

Working Paper

No. 129. September 2013



On the Usefulness of
Constant Gain Least Squares
when Forecasting the
Unemployment Rate

By Jan-Erik Antipin, Jimmy Boumediene
and Pär Österholm

National Institute of Economic Research



On the Usefulness of Constant Gain Least Squares when Forecasting the Unemployment Rate*

Jan-Erik Antipin[#]

Farid Jimmy Boumediene[∇]

Pär Österholm[♣]

* We are grateful to seminar participants at the National Institute of Economic Research for valuable comments.

[#] Finnish Tax Administration, P.O. Box 325, 00052 VERO, Finland
e-mail: jan-erik.antipin@vero.fi Phone: +358 40 668 4931

[∇] Confederation of Swedish Enterprise, Storgatan 19, 114 82 Stockholm, Sweden
email: jimmy.boumediene@svensktnaringsliv.se Phone: +46 70 345 6041

[♣] National Institute of Economic Research, Box 3116, 103 62 Stockholm, Sweden
e-mail: par.osterholm@konj.se Phone: +46 8 453 5948

WORKING PAPER NO 129, SEPTEMBER 2013

PUBLISHED BY THE NATIONAL INSTITUTE OF ECONOMIC RESEARCH (NIER)

NIER prepares analyses and forecasts of the Swedish and international economy and conducts related research. **NIER** is a government agency accountable to the Ministry of Finance and is financed largely by Swedish government funds. Like other government agencies, **NIER** has an independent status and is responsible for the assessments that it publishes.

The **Working Paper** series consists of publications of research reports and other detailed analyses. The reports may concern macroeconomic issues related to the forecasts of the institute, research in environmental economics, or problems of economic and statistical methods. Some of these reports are published in their final form in this series, whereas others are previews of articles that are subsequently published in international scholarly journals under the heading of **Reprints**. Reports in both of these series can be ordered free of charge. Most publications can also be downloaded directly from the **NIER** home page.

THE NATIONAL INSTITUTE OF ECONOMIC RESEARCH (NIER)

KUNSGATAN 12-14, BOX 3116, SE-103 62 STOCKHOLM

TEL: +46 8 453 59 00 FAX: +46 8 453 59 80

E-MAIL: KI@KONJ.SE HOMEPAGE: WWW.KONJ.SE

ISSN 1100-7818

Abstract

In this paper, we assess the usefulness of constant gain least squares (CGLS) when forecasting the unemployment rate. Using quarterly data from 1970 to 2009, we conduct an out-of-sample forecast exercise in which univariate autoregressive models for the unemployment rate in Australia, Sweden, the United Kingdom and the United States are employed. Results show that CGLS very rarely outperforms OLS. At horizons of six to eight quarters, OLS is always associated with higher forecast precision, regardless of model size or gain employed for Australia, Sweden and the United States. Our findings suggest that while CGLS has been shown valuable when forecasting certain macroeconomic time series, it has shortcomings when forecasting the unemployment rate. One problematic feature is found to be an increased tendency for the autoregressive model to have explosive dynamics when estimated with CGLS.

JEL Classification: E24, E27

Keywords: Out-of-sample forecasts

Summary in Swedish

I denna studie jämförs prognosförmågan hos univariata autoregressiva modeller skattade med två olika metoder: *ordinary least squares* (OLS) och *constant gain least squares* (CGLS). Vi utvärderar modellprognoser för arbetslöshetsgraden i Australien, Storbritannien, Sverige och USA. Resultaten visar att CGLS väldigt sällan genererar bättre prognoser än OLS. På prognoshorisonter från sex till åtta kvartal förknippas OLS alltid med en högre prognosprecision än CGLS oavsett modellens storlek eller vilket gain som används för Australien, Sverige och USA. Resultaten antyder att trots att CGLS har visat sig värdefullt när det gäller att prognostisera vissa makroekonomiska tidsserier så förefaller det finnas problem när arbetslöshetsgraden skall prognostiseras. Ett av dessa problem är en ökad tendens för den autoregressiva modellen att ha explosiv dynamik när den skattas med CGLS.

Contents

1. Introduction	7
2. The modelling framework	8
3. Empirical findings	10
3.1 Data and method.....	10
3.2 Main results	12
3.3 What explains the failure of CGLS?	14
4. Conclusions	19
Appendix.....	24

1. Introduction

Constant gain least squares (CGLS) has become increasingly popular in macroeconomic models where the rational-expectations framework has been abandoned; see for example Sargent (1999), Evans and Honkapohja (2001), Orphanides and Williams (2004), Gaspar *et al.* (2006) and Dale *et al.* (2011). In such models, agents in the economy update their beliefs about the economy's true parameter values each period as additional data become available. CGLS attaches a smaller weight to an observation the more time has passed since its occurrence. As such, it allows for the possibility of structural change. However, while being a popular estimation method for forecasting models in theoretical frameworks, the empirical literature employing CGLS in forecasting is limited. Nevertheless, analysis by Branch and Evans (2006) shows that the use of CGLS can be fruitful when forecasting inflation and GDP growth using low-order vector autoregressions (VARs). In addition, Antipin *et al.* (2012) show that CGLS is useful when forecasting inflation in Australia, Sweden, the United Kingdom and the United States using univariate autoregressive (AR) models.

The infrequent use of CGLS in the empirical forecasting literature is surprising, particularly given the potential for CGLS to account for structural change through the explicit use of time-varying coefficients. Many forecasters, policy makers and analysts are interested in forecasting variables where there is reason to believe that the time-series properties are changing over time. One such variable is the unemployment rate. Due to the social consequences of unemployment, politicians and policy institutions in many countries subject the labour market to what can be seen as a reasonably steady flow of policy experiments. For example, in Australia, a set of labour-market programs known as “Working nation” was introduced in 1994. This included intensive counselling services and a job-creation program for long-term unemployed. However, with a shift of government in 1996, the program was abolished.¹ In Sweden, “Youth practice” – a subsidised work program for young unemployed – was introduced in 1992 due to the rapidly rising unemployment rate at the time. In 1995, it was replaced by other programs.² Finally, in the United States, the duration of unemployment benefits are regularly extended during recessions. In addition to policy changes, there are also other aspects of the labour market that might be subject to change, such as the degree of centralization in the wage-bargaining process.³ In light of such changes, one would expect the level and/or dynamics of the unemployment rate to change over time.⁴ Empirical support for time variation in the dynamics and/or equilibrium level of the unemployment rate has been provided by, for example, Jaeger and Parkinson (1994), Gordon (1997), Debelle and Vickery (1998), Apel and Jans-

¹ See, for example, Webster and Harding (2001).

² See, for example, Larsson (2003).

³ See, for example, Uusitalo (2005) and Du Caju *et al.* (2008).

⁴ One concrete example of this is that the equilibrium unemployment rate should rise when the duration of unemployment benefits is extended; see, for example, Mortensen (1977).

son (1999), Papell *et al.* (2000), Cogley and Sargent (2001), Skalin and Teräsvirta (2002), Summers (2004), Lim *et al.* (2009) and Dueker *et al.* (2010).

When it comes to forecasting the unemployment rate, there is a large literature employing a fairly wide range of methods; see, for example, Funke (1992), Montgomery *et al.* (1998), Rothman (1998), Brown and Moshiri (2004), Franses *et al.* (2004), Golan and Perloff (2004), Deschamps (2008) and Milas and Rothman (2008). However, the use of CGLS in unemployment rate forecasting has (to our knowledge) not been investigated previously. The purpose of this paper is therefore to assess the usefulness of CGLS when forecasting the unemployment rate. This will be done by comparing the out-of-sample forecast performance of univariate AR models, specifically *i*) AR models estimated with OLS and *ii*) AR models with time-varying parameters estimated by CGLS. This is a reasonable starting point for an investigation of the usefulness of CGLS since AR models estimated with OLS are commonly used in empirical work and are also generally considered to forecast reasonably well.⁵ Out-of-sample forecast exercises are carried out for four different countries, namely Australia, Sweden, the United Kingdom and the United States. Using quarterly data from 1970 to 2009, we find that CGLS largely is unsuccessful in improving forecast precision relative to OLS. The results in this paper hence suggest that while CGLS has theoretical appeal – and also has been shown to be an empirically relevant forecasting tool in certain settings – it does not seem to be a simple and certain way to improve macroeconomic forecasts.

The rest of this paper is organised as follows: Section 2 discusses the models and estimation. In Section 3, data are presented and the results are discussed. Finally, Section 4 concludes.

2. The modelling framework

We assess the empirical usefulness of CGLS as a forecasting tool through an out-of-sample forecast exercise. Following Antipin *et al.* (2012), univariate AR models are employed for this purpose; these are estimated using two different methods, namely CGLS and OLS. Since OLS is the most commonly employed estimation method for AR models in applied work, it serves as a natural benchmark against which to compare CGLS.

There is, however, also good theoretical motivation for comparing these two methods since OLS and CGLS can be seen as having fundamentally different assumptions regarding the underlying structure of the economy. In particular, OLS is a natural choice when estimating an AR model if one believes that there has been no structural change since it relies on the assumption of parameters being constant over time. We accordingly write the AR(p) model as

⁵ AR models are accordingly often used as a benchmark in the forecasting literature; see, for example, Pesaran *et al.* (2009).

$$u_t = \alpha + \beta_1 u_{t-1} + \beta_2 u_{t-2} + \dots + \beta_p u_{t-p} + \varepsilon_t, \quad (1)$$

where u_t is the unemployment rate and ε_t is an *iid* error term. In contrast, when relying on CGLS as estimation method, time variation of the parameters is explicitly assumed and we write the AR(p) model as

$$u_t = \alpha_t + \beta_{1,t} u_{t-1} + \beta_{2,t} u_{t-2} + \dots + \beta_{p,t} u_{t-p} + \varepsilon_t. \quad (2)$$

Defining the parameter vector as $c_t = (\alpha_t \quad \beta_{1,t} \quad \beta_{2,t} \quad \dots \quad \beta_{p,t})'$, the estimated parameter vector is updated according to

$$\hat{c}_t = \hat{c}_{t-1} + \kappa R_t^{-1} X_t (u_t - X_t' \hat{c}_{t-1}), \quad (3)$$

where

$$R_t = R_{t-1} + \kappa (X_t X_t' - R_{t-1}), \quad (4)$$

where the constant gain is denoted by κ and $X_t = (1 \quad u_{t-1} \quad u_{t-2} \quad \dots \quad u_{t-p})'$. The larger κ is, the higher is the weight put on more recent observations (which means that parameter estimates are updated faster). The explicitly assumed time variation of the parameters is of course the main reason for our interest in using CGLS in empirical work. If one believes that the structure of the economy is evolving in such a way that there is quantitatively meaningful time variation in the parameters of the AR model, it is reasonable to try to take this into account.

