theta_\mu}, \mathbf{\Omega_\mu})$ and is specified in detail in Table 1. The priors for employment and GDP growth are in line with the NIER's assessments, while the priors for the survey data are roughly in line with historical averages.[5] The hyperparameters of the models follow the literature.[6] Finally, the lag length is set to $m = 4$ in all models.[7]

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[3] The nowcasting equations using survey data have the form $e_t = a + bS_{t-1} + v_t$ where $e_t$ is defined as in equation (2), $S_{t-1}$ is series from the ETS and $v_t$ is an error term assumed to be white noise.

[4] In line with Villani (2009) the priors on the dynamics are modified slightly relative to the traditional Minnesota prior. Rather than 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 for variables that are modelled in levels and 0.0 for variables that are expressed as growth rates; all subsequent lags have a prior mean of zero. This is due to the fact 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.

[5] In the case of survey data, there is little guidance to be had from theory or institutional knowledge. We then choose to make the prior distribution less informative for the steady state for these variables. The values are hence set so they roughly meet the arithmetic mean of the series during the sample, see for example Österholm (2010).

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

[7] In choosing lag lenght, we follow Litterman's (1986) suggestion to include as many lags as is computationally feasible. We argue that $m = 4$ is the largest reasonable value given the number of observations available at the first out-of-sample forecast. However, an out-of-sample forecast exercise using alternative lag structures was examined. The results are presented in Table A2 in the Appendix. When we reduce the lag length to 3 and then to 2, we find marginal improvements in the forecasting power. However, the main conclusions are not sensitive to the choice of lag length.

To evaluate the forecasting ability of the models, we conduct an out-of-sample forecast exercise. The first out-of-sample forecast is made using seasonally adjusted quarterly data from 1996Q1 until 2001Q4. The forecast generated from this estimation is

for the 12 following quarters, 2002Q1–2004Q4. We then extend the sample one period, re-estimate the model and generate new forecasts, this time for 2002Q2–2005Q1. The last forecast uses data on employment growth until 2015Q1. This yields a total of 53 out-of-sample forecasts to evaluate at the one-quarter horizon and 42 at the twelve-quarters horizon.

**Table 1. Means, standard deviations and steady-state priors for the Bayesian VAR**

| | Mean 1996-2015 | Mean 2002-2015 | Standard-deviation 1996-2015 | Standard-deviation 2002-2015 | Prior interval |
|---|---|---|---|---|---|
| $e_t$ | 0,2 | 0,2 | 0,4 | 0,4 | (0.00, 0.50) |
| $y_t$ | 0,6 | 0,5 | 0,9 | 1,0 | (0.425, 0.675) |
| $STOTNEE_t$ | 0 | 0 | 13 | 14 | (−5.0, 5.0) |
| $STR202_t$ | 23 | 24 | 16 | 17 | (18.0, 28.0) |
| $STR201_t$ | 38 | 38 | 17 | 18 | (32.0, 42.0) |
| $SIND107_t$ | 7 | 7 | 14 | 16 | (1.0, 11.0) |

Note: Ninety–five percent prior probability intervals for parameters determining the unconditional means. Prior distributions are all assumed to be normal. Variables are defined in equation (5).

Forecast errors are recorded and used to calculate the root mean square forecast errors (RMSFE). The RMSFE is defined as:

$$RMSFE_h = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1}\left(e_{t+h+i} - \hat{e}_{t+h+i|t+i}\right)^2}\,, \qquad (6)$$

where $N$ is the number of forecasts, $e_{t+h+i}$ is the employment outcome at time $t+h+i$ and $\hat{e}_{t+h+i|t+i}$ is the forecast of employment growth for quarter $t+h+i$ made at $t+i$.

# 3 Results

The results from the out-of-sample exercise are given in Table 2. Twelve different models were tested. As can be seen, all models including survey data outperform a univariate model at short horizons. Improvements using survey data are large and indicate a reduction in RMSFE with about 15 to 25 per cent at one-quarter horizons (see Figure 2). The models including survey data also outperform a bivariate model including employment growth and GDP growth at short horizon.