We employ seven different gains for the CGLS algorithm in the out-of-sample forecast exercise in this paper: $\kappa = (0.01 \quad 0.02 \quad 0.03 \quad 0.04 \quad 0.05 \quad 0.075 \quad 0.10)$. These values cover the most relevant range for the gain used in both the theoretical and the empirical literature.⁶ The initial value of the parameter vector is set to $c = (0 \quad 1 \quad 0 \quad \dots \quad 0)'$. This is consistent with a univariate random walk without drift, which seems reasonable given that the unemployment rate is often de-

⁶ As a comparison, it can be noted that Branch and Evans (2006) found a gain of 0.0345 successful. The results of Antipin *et al.* (2012) pointed to 0.05 being a reasonable choice.

scribed as being a unit-root process, or at least highly persistent;⁷ see for example León-Ledesma (2002), Camarero and Tamarit (2004) and Gustavsson and Österholm (2007). The initial value for R is set to $R = bb' + M$, where b is a $(p+1) \times 1$ vector, $b = \begin{pmatrix} 1 & u_{t-2} & u_{t-3} & \dots & u_{t-p-1} \end{pmatrix}'$. M is a $(p+1) \times (p+1)$ diagonal matrix, $M = \text{diag}(0 \quad 0.01 \quad \dots \quad 0.01)$, which is added to bb' so that the starting value of R will be non-singular. This way, we get a reasonable starting value for R .⁸

Having briefly presented our modelling framework, we next turn to the issue of out-of-sample forecast performance. While one can hypothesise regarding time-variation in the univariate time-series representation of unemployment rates, our main objective here is to assess the merit of such an assumption on the forecasting performance of the AR models. In practice, there are of course many ways in which parameters can be time varying and CGLS may not always be able to approximate this well. Hence, it is not necessarily the case that CGLS can generate better forecasts than OLS even if the parameters of the model truly are time varying.

3. Empirical findings

3.1 Data and method

We use quarterly data on seasonally adjusted unemployment rates for Australia, Sweden, the United Kingdom and the United States from 1970Q1 to 2009Q4. The data are plotted in Figure 1. A noteworthy feature is that while a unique equilibrium level over time in each country certainly cannot be dismissed based solely on a visual inspection, it does not seem unlikely that the unconditional mean changes over time. For example, in Sweden, the unemployment rate fluctuated between 1.8 and 3.7 percent in the 1970s. During the last ten years, on the other hand, it has not dropped below 5.7 percent. Similarly, the UK unemployment rate was substantially higher on average in the 1980s than in the 1970s, with the means for the two decades being 9.9 and 4.6 percent respectively. Figure 1 hence seems to lend some support to the claim made above that the time-series properties of the unemployment rate may be time varying and, accordingly, that CGLS might be of interest from a forecasting perspective. On the other hand, it is also possible that the observed movements are due to a data-generating process which is stable over time but characterised by high persistence.

We conduct the out-of-sample forecast exercise as follows: The parameter values estimated by CGLS are updated according to equations (3) and (4) each quarter and forecasts from one to eight

⁷ These coefficient values are also commonly used as priors in Bayesian analysis of AR and VAR models; see, for example, Litterman (1986) and Beechey and Österholm (2010).

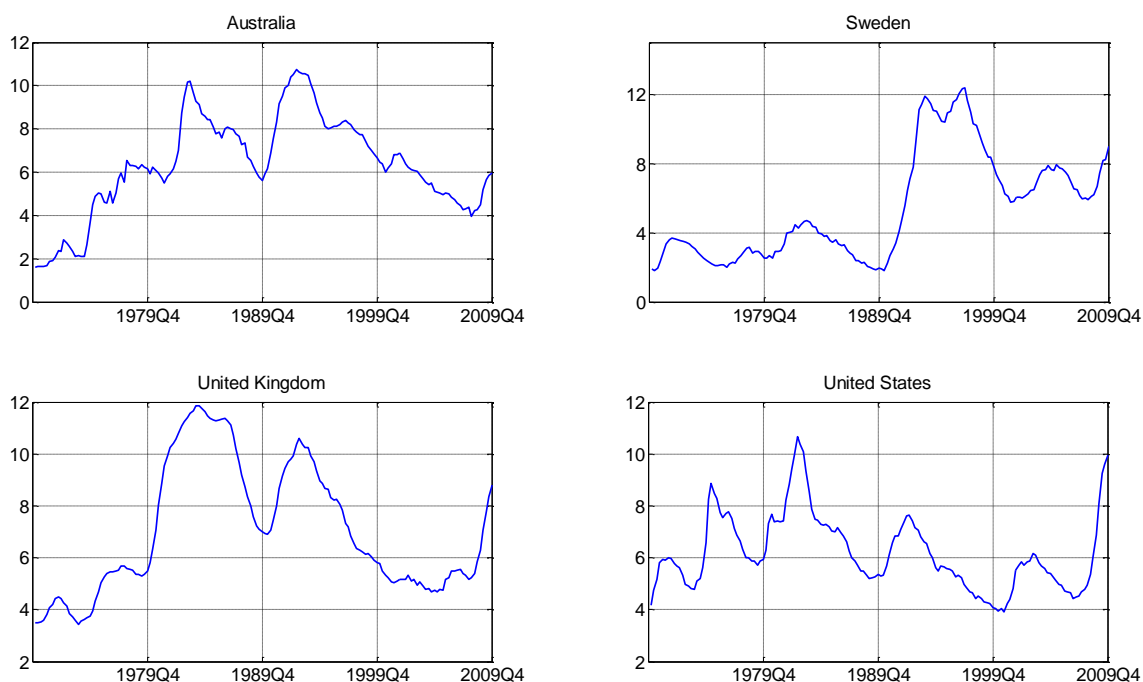
⁸ Given that our samples all range from 1970Q1 to 2009Q4 (see the discussion in Section 3), the CGLS estimation is initialised at $t = 1971Q2$ to allow for a sufficient number of lags.

quarters ahead are generated at each point in time. The first forecasts are generated in 1983Q1 and the last in 2007Q4. We hence have the same number of forecasts – 100 to be specific – to evaluate for all horizons. The AR model in equation (1) is estimated using OLS on an expanding sample; that is, the model is re-estimated each quarter.⁹ Forecasts from this model are also generated up to eight quarters ahead every quarter from 1983Q1 to 2007Q4. Forecast errors are recorded and used to calculate the root mean square forecast errors (RMSFEs). The RMSFE is defined as

$$RMSFE_h = \sqrt{N_h^{-1} \sum_{i=0}^{N_h-1} (u_{t+h+i} - u_{t+h+i|t})^2}, \quad (5)$$

where N_h is the number of forecasts at horizon h , u_{t+h} is the outcome at time $t+h$ and $u_{t+h|t}$ is the forecast of the unemployment rate at time $t+h$ made at time t . The RMSFEs of the different models are then compared in order to identify the model that generates the most accurate forecasts.

Figure 1. Unemployment rates.



An issue of particular interest to economists doing empirical work is the choice of lag length in AR models. Many approaches have been suggested in the literature and opinions differ concerning the appropriateness of the various alternatives.¹⁰ We circumvent this issue to a large extent by investi-

⁹ While the model in equation (1) has constant parameters within each sample, the fact that it is re-estimated each quarter means that there is variation over time in the parameters used to generate the forecasts. This time variation is reasonable though, seeing that the approach mimics how out-of-sample forecasts would be generated in real time.

¹⁰ See, for example, Akaike (1974), Schwarz (1978), Hannan and Quinn (1979), Hendry (1995) and Lütkepohl (2007).

gating forecasting performance with respect to all lag lengths, $p = (1 \ 2 \ 3 \ 4)$; comparisons between OLS and CGLS are then focused on models of a given lag length. As a reference point, we still provide optimal lag length based on the Schwarz (1978) information criterion when applied to equation (1) estimated with OLS. This is done for the initial sample used to estimate the models before the first forecast is generated, that is, 1970Q1 to 1983Q1. This is the most relevant sample for our purposes, since this is the one that would initially be used in practice in real time. Results from this exercise are given in Table 1.

Table 1. Optimal lag length for AR model estimated with OLS.

	Lag length
Australia	1
Sweden	4
United Kingdom	4
United States	2

Note: Lag length established using the Schwarz (1978) information criterion. Sample periods: 1970Q1 to 1983Q1.

3.2 Main results

Concerning the evaluation of the forecasts, we focus solely on the RMSFE and define the best estimation method as the one associated with the lowest RMSFE.¹¹ The results from the out-of-sample forecasts are given in Tables A1 to A4 in the Appendix.

Turning first to the results for Australia in Table A1, it can be seen that regardless of lag length, the lowest RMSFEs are almost always obtained when OLS is employed. Only at the one-quarter horizon for the AR(1) model and the one- and two-quarter horizons for the AR(2) model does CGLS offer any kind of improvement over OLS. These improvements are, however, very small – the largest reduction in the RMSFE is three percent. The loss in forecast precision from using CGLS grows with the forecast horizon and tends to be substantial at the longest horizons; at the eight-quarter horizon, CGLS is always at least ten percent worse than OLS. It should also be noted that for large gains, CGLS generates a dramatic loss in forecast precision. For example, at the eight-quarter horizon and using a gain of ten percent, the RMSFE is between 39 and 90 percent larger when CGLS is used. It hence appears that there are virtually no reasons from a forecasting point of view for using CGLS instead of OLS on the Australian data.

Table A2 shows the results for Sweden. Also for Sweden is it – with only a few exceptions – better to use OLS than CGLS. Only at short horizons for the AR(1) model can any improvements from using CGLS be found. At longer horizons, the deterioration in forecasting precision from using CGLS is typically

¹¹ No tests for whether differences in forecasting performance are statistically significant are conducted. In line with Armstrong (2007) and Beechey and Österholm (2010), we argue that significance testing is not particularly interesting in the present setting. The performance of two reasonable alternatives is compared and in such a situation few forecasters would choose a model or a method with a larger RMSFE just because it was not significantly larger.

substantial. For example, at the eight-quarter horizon the increase in the RMSFEs for the AR(4) model – which was judged optimal according to the Schwarz information criterion – ranges from 16 to 44 percent depending on the gain employed. Furthermore, similar to the results found for Australia, the poor forecasting performance of CGLS at long horizons is particularly evident for large gains.¹²

For the United Kingdom, results are presented in Table A3 and are more favourable to CGLS than what was the case for Australia and Sweden. For example, for the AR(1) model, the RMSFEs are almost exclusively lower for CGLS than OLS (with horizons of five to eight quarters for a gain of 0.01 being the exceptions). It can also be noted that large gains perform unusually well for this model. The AR(1) model is by far the worst in terms of forecasting performance though – its RMSFEs are substantially larger than those of the other models. Hence, it is perhaps more interesting to look at the other models, particularly since the Schwarz information criterion suggests that the AR(4) model is optimal for UK unemployment. For the larger models, it is still the case that CGLS does fairly well at short horizons; the RMSFEs are in many cases lower when CGLS is used than when OLS is used. However, at forecast horizons from six to eight quarters, OLS always outperforms CGLS for the AR(2), AR(3) and AR(4) models. However, the loss in forecasting precision at long horizons from using CGLS is not as large as it was for Australia or Sweden – the RMSFE is never more than 24 percent larger for CGLS.

The results for the United States are given in Table A4. As can be seen, OLS has a lower RMSFE than CGLS in almost all cases. Only when a low gain is used to forecast at short horizons using the AR(1) model is CGLS associated with a lower RMSFE than OLS. For the AR(3) and AR(4) models, we once again find larger gains associated with a very large deterioration in forecast precision at longer horizons. For both the AR(3) and AR(4) models, the RMSFE at the eight-quarter horizon increases by approximately 85 percent when CGLS with a gain of 0.10 is employed instead of OLS.

The general inability of CGLS to outperform OLS is also exemplified in Figure 2 where we present a selection of relative RMSFEs for the AR(p) models given in Table 1. The relative RMSFE at horizon b is calculated as

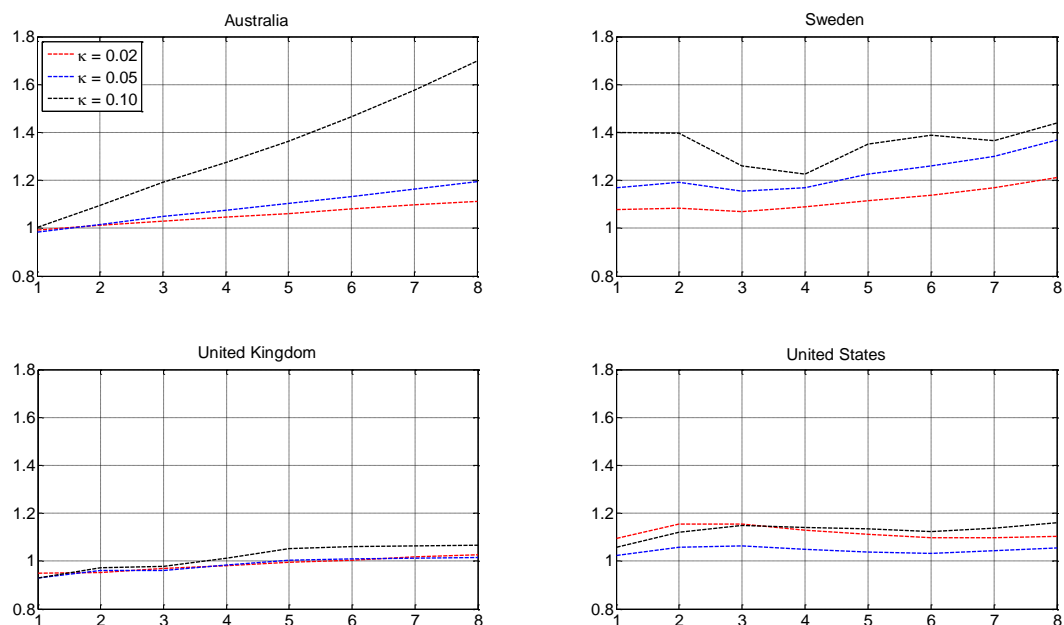
$$RR_h = \frac{RMSFE_{CGLS,h}}{RMSFE_{OLS,h}}, \quad (6)$$

where $RMSFE_{CGLS,h}$ is the RMSFE of the AR model estimated with CGLS at horizon b and $RMSFE_{OLS,h}$ is the corresponding-horizon RMSFE for the AR model estimated with OLS. A

¹² It can be noted that the RMSFEs for Sweden are substantially larger than those for the other countries. The reason for this is some very large forecast errors at a few timepoints where the estimated models are associated with explosive dynamics (that is, where the sum of the AR coefficients is larger than unity).

relative RMSFE smaller than unity hence means that CGLS is associated with higher forecast precision than OLS; as can be seen from Figure 2, this is rarely the case.

Figure 2. Relative RMSFEs for out-of-sample forecasts generated 1983Q1-2007Q4.



Note: Forecast horizon in quarters on the horizontal axis and relative RMSFE on the vertical. A relative RMSFE smaller than unity indicates that CGLS generates better forecasts than OLS. Lag length used for the respective country is given in Table 1.

3.3 What explains the failure of CGLS?

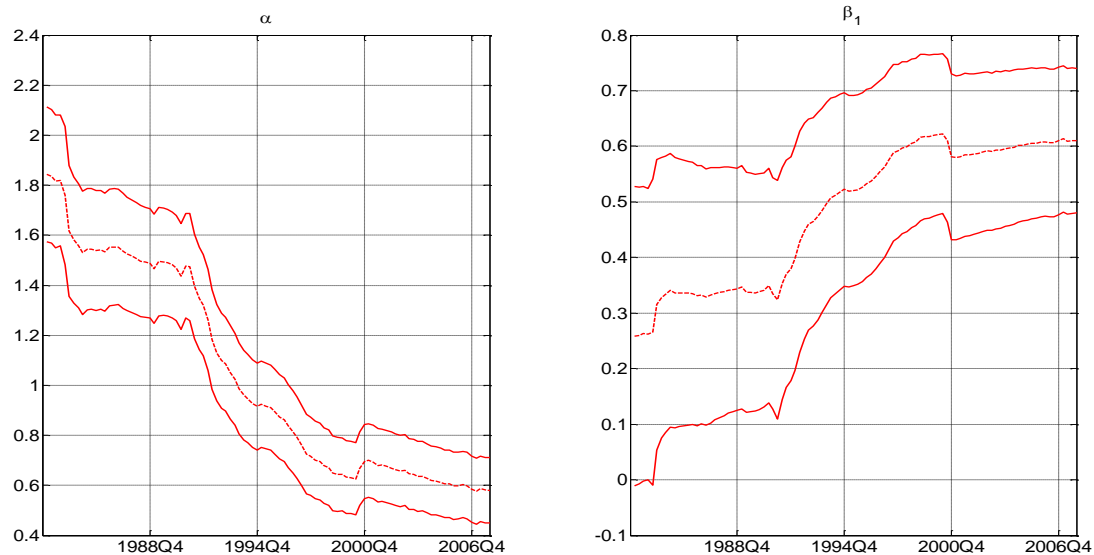
Summing up the results, it can be concluded that CGLS in general does not offer an improvement on the forecast accuracy of OLS on the unemployment data considered here. This might seem both surprising and disappointing given the reliable improvements in forecasting precision documented by Antipin *et al.* (2012) when forecasting inflation in the same four countries. So what might explain the poor performance of CGLS? As suggested earlier, CGLS should be superior to OLS if there is quantitatively meaningful time variation in the univariate time-series representation. One interpretation of the results from our out-of-sample forecast exercise is accordingly that the data-generating process – despite the fairly extensive literature documenting the opposite – has been reasonably stable.¹⁵

This hypothesis finds some support in the data. Figures 3 and 4 show recursive coefficient estimates from two AR(1) models estimated with OLS – one for Australian inflation and one for the

¹⁵ Alternatively, it could be argued that the time series studied are subject to time variation in parameters that CGLS is not able to approximate well.

Australian unemployment rate.¹⁴ As pointed out above, the AR(1) model for the Australian unemployment rate did generally forecast a fair bit better when estimated with OLS rather than CGLS. As shown by Antipin *et al.* (2012) though, the AR(1) model for inflation generated better forecasts when CGLS was used, regardless of the gain employed. Looking at Figure 3, the recursive estimates are moving around substantially over time, indicating that the data-generating process for Australian inflation is not stable. Turning to Figure 4, on the other hand, it can be seen that the recursive estimates are reasonably stable over time for the unemployment rate. This suggests that the data-generating process for the Australian unemployment rate might be fairly stable, which could help explain why CGLS does not offer improvements in forecast precision relative to OLS in this case.

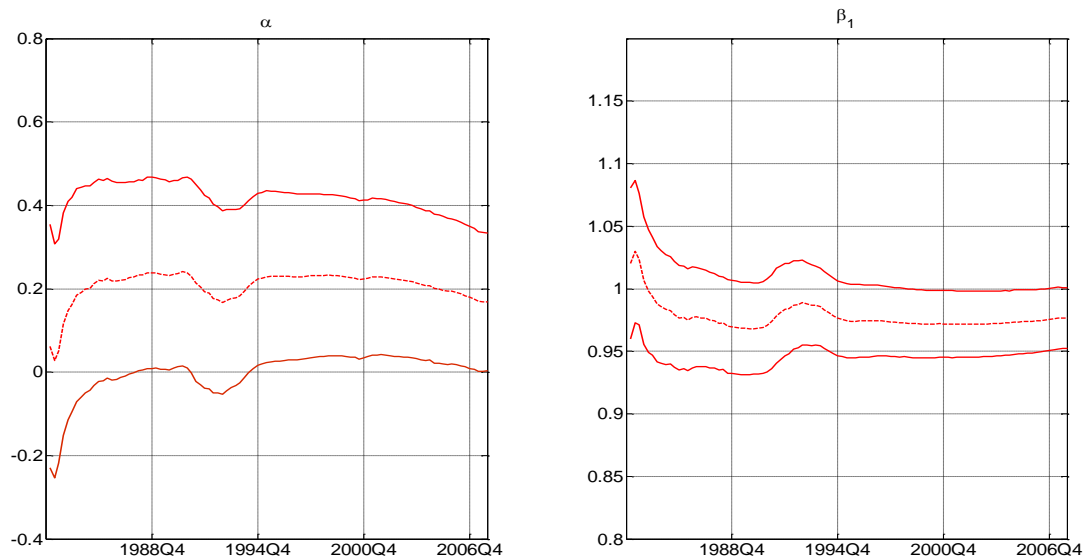
Figure 3. Recursively estimated coefficients using OLS for AR(1) model for Australian inflation.



Note: Dashed line gives point estimate. Solid lines give plus/minus two standard errors. Sample is 1970Q1-1983Q1/2007Q4.

¹⁴ The recursive coefficient estimates are generated by estimating the models on an expanding sample (adding one observation at a time) and recording point estimates and standard errors each time. The first sample is 1970Q1 to 1983Q1 and the last sample is 1970Q1 to 2007Q4. 100 recursive estimates are hence generated for each model.

Figure 4. Recursively estimated coefficients using OLS for AR(1) model for the Australian unemployment rate.