**Table 2. Root mean square forecast errors for estimated models**

| Model | h=1 | h=2 | h=3 | h=4 | h=5 | h=6 | h=7 | h=8 | h=9 | h=10 | h=11 | h=12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $e_t$ | 0.350 | 0.376 | 0.411 | 0.430 | **0.435** | **0.439** | **0.432** | **0.424** | 0.421 | 0.416 | **0.416** | **0.413** |
| $e_t, y_t$ | 0.319 | 0.355 | 0.400 | 0.427 | **0.435** | **0.439** | **0.432** | **0.424** | **0.420** | **0.415** | 0.418 | **0.413** |
| $e_t, y_t, STOTNEE_t$ | 0.272 | 0.318 | 0.377 | 0.430 | 0.462 | 0.483 | 0.477 | 0.473 | 0.459 | 0.443 | 0.434 | 0.426 |
| $e_t, y_t, STR202_t$ | 0.270 | 0.302 | 0.368 | **0.410** | 0.436 | 0.454 | 0.449 | 0.445 | 0.434 | 0.427 | 0.422 | 0.418 |
| $e_t, y_t, STR201_t$ | 0.259 | **0.287** | **0.359** | 0.411 | 0.439 | 0.459 | 0.457 | 0.453 | 0.444 | 0.432 | 0.430 | 0.424 |
| $e_t, y_t, SIND107_t$ | 0.290 | 0.315 | 0.378 | 0.413 | 0.443 | 0.454 | 0.450 | 0.447 | 0.437 | 0.426 | 0.424 | 0.418 |
| $e_t, y_t, STOTNEE_t, STR202_t$ | 0.264 | 0.306 | 0.371 | 0.422 | 0.455 | 0.476 | 0.471 | 0.468 | 0.454 | 0.440 | 0.434 | 0.426 |
| $e_t, y_t, STOTNEE_t, STR201_t$ | **0.255** | 0.294 | 0.361 | 0.420 | 0.450 | 0.473 | 0.470 | 0.466 | 0.455 | 0.441 | 0.435 | 0.427 |
| $e_t, y_t, STOTNEE_t, SIND107_t$ | 0.272 | 0.312 | 0.376 | 0.432 | 0.468 | 0.487 | 0.484 | 0.483 | 0.465 | 0.447 | 0.439 | 0.427 |
| $e_t, y_t, STR201_t, STR202_t$ | 0.260 | 0.292 | 0.364 | 0.415 | 0.444 | 0.465 | 0.460 | 0.458 | 0.446 | 0.436 | 0.432 | 0.425 |
| $e_t, y_t, STR201_t, SIND107_t$ | 0.261 | 0.290 | 0.365 | 0.415 | 0.449 | 0.470 | 0.464 | 0.463 | 0.451 | 0.439 | 0.434 | 0.425 |
| $e_t, y_t, STR202_t, SIND107_t$ | 0.272 | 0.303 | 0.370 | 0.415 | 0.447 | 0.464 | 0.458 | 0.456 | 0.444 | 0.431 | 0.426 | 0.421 |