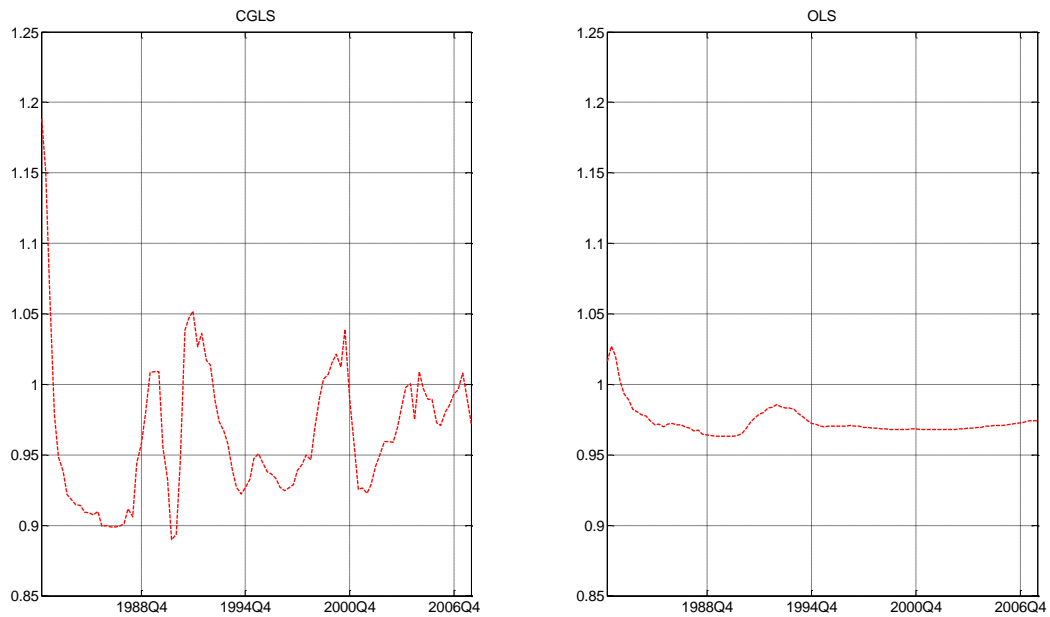


Note: Dashed line gives point estimate. Solid lines give plus/minus two standard errors. Sample is 1970Q1-1983Q1/2007Q4.

But while stability of the data-generating process might have some relevance in explaining our results, it is only part of the explanation. For Australia and Sweden, it appears that the main driver of our results is the fact that the CGLS estimator has a tendency to generate estimates of the AR coefficients that imply an explosive process, that is, the sum of the AR coefficients is larger than unity. This can be seen in Figures 5 and 6 which show the sum of the estimated AR coefficients for the AR(1) and AR(4) models for Australian and Swedish unemployment rate respectively. The left panel shows the sum of estimated coefficients when CGLS with a gain of $\kappa = 0.10$ has been used and the right panel shows the corresponding sum when OLS has been used.¹⁵

¹⁵ Figures A1 and A2 in the appendix show the corresponding graphs for the United Kingdom and the United States.

Figure 5. Estimated autoregressive coefficient from AR(1) models for the Australian unemployment rate.

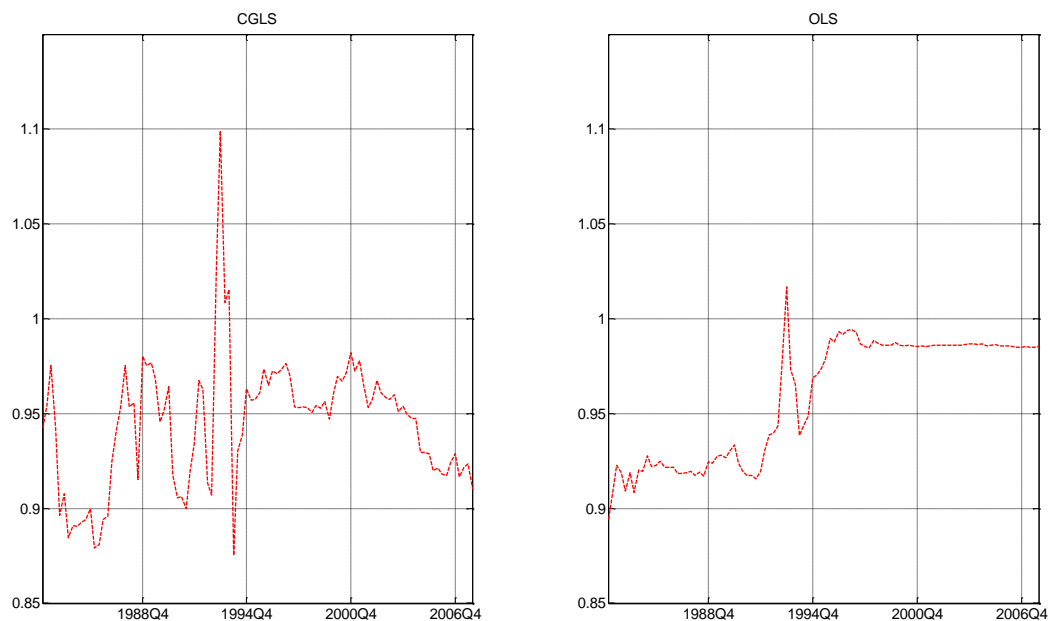


Note: CGLS gives estimates of autoregressive coefficient from model estimated with CGLS using a gain of 0.10; estimation is initialised at 1971Q2. OLS gives recursively estimated autoregressive coefficient from model estimated with OLS; sample is 1970Q1-1983Q1/2007Q4.

Figure 5 clearly shows how the CGLS estimator in many cases generates dynamics that imply an explosive process. This can be contrasted with the OLS estimator where this kind of dynamics is found only in the beginning of the evaluation period. For the Swedish data, Figure 6 shows that the number of occasions where CGLS generates explosive dynamics is fewer than in the Australian case. The problem is nevertheless present and still relevant in explaining our findings. It can be noted that CGLS generates explosive dynamics more often than OLS and that in the cases when both methods generate explosive dynamics, the sum of the AR coefficients is a fair bit larger for CGLS than for OLS; for forecasts at long horizons, this larger sum makes a substantial difference.¹⁶

¹⁶ While the estimated sum of the AR coefficients is considered the main problem, it should be noted that the estimate of the intercept of course also matters for the forecasts. It can alleviate or exacerbate the problem.

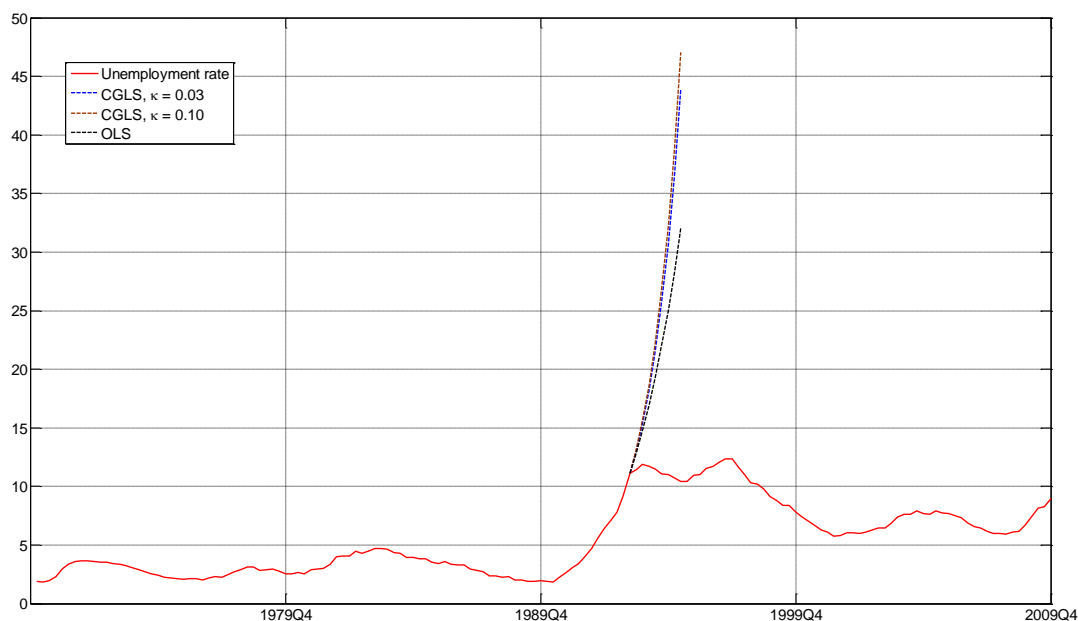
Figure 6. Sum of estimated autoregressive coefficients from AR(4) models for the Swedish unemployment rate.



Note: CGLS gives the sum of estimated of autoregressive coefficients from model estimated with CGLS using a gain of 0.10; estimation is initialised at 1971Q2. OLS gives the sum of recursively estimated autoregressive coefficients from model estimated with OLS; sample is 1970Q1-1983Q1/2007Q4.

The problems associated with forecasting with an explosive process are illustrated in Figure 7. The figure shows three forecasts – using data up to and including 1993Q2 – from AR(4) models for Swedish unemployment; these forecasts are based on models estimated with i) OLS, ii) CGLS with a gain of 0.03 and iii) CGLS with a gain of 0.10. In this case, all three models have explosive dynamics and generate forecasts that diverge. The problem is substantial for all three models. The model estimated with OLS does not perform as badly as the models estimated with CGLS but still generates a forecast for the unemployment rate eight quarters ahead which is more than 30 percent; needless to say, this would have been perceived as unreasonable by any economist in real time.

Figure 7. Forecasts from AR(4) models for Swedish unemployment rate made using data including 1993Q2.



Note: CGLS estimation is initialised at 1971Q2. OLS sample is 1970Q1-1993Q2.

But while all models suffer from this problem, it is most severe for CGLS with a gain of 0.10. The extent of the problem can be seen by noting that the squared forecast error at the eight-quarter horizon is 1339. This single observation contributes in a spectacular way to the RMSFE; in fact, roughly half of the sum of the squared forecast errors in equation (5) for the eight-quarter horizon stems from this observation. By comparison, the corresponding squared forecast error for the model estimated with OLS is 466. While this is also a very large number, it is roughly 873 units smaller than that from CGLS with a gain of 0.10. Needless to say, this makes a substantial difference for the RMSFE and helps explain why CGLS performs so badly for Sweden.¹⁷ From a more general perspective, it shows that a forecaster relying on CGLS to forecast highly persistent time series needs to pay extra attention to the forecasts being generated by the model.

4. Conclusions

This paper has added to the empirical literature on CGLS as a macroeconomic forecasting tool by investigating the out-of-sample forecast performance of AR models estimated with CGLS and OLS when forecasting the unemployment rate. Using data from Australia, Sweden, the United Kingdom and the United States, we find that CGLS does not appear particularly useful in terms of improving forecast precision relative to OLS. The failure of CGLS is particularly evident at longer forecast

¹⁷ That explosive dynamics constitutes a problem is also confirmed by the fact that CGLS performs approximately as well as OLS for the United Kingdom. As can be seen in Figure A1, the AR(4) model estimated with CGLS using a gain of 0.10 is not associated with explosive dynamics at any point in time.

horizons. At horizons of six to eight quarters, OLS is always associated with higher forecast precision than CGLS, regardless of model size or gain employed for Australia, Sweden and the United States.

The fact that OLS tends to outperform CGLS is consistent with the time-series properties of the unemployment rate in the studied countries being stable; if the data-generating process does not change in a quantitatively meaningful way over time, we would expect the model which assumes parameter stability to work better from a forecasting perspective. However, for both Australia and Sweden, it appears that the main cause for the failure of CGLS is the fact that it has an increased tendency to generate estimates of the AR coefficients that imply an explosive process. With an explosive process, forecasts diverge and are in some cases associated with extremely large forecast errors. A forecaster can of course use good judgement and say that a given model forecast is unreasonable, thereby reducing the extent of this problem in practice. This does require both monitoring and a forecaster with good judgement though. We accordingly conclude that while CGLS in previous studies has been shown to have the potential to be a valuable contribution to the toolkit employed by forecasters, it is by no means a recipe for guaranteed success in macroeconomic forecasting.

References

- Akaike, H. (1974), "A New Look at the Statistical Model Identification", *IEEE Transactions on Automatic Control* 19, 716-723.
- Antipin, J.-E., Boumedienne, F. J. and Österholm, P. (2012), "Forecasting Inflation Using Constant Gain Least Squares", Working Paper 126, National Institute of Economic Research.
- Apel, M. and Jansson, P. (1999), "A Theory-Consistent System Approach for Estimating Potential Output and the NAIRU", *Economics Letters* 64, 271-275.
- Armstrong, J. S. (2007), "Significance Tests Harm Progress in Forecasting", *International Journal of Forecasting* 23, 321-327.
- Beechey, M. and Österholm, P. (2010), "Forecasting Inflation in an Inflation Targeting Regime: A Role for Informative Steady-State Priors", *International Journal of Forecasting* 26, 248-264.
- Branch, W. A. and Evans, G. H. (2006), "A Simple Recursive Forecasting Model", *Economics Letters* 91, 158-166.
- Brown, L. and Moshiri, S. (2004), "Unemployment Variation over the Business Cycles: A Comparison of Forecasting Models", *Journal of Forecasting* 23, 497-511.
- Camarero, M. and Tamarit, C. (2004), "Hysteresis vs. Natural Rate of Unemployment: New Evidence for OECD Countries", *Economics Letters* 84, 413-417.
- Cogley, T. and Sargent, T. J. (2001), "Evolving Post-World War II U.S. Inflation Dynamics", *NBER Macroeconomics Annual* 16, 331-373.
- Dale, S., Orphanides, A. and Österholm, P. (2011), "Imperfect Central Bank Communication: Information versus Distraction", *International Journal of Central Banking* 7, 3-39.
- Debelle, G. and Vickery, J. (1998), "Is the Phillips Curve a Curve? Some Evidence and Implications for Australia", *Economic Record* 74, 384-98.
- Deschamps, P. J. (2008), "Comparing Smooth Transition and Markov Switching Autoregressive Models of US Unemployment", *Journal of Applied Econometrics* 23, 435-462.
- Du Caju, P., Gautier, E., Momferatou, D. and Ward-Warmedinger, M. (2008), "Institutional Features of Wage Bargaining in 23 European Countries, the US and Japan," Working Paper 974, European Central Bank.
- Dueker, M., Owyang, M. T. and Sola, M. (2010), "A Time-Varying Threshold STAR Model of Unemployment and the Natural Rate", Working Paper 2010-029A, Federal Reserve Bank of St. Louis.
- Evans, G. W. and Honkapohja, S. (2001), *Learning and Expectations in Macroeconomics*, Princeton University Press, Princeton.

- Franses, P. H., Paap, R. and Vroomen, B. (2004), "Forecasting Unemployment Using an Autoregression with Censored Latent Effects Parameters", *International Journal of Forecasting* 20, 255-271.
- Funke, M. (1992), "Time-Series Forecasting of the German Unemployment Rate", *Journal of Forecasting* 11, 111-125.
- Gaspar, V., Smets, F. and Vestin, D. (2006), "Adaptive Learning, Persistence and Optimal Monetary Policy", *Journal of the European Economic Association* 4, 376-685.
- Golan A. and Perloff, J. M. (2004) "Superior Forecasts of the US Unemployment Rate Using a Nonparametric Method", *Review of Economics and Statistics* 86, 433-438.
- Gordon, R. J. (1997), "The Time-Varying NAIRU and Its Implications for Economic Policy", *Journal of Economic Perspectives* 11, 11-32.
- Gustavsson, M. and Österholm, P. (2007), "Does Unemployment Hysteresis Equal Employment Hysteresis?", *Economic Record* 83, 159-173.
- Hannan, E. J. and Quinn, B. G. (1979), "The Determination of the Order of an Autoregression", *Journal of the Royal Statistical Society (Series B)*, 41, 190-195.
- Hendry, D. F. (1995), *Dynamic Econometrics*. Oxford University Press, Oxford.
- Jaeger, A. and Parkinson, M. (1994), "Some Evidence on Hysteresis in Unemployment Rates", *European Economic Review* 38, 329-342.
- Larsson, L. (2003), "Evaluating Swedish Youth Labour Market Programs", *Journal of Human Resources* 38, 891-927.
- Lim, G. C., Dixon, R. and Tsiaplias, S. (2009), "Phillips Curve and the Equilibrium Unemployment Rate", *Economic Record* 85, 371-382.
- Litterman, R. B. (1986), "Forecasting with Bayesian Vector Autoregressions – Five Years of Experience", *Journal of Business and Economic Statistics* 5, 25-38.
- León-Ledesma, M. A. (2002), "Unemployment Hysteresis in the US States and the EU: A Panel Approach", *Bulletin of Economic Research* 54, 95-105.
- Lütkepohl, H. (2007), "General-to-Specific or Specific-to-General Modelling? An Opinion on Current Econometric Terminology", *Journal of Econometrics* 136, 319-324.
- Milas, C. and Rothman, P. (2008), "Out-of-Sample Forecasting of Unemployment Rates with Pooled STVECM Forecasts", *International Journal of Forecasting* 24, 101-121.
- Montgomery, A. L., Zarnowitz, V., Tsay, R. S. and Tiao, G. C. (1998), "Forecasting the U.S. Unemployment Rate", *Journal of the American Statistical Association* 93, 478-493.
- Mortensen, D. T. (1977), "Unemployment Insurance and Job Search Decisions", *Industrial and Labor Relations Review* 30, 505-517.

- Orphanides, A. and Williams, J. C. (2004), "Imperfect Knowledge, Inflation Expectations and Monetary Policy", In: Bernanke, B. and Woodford, M. (eds), *The Inflation Targeting Debate*, University of Chicago Press, Chicago.
- Papell, D. H., Murray, C. J. and Ghiblawi, H. (2000), "The Structure of Unemployment", *Review of Economics and Statistics* 82, 309-315.
- Pesaran, M. H., Schuermann, T. and Smith, L. V. (2009), "Forecasting Economic and Financial Variables with Global VARs", *International Journal of Forecasting* 25, 642-675.
- Rothman, P. (1998), "Forecasting Asymmetric Unemployment Rates", *Review of Economics and Statistics* 80, 164-168.
- Sargent, T. J. (1999), *The Conquest of American Inflation*, Princeton University Press, Princeton.
- Schwarz, G. (1978), "Estimating the Dimension of a Model", *Annals of Statistics* 6, 461-464.
- Skalin, J. and Teräsvirta, T. (2002), "Modeling Asymmetries and Moving Equilibria in Unemployment Rates", *Macroeconomic Dynamics* 6, 202-241.
- Summers, P. M. (2004), "Bayesian Evidence on the Structure of Unemployment", *Economics Letters* 83, 299-306.
- Uusitalo, R. (2005). "Do Centralized Bargains Lead to Wage Moderation? Time-Series Evidence from Finland", In: Piekkola, H. and Snellman, K (eds), *Collective Bargaining and Wage Formation. Performance and Challenges*, Physica-Verlag, Heidelberg.
- Webster, E. and Harding, G. (2001) "Outsourcing Public Employment Services: The Australian Experience", *Australian Economic Review* 34, 231-242.

Appendix

Table A1. RMSFEs at different forecasting horizons for model estimated by CGLS and OLS – Australia.

	Gain	0.01	0.02	0.03	0.04	0.05	0.075	0.10	OLS
1 lag	Horizon								
	1	0.305	0.302	0.300	0.299	0.299	0.302	0.305	0.304
	2	0.559	0.554	0.551	0.553	0.557	0.576	0.600	0.548
	3	0.818	0.812	0.810	0.815	0.827	0.876	0.939	0.788
	4	1.066	1.058	1.058	1.068	1.089	1.175	1.289	1.012
	5	1.304	1.295	1.298	1.315	1.346	1.480	1.663	1.220
	6	1.534	1.525	1.531	1.557	1.601	1.793	2.071	1.413
	7	1.747	1.738	1.749	1.784	1.843	2.103	2.499	1.585
	8	1.954	1.945	1.963	2.008	2.085	2.425	2.970	1.747
2 lags	Horizon								
	1	0.246	0.241	0.239	0.237	0.236	0.237	0.240	0.242
	2	0.453	0.438	0.430	0.425	0.424	0.432	0.451	0.436
	3	0.696	0.676	0.665	0.660	0.661	0.686	0.731	0.660
	4	0.933	0.907	0.893	0.887	0.891	0.935	1.010	0.873
	5	1.159	1.128	1.113	1.107	1.115	1.185	1.298	1.067
	6	1.379	1.344	1.327	1.322	1.334	1.431	1.592	1.248
	7	1.578	1.538	1.519	1.516	1.531	1.656	1.869	1.402
	8	1.776	1.731	1.712	1.710	1.728	1.881	2.152	1.548
3 lags	Horizon								
	1	0.229	0.226	0.225	0.224	0.225	0.230	0.242	0.223
	2	0.414	0.409	0.406	0.406	0.408	0.426	0.460	0.393
	3	0.646	0.639	0.638	0.640	0.648	0.696	0.778	0.603
	4	0.870	0.861	0.859	0.863	0.877	0.957	1.090	0.801
	5	1.089	1.076	1.073	1.080	1.101	1.221	1.419	0.987
	6	1.305	1.288	1.286	1.295	1.324	1.487	1.755	1.163
	7	1.502	1.481	1.479	1.491	1.526	1.732	2.078	1.314
	8	1.699	1.675	1.673	1.688	1.730	1.980	2.410	1.459
4 lags	Horizon								
	1	0.233	0.231	0.230	0.231	0.232	0.241	0.257	0.225
	2	0.428	0.424	0.424	0.426	0.431	0.457	0.499	0.402
	3	0.670	0.669	0.671	0.677	0.689	0.745	0.835	0.618
	4	0.903	0.901	0.906	0.916	0.936	1.030	1.182	0.821
	5	1.130	1.128	1.135	1.150	1.180	1.323	1.551	1.010
	6	1.354	1.351	1.360	1.382	1.424	1.628	1.954	1.188
	7	1.557	1.552	1.565	1.593	1.648	1.921	2.363	1.341
	8	1.760	1.753	1.769	1.805	1.875	2.227	2.816	1.487

Note: Forecasting horizon is given in quarters.