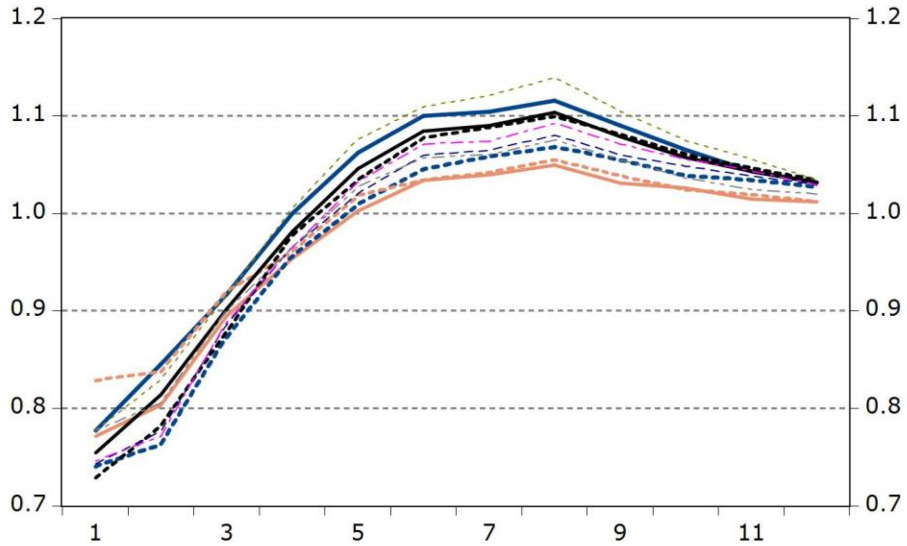
The trivariate model including employment growth, GDP growth and business activity (sales) expectations in the trade sector ($STR201_t$) has the lowest RMSFE, for the second and the third quarter. Employment expectations in the total business sector ($STOTNEE_t$) is widely used to predict employment in the short-term, both within the NIER and other forecast institutes in Sweden. Our results indicate that employment expectations indeed add valuable information. A four-variate model including employment growth, GDP growth, employment expectations in the total business sector ($STOTNEE_t$) and business activity (sales) expectations in the trade sector ($STR201_t$) has the lowest RMSFE the first forecasting quarter. However, after four to five quarters the univariate model and the model with GDP have the lowest RMSFEs (see Figure 2).[8] [9]

[8] We also conduct an out-of-sample forecast exercise using a traditionally specified VAR model estimated with classical methods. That is, the model given as: $\mathbf{G}(L)\mathbf{x}_t = \delta + \boldsymbol{\eta}_t$ . The results are presented in Table A3 in the Appendix, and show that VAR models rarely outperform the Bayesian VAR models. The results indicate very large forecast errors around the financial crisis where the estimated dynamics appear somewhat problematic (see Figure A2 in Appendix).

[9] The models including survey data tend to outperform the forecasts conducted by the NIER, see Table A4 in the Appendix. However, the forecasting errors from this excerise are not strictly comparable to those from the Bayesian VAR models since the evaluation periods are somewhat different and data may have been revised.

**Figure 2. Root mean square forecast errors for Bayesian VAR models including survey data**

Relative to univariate Bayesian VAR




Note: The x-axis represents horizons.

Impulse response functions from the best performing model at the first horizon are given in Figure 3.[10] They show that the model behaves well in general.[11] We can see that the effects on employment growth are all in line with our expectations. A one standard deviation positive shock to the GDP growth will have a significant positive impact on the employment growth with fairly short delay (see the second chart in the first row). That is also the case of a positive chock to survey data (which in Figure 2 are employment expectations in the total business sector, $STOTNEE_t$ , and business activity (sales) expectations in the trade sector, $STR201_t$ , see the third and fourth charts in the first row).

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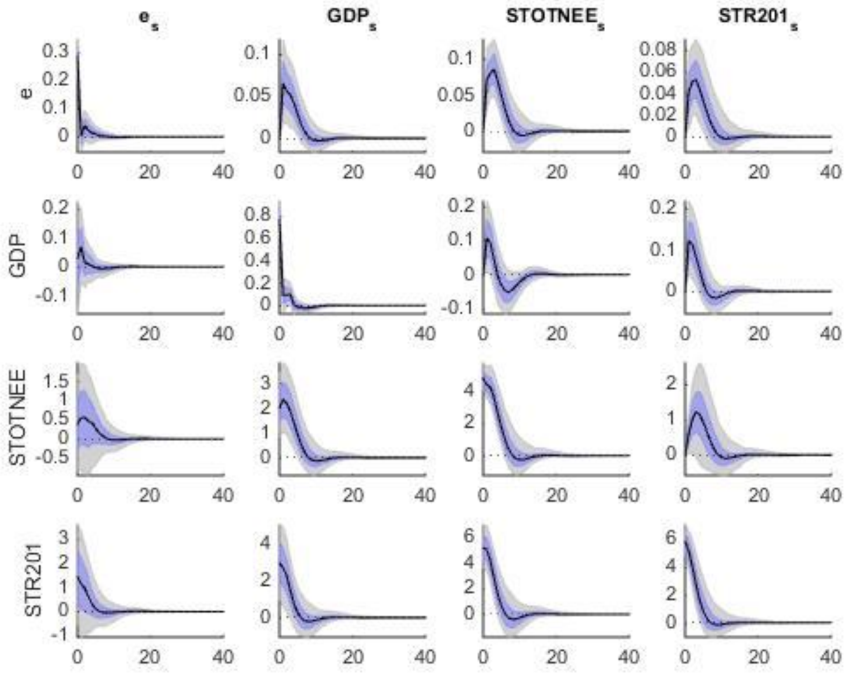
[10] We conclude that the best estimation method is the one with the lowest RMSFE. There will be no test for whether differences in forecast performance are statistically significant. Significance testing is not particularly interesting in our setting. We compare how different reasonable alternatives perform and the best of these methods is that whose forecasts minimise the loss function of the forecaster, see Armstrong (2007) and Beechey and Österholm (2010).