Table A2. RMSFEs at different forecasting horizons for model estimated by CGLS and OLS – Sweden.

	Gain	0.01	0.02	0.03	0.04	0.05	0.075	0.10	OLS
1 lag									
	Horizon								
	1	0.428	0.426	0.423	0.418	0.414	0.400	0.387	0.431
	2	0.852	0.856	0.853	0.847	0.840	0.815	0.789	0.851
	3	1.326	1.346	1.352	1.349	1.341	1.309	1.271	1.312
	4	1.849	1.902	1.928	1.936	1.932	1.897	1.850	1.811
	5	2.427	2.533	2.594	2.624	2.634	2.612	2.561	2.350
	6	3.048	3.230	3.344	3.410	3.444	3.454	3.413	2.916
	7	3.722	4.007	4.195	4.314	4.385	4.452	4.442	3.518
	8	4.453	4.876	5.165	5.354	5.477	5.625	5.670	4.158
2 lags									
	Horizon								
	1	0.352	0.335	0.329	0.327	0.327	0.330	0.337	0.318
	2	0.739	0.701	0.688	0.687	0.691	0.706	0.724	0.638
	3	1.211	1.160	1.145	1.149	1.159	1.190	1.219	1.026
	4	1.762	1.709	1.695	1.706	1.726	1.775	1.813	1.462
	5	2.406	2.367	2.364	2.390	2.425	2.499	2.545	1.951
	6	3.123	3.114	3.128	3.176	3.234	3.348	3.411	2.452
	7	3.936	3.979	4.020	4.100	4.190	4.362	4.452	2.980
	8	4.858	4.976	5.058	5.179	5.314	5.567	5.697	3.530
3 lags									
	Horizon								
	1	0.345	0.333	0.329	0.328	0.329	0.340	0.359	0.314
	2	0.698	0.679	0.674	0.678	0.687	0.725	0.786	0.622
	3	1.148	1.123	1.119	1.130	1.148	1.217	1.305	0.999
	4	1.684	1.659	1.660	1.679	1.708	1.803	1.898	1.434
	5	2.321	2.310	2.323	2.356	2.401	2.525	2.627	1.935
	6	3.039	3.054	3.085	3.140	3.205	3.369	3.491	2.459
	7	3.861	3.919	3.980	4.065	4.159	4.373	4.517	3.021
	8	4.792	4.911	5.012	5.138	5.271	5.550	5.710	3.605
4 lags									
	Horizon								
	1	0.349	0.351	0.357	0.368	0.381	0.418	0.456	0.326
	2	0.684	0.695	0.714	0.738	0.764	0.833	0.895	0.641
	3	1.072	1.083	1.111	1.142	1.171	1.233	1.278	1.014
	4	1.563	1.581	1.620	1.663	1.699	1.759	1.778	1.452
	5	2.138	2.185	2.258	2.334	2.403	2.546	2.653	1.962
	6	2.767	2.842	2.949	3.056	3.151	3.342	3.475	2.501
	7	3.479	3.601	3.752	3.893	4.005	4.168	4.207	3.081
	8	4.251	4.436	4.652	4.850	5.011	5.245	5.277	3.665

Note: Forecasting horizon is given in quarters.

Table A3. RMSFEs at different forecasting horizons for model estimated by CGLS and OLS – United Kingdom.

	Gain	0.01	0.02	0.03	0.04	0.05	0.075	0.10	OLS
1 lag	Horizon								
	1	0.263	0.257	0.252	0.247	0.243	0.233	0.224	0.269
	2	0.508	0.495	0.483	0.474	0.466	0.450	0.435	0.517
	3	0.757	0.737	0.719	0.706	0.695	0.676	0.660	0.766
	4	1.007	0.978	0.955	0.937	0.924	0.907	0.895	1.012
	5	1.265	1.227	1.196	1.173	1.159	1.147	1.145	1.261
	6	1.527	1.479	1.441	1.413	1.396	1.391	1.406	1.511
	7	1.788	1.729	1.683	1.648	1.629	1.632	1.670	1.758
	8	2.048	1.978	1.921	1.880	1.857	1.869	1.935	2.001
2 lags	Horizon								
	1	0.161	0.155	0.153	0.152	0.150	0.147	0.146	0.157
	2	0.309	0.287	0.282	0.279	0.278	0.279	0.283	0.284
	3	0.502	0.458	0.447	0.442	0.440	0.441	0.452	0.446
	4	0.713	0.643	0.625	0.618	0.615	0.621	0.643	0.616
	5	0.949	0.852	0.824	0.814	0.809	0.818	0.854	0.801
	6	1.206	1.081	1.042	1.025	1.016	1.023	1.073	1.001
	7	1.463	1.310	1.260	1.236	1.222	1.226	1.292	1.192
	8	1.730	1.554	1.493	1.464	1.444	1.446	1.530	1.391
3 lags	Horizon								
	1	0.150	0.147	0.145	0.143	0.143	0.142	0.144	0.157
	2	0.286	0.282	0.282	0.283	0.285	0.290	0.298	0.291
	3	0.462	0.451	0.450	0.452	0.454	0.466	0.486	0.456
	4	0.655	0.637	0.633	0.634	0.638	0.659	0.695	0.628
	5	0.874	0.844	0.836	0.836	0.841	0.872	0.927	0.812
	6	1.113	1.069	1.054	1.047	1.048	1.082	1.155	1.010
	7	1.355	1.294	1.269	1.255	1.251	1.283	1.373	1.194
	8	1.605	1.528	1.496	1.475	1.465	1.495	1.604	1.388
4 lags	Horizon								
	1	0.150	0.149	0.148	0.147	0.146	0.145	0.146	0.157
	2	0.287	0.284	0.285	0.286	0.286	0.286	0.290	0.298
	3	0.463	0.457	0.457	0.456	0.454	0.450	0.461	0.472
	4	0.656	0.646	0.649	0.650	0.647	0.645	0.666	0.658
	5	0.875	0.858	0.863	0.867	0.866	0.869	0.906	0.862
	6	1.114	1.085	1.088	1.092	1.090	1.093	1.144	1.080
	7	1.356	1.312	1.311	1.312	1.306	1.306	1.371	1.290
	8	1.606	1.549	1.544	1.543	1.534	1.531	1.612	1.510

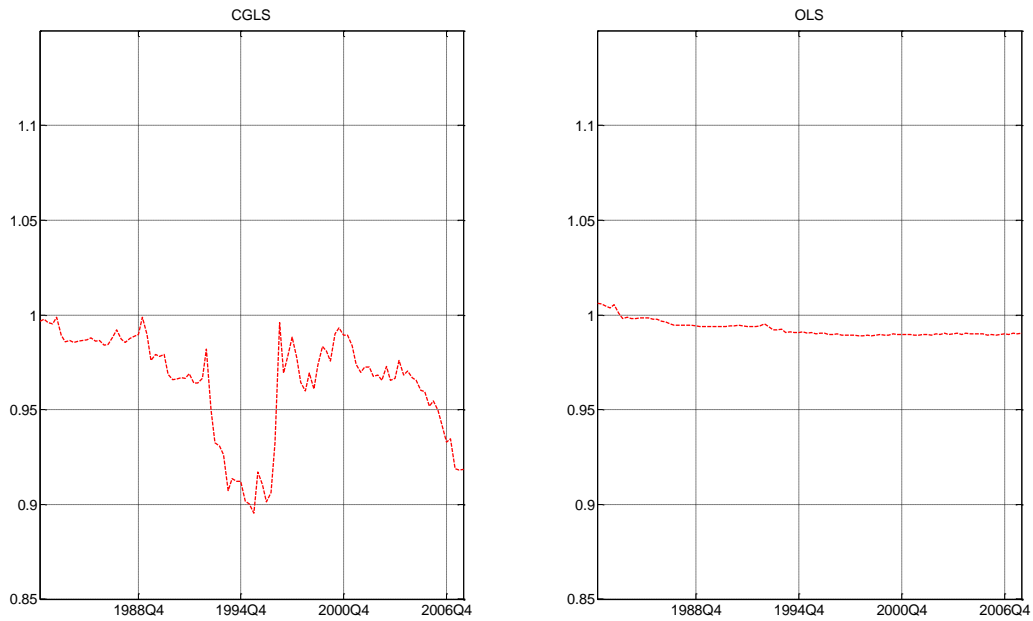
Note: Forecasting horizon is given in quarters.

Table A4. RMSFEs at different forecasting horizons for model estimated by CGLS and OLS – United States.

	Gain	0.01	0.02	0.03	0.04	0.05	0.075	0.10	OLS
1 lag									
	Horizon								
	1	0.242	0.244	0.245	0.245	0.246	0.245	0.243	0.245
	2	0.452	0.457	0.460	0.462	0.464	0.464	0.462	0.455
	3	0.647	0.657	0.663	0.667	0.670	0.673	0.672	0.648
	4	0.825	0.840	0.850	0.858	0.863	0.869	0.870	0.823
	5	0.999	1.020	1.035	1.047	1.055	1.066	1.070	0.994
	6	1.184	1.212	1.233	1.248	1.260	1.277	1.286	1.177
	7	1.363	1.400	1.426	1.446	1.462	1.488	1.503	1.353
	8	1.531	1.576	1.609	1.634	1.654	1.689	1.714	1.516
2 lags									
	Horizon								
	1	0.203	0.187	0.180	0.176	0.175	0.178	0.181	0.171
	2	0.402	0.368	0.348	0.339	0.337	0.344	0.357	0.319
	3	0.602	0.553	0.523	0.510	0.509	0.525	0.550	0.479
	4	0.792	0.728	0.690	0.675	0.675	0.698	0.734	0.644
	5	0.983	0.902	0.856	0.841	0.843	0.875	0.921	0.812
	6	1.189	1.092	1.039	1.023	1.028	1.067	1.119	0.995
	7	1.392	1.277	1.217	1.204	1.213	1.262	1.324	1.163
	8	1.587	1.454	1.389	1.378	1.392	1.454	1.528	1.318
3 lags									
	Horizon								
	1	0.207	0.192	0.183	0.179	0.178	0.181	0.187	0.176
	2	0.421	0.388	0.364	0.351	0.348	0.359	0.379	0.328
	3	0.630	0.586	0.551	0.533	0.532	0.567	0.620	0.491
	4	0.824	0.767	0.724	0.704	0.707	0.775	0.877	0.659
	5	1.016	0.943	0.889	0.868	0.876	0.989	1.171	0.825
	6	1.224	1.133	1.070	1.046	1.058	1.217	1.510	1.005
	7	1.428	1.320	1.248	1.224	1.241	1.466	1.932	1.168
	8	1.625	1.500	1.420	1.397	1.422	1.730	2.448	1.319
4 lags									
	Horizon								
	1	0.202	0.191	0.184	0.181	0.181	0.188	0.197	0.178
	2	0.414	0.387	0.366	0.356	0.354	0.370	0.393	0.330
	3	0.650	0.607	0.570	0.549	0.545	0.576	0.626	0.492
	4	0.861	0.810	0.760	0.731	0.726	0.786	0.883	0.656
	5	1.057	0.997	0.937	0.903	0.900	1.001	1.165	0.822
	6	1.252	1.183	1.117	1.083	1.085	1.238	1.503	1.002
	7	1.443	1.363	1.293	1.261	1.272	1.504	1.927	1.166
	8	1.629	1.538	1.463	1.434	1.455	1.789	2.446	1.319

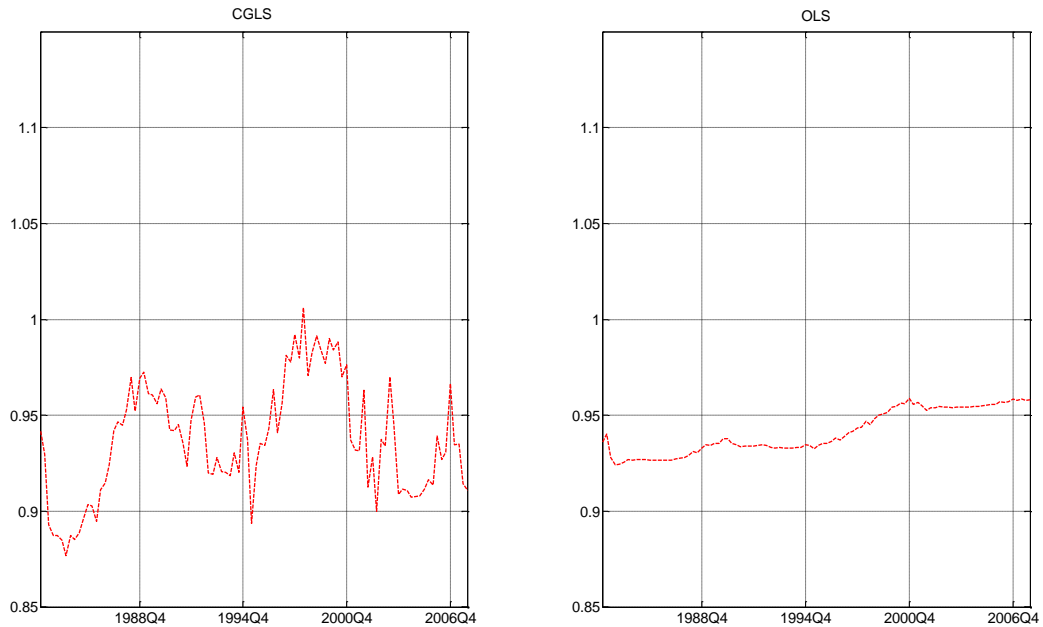
Note: Forecasting horizon is given in quarters

Figure A1. Sum of estimated autoregressive coefficients from AR(4) models for the UK unemployment rate.



Note: CGLS gives the sum of estimated of autoregressive coefficients from model estimated with CGLS using a gain of 0.10; estimation is initialised at 1971Q2. OLS gives the sum of recursively estimated autoregressive coefficients from model estimated with OLS; sample is 1970Q1-1983Q1/2007Q4.

Figure A2. Sum of estimated autoregressive coefficients from AR(2) models for the US unemployment rate.



Note: CGLS gives the sum of estimated of autoregressive coefficients from model estimated with CGLS using a gain of 0.10; estimation is initialised at 1971Q2. OLS gives the sum of recursively estimated autoregressive coefficients from model estimated with OLS; sample is 1970Q1-1983Q1/2007Q4.

Titles in the Working Paper Series

No	Author	Title	Year
1	Warne, Anders and Anders Vredin	Current Account and Business Cycles: Stylized Facts for Sweden	1989
2	Östblom, Göran	Change in Technical Structure of the Swedish Economy	1989
3	Söderling, Paul	Mamtax. A Dynamic CGE Model for Tax Reform Simulations	1989
4	Kanis, Alfred and Aleksander Markowski	The Supply Side of the Econometric Model of the NIER	1990
5	Berg, Lennart	The Financial Sector in the SNEPQ Model	1991
6	Ågren, Anders and Bo Jonsson	Consumer Attitudes, Buying Intentions and Consumption Expenditures. An Analysis of the Swedish Household Survey Data	1991
7	Berg, Lennart and Reinhold Bergström	A Quarterly Consumption Function for Sweden 1979-1989	1991
8	Öller, Lars-Erik	Good Business Cycle Forecasts - A Must for Stabilization Policies	1992
9	Jonsson, Bo and Anders Ågren	Forecasting Car Expenditures Using Household Survey Data	1992
10	Löfgren, Karl-Gustaf, Bo Ranneby and Sara Sjöstedt	Forecasting the Business Cycle Not Using Minimum Autocorrelation Factors	1992
11	Gerlach, Stefan	Current Quarter Forecasts of Swedish GNP Using Monthly Variables	1992
12	Bergström, Reinhold	The Relationship Between Manufacturing Production and Different Business Survey Series in Sweden	1992
13	Edlund, Per-Olov and Sune Karlsson	Forecasting the Swedish Unemployment Rate: VAR vs. Transfer Function Modelling	1992
14	Rahiala, Markku and Timo Teräsvirta	Business Survey Data in Forecasting the Output of Swedish and Finnish Metal and Engineering Industries: A Kalman Filter Approach	1992
15	Christofferson, Anders, Roland Roberts and Ulla Eriksson	The Relationship Between Manufacturing and Various BTS Series in Sweden Illuminated by Frequency and Complex Demodulate Methods	1992
16	Jonsson, Bo	Sample Based Proportions as Values on an Independent Variable in a Regression Model	1992
17	Öller, Lars-Erik	Eliciting Turning Point Warnings from Business Surveys	1992
18	Forster, Margaret M	Volatility, Trading Mechanisms and International Cross-Listing	1992
19	Jonsson, Bo	Prediction with a Linear Regression Model and Errors in a Regressor	1992

20	Gorton, Gary and Richard Rosen	Corporate Control, Portfolio Choice, and the Decline of Banking	1993
21	Gustafsson, Claes-Håkan and Åke Holmén	The Index of Industrial Production – A Formal Description of the Process Behind it	1993
22	Karlsson, Tohmas	A General Equilibrium Analysis of the Swedish Tax Reforms 1989-1991	1993
23	Jonsson, Bo	Forecasting Car Expenditures Using Household Survey Data- A Comparison of Different Predictors	1993
24	Gennotte, Gerard and Hayne Leland	Low Margins, Derivative Securitates and Volatility	1993
25	Boot, Arnoud W.A. and Stuart I. Greenbaum	Discretion in the Regulation of U.S. Banking	1993
26	Spiegel, Matthew and Deane J. Seppi	Does Round-the-Clock Trading Result in Pareto Improvements?	1993
27	Seppi, Deane J.	How Important are Block Trades in the Price Discovery Process?	1993
28	Glosten, Lawrence R.	Equilibrium in an Electronic Open Limit Order Book	1993
29	Boot, Arnoud W.A., Stuart I Greenbaum and Anjan V. Thakor	Reputation and Discretion in Financial Contracting	1993
30a	Bergström, Reinhold	The Full Tricotomous Scale Compared with Net Balances in Qualitative Business Survey Data – Experiences from the Swedish Business Tendency Surveys	1993
30b	Bergström, Reinhold	Quantitative Production Series Compared with Qualitative Business Survey Series for Five Sectors of the Swedish Manufacturing Industry	1993
31	Lin, Chien-Fu Jeff and Timo Teräsvirta	Testing the Constancy of Regression Parameters Against Continous Change	1993
32	Markowski, Aleksander and Parameswar Nandakumar	A Long-Run Equilibrium Model for Sweden. The Theory Behind the Long-Run Solution to the Econometric Model KOSMOS	1993
33	Markowski, Aleksander and Tony Persson	Capital Rental Cost and the Adjustment for the Effects of the Investment Fund System in the Econometric Model Kosmos	1993
34	Kanis, Alfred and Bharat Barot	On Determinants of Private Consumption in Sweden	1993
35	Kääntä, Pekka and Christer Tallbom	Using Business Survey Data for Forecasting Swedish Quantitative Business Cycle Variable. A Kalman Filter Approach	1993
36	Ohlsson, Henry and Anders Vredin	Political Cycles and Cyclical Policies. A New Test Approach Using Fiscal Forecasts	1993

37	Markowski, Aleksander and Lars Ernsäter	The Supply Side in the Econometric Model KOSMOS	1994
38	Gustafsson, Claes-Håkan	On the Consistency of Data on Production, Deliveries, and Inventories in the Swedish Manufacturing Industry	1994
39	Rahiala, Markku and Tapani Kovalainen	Modelling Wages Subject to Both Contracted Increments and Drift by Means of a Simultaneous-Equations Model with Non-Standard Error Structure	1994
40	Öller, Lars-Erik and Christer Tallbom	Hybrid Indicators for the Swedish Economy Based on Noisy Statistical Data and the Business Tendency Survey	1994
41	Östblom, Göran	A Converging Triangularization Algorithm and the Intertemporal Similarity of Production Structures	1994
42a	Markowski, Aleksander	Labour Supply, Hours Worked and Unemployment in the Econometric Model KOSMOS	1994
42b	Markowski, Aleksander	Wage Rate Determination in the Econometric Model KOSMOS	1994
43	Ahlroth, Sofia, Anders Björklund and Anders Forslund	The Output of the Swedish Education Sector	1994
44a	Markowski, Aleksander	Private Consumption Expenditure in the Econometric Model KOSMOS	1994
44b	Markowski, Aleksander	The Input-Output Core: Determination of Inventory Investment and Other Business Output in the Econometric Model KOSMOS	1994
45	Bergström, Reinhold	The Accuracy of the Swedish National Budget Forecasts 1955-92	1995
46	Sjöö, Boo	Dynamic Adjustment and Long-Run Economic Stability	1995
47a	Markowski, Aleksander	Determination of the Effective Exchange Rate in the Econometric Model KOSMOS	1995
47b	Markowski, Aleksander	Interest Rate Determination in the Econometric Model KOSMOS	1995
48	Barot, Bharat	Estimating the Effects of Wealth, Interest Rates and Unemployment on Private Consumption in Sweden	1995
49	Lundvik, Petter	Generational Accounting in a Small Open Economy	1996
50	Eriksson, Kimmo, Johan Karlander and Lars-Erik Öller	Hierarchical Assignments: Stability and Fairness	1996
51	Url, Thomas	Internationalists, Regionalists, or Eurocentrists	1996
52	Ruist, Erik	Temporal Aggregation of an Econometric Equation	1996
53	Markowski, Aleksander	The Financial Block in the Econometric Model KOSMOS	1996