[11] The impulse response functions are based on a Cholesky decomposition of the covariance matrix with the ordering of the variables given by equation (5), that is, it is the same as the columns of the figure.

**Figure 3. Impulse response functions from a four–variate Bayesian VAR model**




Note: Shocks in columns. Black line is the median. Coloured bands are 68 and 95 per cent confidence bands. Maximum horizon is 40 quarters.

Overall, we conclude that employment forecasts can be improved in the short run using business survey data. Results show that several of the survey data employed have predictive power for the employment growth at short horizons.

# 4 Conclusions

In this paper, we use Bayesian VAR models in order to forecast employment growth in Sweden. Our results indicate that a Bayesian VAR model with employment growth, GDP growth and survey data outperforms smaller models at forecast horizons up to four quarters. In particular, employment expectations for the business sector in total and sales expectations in the trade sector increase the forecasting power.

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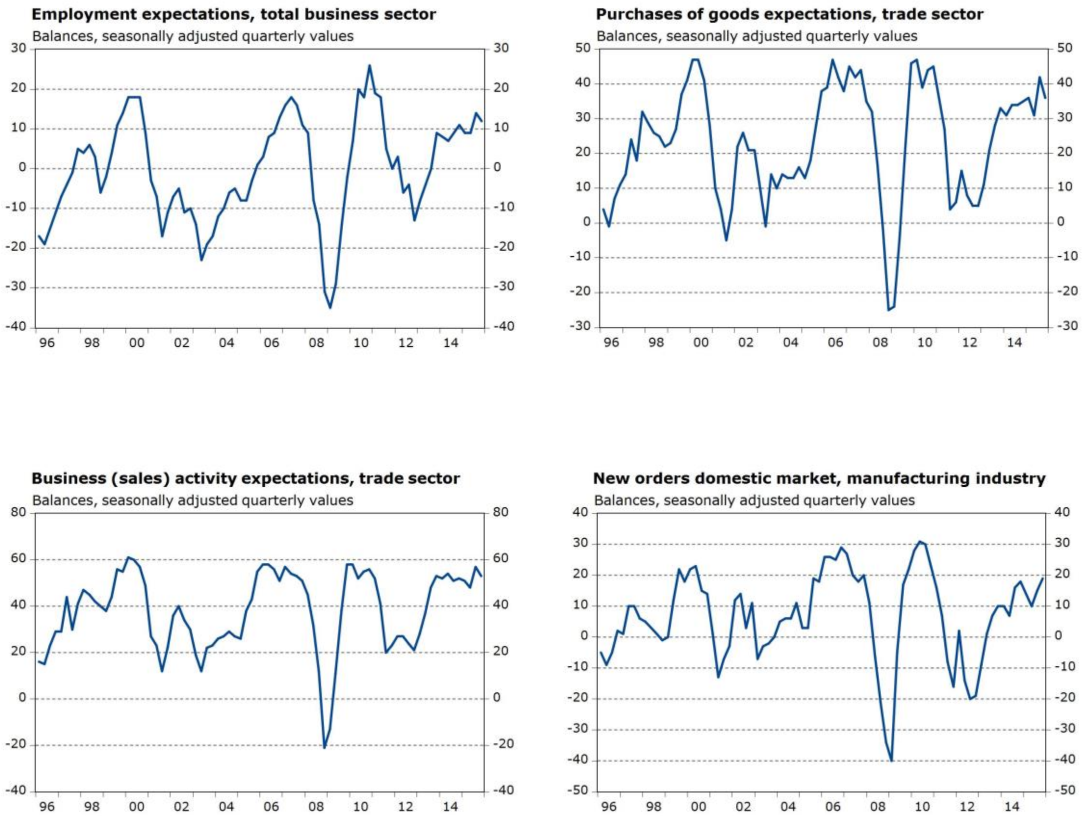
# Appendix

**Figure A1. Survey data**




Source: NIER.

**Table A1. Root mean square forecast errors**

| | | | | |
|---|---|---|---|---|
| AR(1) | 0.453 | | | |
| **Equations total business sector** | | | | |
| Shortage of labour | 0.475 | | | |
| Number of employees, present | 0.394 | | | |
| Demand situation, present | 0.427 | | | |
| Main factor currently limiting production: insufficient demand | 0.427 | | | |
| Sales prices, present | 0.474 | | | |
| Number of employees, expectations, *STOTNEE* | 0.347 | | | |
| Sales prices, expectations | 0.451 | | | |
| **Equations different sectors** | **Manufactur-ing** | **Construction** | **Trade** | **Private service sector** |
| 101 | 0.364 | 0.386 | 0.358 | 0.459 |
| 102 | 0.479 | 0.409 | 0.411 | 0.369 |
| 103 | 0.457 | 0.429 | 0.363 | 0.448 |
| 104 | 0.465 | 0.478 | 0.429 | 0.489 |
| 105 | 0.476 | 0.472 | 0.43 | 0.478 |
| 106 | 0.473 | 0.435 | 0.476 | 0.428 |
| 107 | 0.357 | | 0.487 | 0.482 |
| 1072 | | 0.446 | | |
| 1074 | | 0.441 | | |
| 108 | 0.420 | | 0.374 | 0.507 |
| 109 | 0.389 | | | |
| 110 | 0.402 | | | 0.496 |
| 111 | | | | 0.491 |
| 112 | 0.483 | | | 0.497 |
| 113 | 0.493 | | | 0.457 |
| 114 | 0.530 | | | 0.493 |
| 115 | 0.436 | | | 0.475 |
| 116 | 0.399 | | | |
| 117 | 0.470 | | | |
| 118 | 0.491 | | | |
| 119 | 0.504 | | | |
| 120 | 0.449 | | | |
| 121 | 0.507 | | | |
| 122 | 0.462 | | | |
| 124 | 0.457 | | | |
| 201 | 0.414 | 0.407 | 0.306 | 0.381 |
| 202 | 0.472 | 0.393 | 0.296 | 0.436 |
| 203 | 0.467 | 0.391 | 0.356 | 0.395 |
| 204 | 0.479 | 0.412 | 0.479 | 0.359 |
| 205 | 0.421 | 0.417 | 0.378 | |
| 206 | 0.495 | | | |
| 207 | 0.376 | | | |

Note: The numbers in the far left column refer to the number a specific question has in the *Economic Tendency Survey,* see NIER (2015) for details. The first out-of-sample forecast is made using data from 1994Q1 until 2003Q4. Data concerning the trade sector start 1996Q1 and the private service sector only 2003Q1. The forecast generated from this estimation is for 2004Q1. We then extend the sample one period, re-estimate the model and generate a new forecast, this time for 2004Q2. The last forecast uses data on employment growth until 2014Q1.

**Table A2. Root mean square forecast errors, BVAR-models with different lag lengths**

| | h=1 | h=2 | h=3 | h=4 | h=5 | h=6 | h=7 | h=8 | h=9 | h=10 | h=11 | h=12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 lag lengths | | | | | | | | | | | | |
| $e_t$ | 0,344 | 0,372 | 0,409 | 0,425 | 0,429 | 0,433 | 0,426 | 0,42 | 0,417 | 0,414 | 0,415 | 0,412 |
| $e_t, y_t$ | 0,311 | 0,348 | 0,398 | 0,421 | 0,428 | 0,43 | 0,425 | 0,419 | 0,416 | 0,414 | 0,416 | 0,414 |
| $e_t, y_t, STOTNEE_t, STR201_t$ | 0,248 | 0,293 | 0,368 | 0,427 | 0,461 | 0,485 | 0,484 | 0,477 | 0,465 | 0,447 | 0,438 | 0,428 |
| 3 lag lengths | | | | | | | | | | | | |
| $e_t$ | 0,347 | 0,372 | 0,409 | 0,429 | 0,434 | 0,438 | 0,429 | 0,422 | 0,42 | 0,415 | 0,416 | 0,413 |
| $e_t, y_t$ | 0,312 | 0,351 | 0,399 | 0,426 | 0,434 | 0,438 | 0,431 | 0,423 | 0,419 | 0,416 | 0,417 | 0,415 |
| $e_t, y_t, STOTNEE_t, STR201_t$ | 0,254 | 0,295 | 0,367 | 0,425 | 0,458 | 0,482 | 0,479 | 0,474 | 0,463 | 0,447 | 0,438 | 0,429 |

**Table A3. Root mean square forecast errors, VAR-models**

| Model | h=1 | h=2 | h=3 | h=4 | h=5 | h=6 | h=7 | h=8 | h=9 | h=10 | h=11 | h=12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $e_t$ | 0.329 | 0.354 | 0.412 | 0.45 | 0.461 | 0.478 | 0.469 | 0.459 | 0.45 | 0.441 | 0.436 | 0.422 |
| $e_t, y_t$ | 0.356 | 0.435 | 0.613 | 0.757 | 0.84 | 0.893 | 0.929 | 0.946 | 0.88 | 0.813 | 0.799 | 0.718 |
| $e_t, y_t, STOTNEE_t, STR201_t$ | 0.406 | 0.418 | 0.496 | 0.729 | 0.709 | 0.784 | 0.816 | 0.779 | 0.727 | 0.643 | 0.553 | 0.464 |

**Figure A2. Forecasts from a four-variate VAR model**

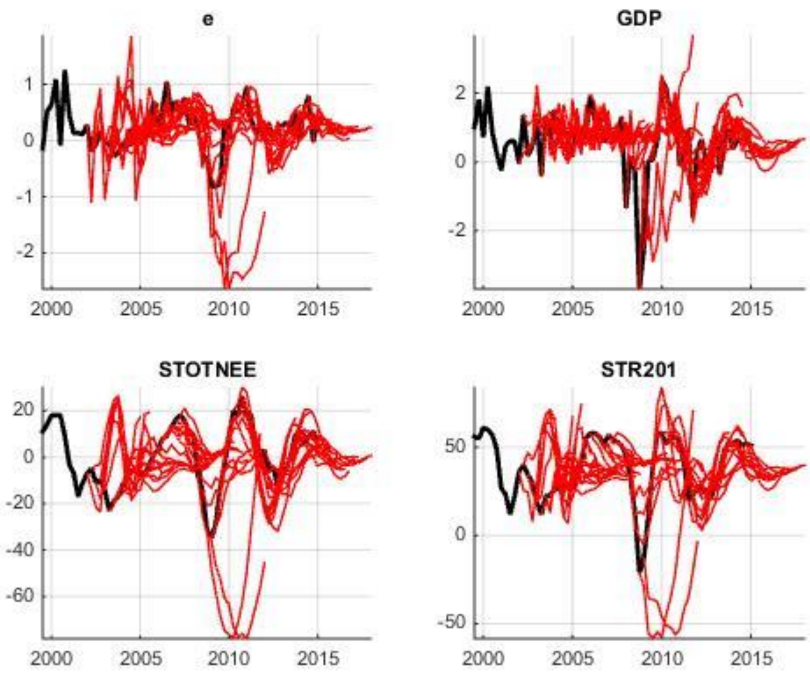


**Table A4. Root mean square forecast errors, NIER's employment forecasts 2004:2–2014:2**

| | h=1 | h=2 | h=3 | h=4 | h=5 | h=6 |
|---|---|---|---|---|---|---|
| Real time data | 0.28 | 0.42 | 0.50 | 0.55 | 0.57 | 0.56 |
| Actual data | 0.29 | 0.38 | 0.46 | 0.48 | 0.50 | 0.49 |

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