54	Östblom, Göran	Emissions to the Air and the Allocation of GDP: Medium Term Projections for Sweden. In Conflict with the Goals of SO ₂ , SO ₂ and NOX Emissions for Year 2000	1996
55	Koskinen, Lasse, Aleksander Markowski, Parameswar Nandakumar and Lars-Erik Öller	Three Seminar Papers on Output Gap	1997
56	Oke, Timothy and Lars-Erik Öller	Testing for Short Memory in a VARMA Process	1997
57	Johansson, Anders and Karl-Markus Modén	Investment Plan Revisions and Share Price Volatility	1997
58	Lyhagen, Johan	The Effect of Precautionary Saving on Consumption in Sweden	1998
59	Koskinen, Lasse and Lars-Erik Öller	A Hidden Markov Model as a Dynamic Bayesian Classifier, with an Application to Forecasting Business-Cycle Turning Points	1998
60	Kragh, Börje and Aleksander Markowski	Kofi – a Macromodel of the Swedish Financial Markets	1998
61	Gajda, Jan B. and Aleksander Markowski	Model Evaluation Using Stochastic Simulations: The Case of the Econometric Model KOSMOS	1998
62	Johansson, Kerstin	Exports in the Econometric Model KOSMOS	1998
63	Johansson, Kerstin	Permanent Shocks and Spillovers: A Sectoral Approach Using a Structural VAR	1998
64	Öller, Lars-Erik and Bharat Barot	Comparing the Accuracy of European GDP Forecasts	1999
65	Huhtala, Anni and Eva Samakovlis	Does International Harmonization of Environmental Policy Instruments Make Economic Sense? The Case of Paper Recycling in Europe	1999
66	Nilsson, Charlotte	A Unilateral Versus a Multilateral Carbon Dioxide Tax - A Numerical Analysis With The European Model GEM-E3	1999
67	Braconier, Henrik and Steinar Holden	The Public Budget Balance – Fiscal Indicators and Cyclical Sensitivity in the Nordic Countries	1999
68	Nilsson, Kristian	Alternative Measures of the Swedish Real Exchange Rate	1999
69	Östblom, Göran	An Environmental Medium Term Economic Model – EMEC	1999
70	Johnsson, Helena and Peter Kaplan	An Econometric Study of Private Consumption Expenditure in Sweden	1999
71	Arai, Mahmood and Fredrik Heyman	Permanent and Temporary Labour: Job and Worker Flows in Sweden 1989-1998	2000

72	Öller, Lars-Erik and Bharat Barot	The Accuracy of European Growth and Inflation Forecasts	2000
73	Ahlroth, Sofia	Correcting Net Domestic Product for Sulphur Dioxide and Nitrogen Oxide Emissions: Implementation of a Theoretical Model in Practice	2000
74	Andersson, Michael K. And Mikael P. Gredenhoff	Improving Fractional Integration Tests with Bootstrap Distribution	2000
75	Nilsson, Charlotte and Anni Huhtala	Is CO ₂ Trading Always Beneficial? A CGE-Model Analysis on Secondary Environmental Benefits	2000
76	Skånberg, Kristian	Constructing a Partially Environmentally Adjusted Net Domestic Product for Sweden 1993 and 1997	2001
77	Huhtala, Anni, Annie Toppinen and Mattias Boman,	An Environmental Accountant's Dilemma: Are Stumpage Prices Reliable Indicators of Resource Scarcity?	2001
78	Nilsson, Kristian	Do Fundamentals Explain the Behavior of the Real Effective Exchange Rate?	2002
79	Bharat, Barot	Growth and Business Cycles for the Swedish Economy	2002
80	Bharat, Barot	House Prices and Housing Investment in Sweden and the United Kingdom. Econometric Analysis for the Period 1970-1998	2002
81	Hjelm, Göran	Simultaneous Determination of NAIRU, Output Gaps and Structural Budget Balances: Swedish Evidence	2003
82	Huhtala, Anni and Eva Samalkovis	Green Accounting, Air Pollution and Health	2003
83	Lindström, Tomas	The Role of High-Tech Capital Formation for Swedish Productivity Growth	2003
84	Hansson, Jesper, Per Jansson and Märten Löv	Business survey data: do they help in forecasting the macro economy?	2003
85	Boman, Mattias, Anni Huhtala, Charlotte Nilsson, Sofia Ahlroth, Göran Bostedt, Leif Mattson and Peichen Gong	Applying the Contingent Valuation Method in Resource Accounting: A Bold Proposal	
86	Gren, Ing-Marie	Monetary Green Accounting and Ecosystem Services	2003
87	Samakovlis, Eva, Anni Huhtala, Tom Bellander and Magnus Svartengren	Air Quality and Morbidity: Concentration-response Relationships for Sweden	2004
88	Alsterlind, Jan, Alek Markowski and Kristian Nilsson	Modelling the Foreign Sector in a Macroeconometric Model of Sweden	2004
89	Lindén, Johan	The Labor Market in KIMOD	2004

90	Henrik Braconier, Tomas Forsfält	A New Method for Constructing a Cyclically Adjusted Budget Balance: the Case of Sweden	2004
91	Hansen, Sten and Tomas Lindström	Is Rising Returns to Scale a Figment of Poor Data?	2004
92	Hjelm, Göran	When Are Fiscal Contractions Successful? Lessons for Countries Within and Outside the EMU	2004
93	Östblom, Göran and Samakovlis, Eva	Costs of Climate Policy when Pollution Affects Health and Labour Productivity. A General Equilibrium Analysis Applied to Sweden	2004
94	Forslund Johanna, Eva Samakovlis and Maria Vredin Johans- son	Matters Risk? The Allocation of Government Subsidies for Remediation of Contaminated Sites under the Local Investment Programme	2006
95	Erlandsson Mattias and Alek Markowski	The Effective Exchange Rate Index KIX - Theory and Practice	2006
96	Östblom Göran and Charlotte Berg	The EMEC model: Version 2.0	2006
97	Hammar, Henrik, Tommy Lundgren and Magnus Sjöström	The significance of transport costs in the Swedish forest industry	2006
98	Barot, Bharat	Empirical Studies in Consumption, House Prices and the Accuracy of European Growth and Inflation Forecasts	2006
99	Hjelm, Göran	Kan arbetsmarknadens parter minska jämviktsarbetslösheten? Teori och modellsimuleringar	2006
100	Bergvall, Anders, To- mas Forsfält, Göran Hjelm, Jonny Nilsson and Juhana Vartiainen	KIMOD 1.0 Documentation of NIER's Dynamic Macroeconomic General Equilibrium Model of the Swedish Economy	2007
101	Östblom, Göran	Nitrogen and Sulphur Outcomes of a Carbon Emissions Target Excluding Traded Allowances - An Input-Output Analysis of the Swedish Case	2007
102	Hammar, Henrik and Åsa Löfgren	Explaining adoption of end of pipe solutions and clean technologies – Determinants of firms' investments for reducing emissions to air in four sectors in Sweden	2007
103	Östblom, Göran and Henrik Hammar	Outcomes of a Swedish Kilometre Tax. An Analysis of Economic Effects and Effects on NOx Emissions	2007
104	Forsfält, Tomas, Johnny Nilsson and Juhana Vartianinen	Modellansatser i Konjunkturinstitutets medel- fristprognoser	208
105	Samakovlis, Eva	How are Green National Accounts Produced in Practice?	2008

106	Alek Markowski, Kristian Nilsson, Marcus Widén	Strukturell utveckling av arbetskostnad och priser i den svenska ekonomin	2011
107	Forslund, Johanna, Per Johansson, Eva Samakovlis and Maria Vredin Johansson	Can we by time? Evaluation. Evaluation of the government's directed grant to remediation in Sweden	2009
108	Forslund, Johanna Eva Samakovlis, Maria Vredin Johansson and Lars Barregård	Does Remediation Save Lives? On the Cost of Cleaning Up Arsenic-Contaminated Sites in Sweden	2009
109	Sjöström, Magnus and Göran Östblom	Future Waste Scenarios for Sweden on the Basis of a CGE-model	2009
110	Österholm, Pär	The Effect on the Swedish Real Economy of the Financial Crisis	2009
111	Forsfält, Tomas	KIMOD 2.0 Documentation of changes in the model from January 2007 to January 2009	2009
112	Österholm, Pär	Improving Unemployment Rate Forecasts Using Survey Data	2009
113	Österholm, Pär	Unemployment and Labour-Force Participation in Sweden	2009
114	Jonsson, Thomas and Pär Österholm	The Properties of Survey-Based Inflation Expectations in Sweden	2009
115	Hjelm, Göran and Kristian Jönsson	In Search of a Method for Measuring the Output Gap of the Swedish Economy	2010
116	Vartiainen, Juhana	Interpreting Wage Bargaining Norms	2010
117	Mossfeldt, Marcus and Pär Österholm	The Persistent Labour-Market Effects of the Financial Crisis	2010
118	Östblom, Göran, Maria Ljunggren Söderman and Magnus Sjöström	Analysing future solid waste generation – Soft linking a model of waste management with a CGE-model for Sweden	2010
119	Broberg, Thomas, Per-Olov Marklund, Eva Samakovlisa and Henrik Hammar	Does environmental leadership pay off for Swedish industry? - Analyzing the effects of environmental investments on efficiency	2010
120	Gustavsson, Magnus and Pär Österholm	Labor-Force Participation Rates and the Informational Value of Unemployment Rates: Evidence from Disaggregated US Data	2010
121	Jonsson, Thomas and Pär österholm	The Forecasting Properties of Survey-Based Wage-Growth Expectations	2010
123	Broberg, Thomas, Tomas Forsfält and Göran Östblom	The Excess Cost of Supplementary Constraints in Climate Policy: The Case of Sweden's Energy Intensity Target	2011

124	Patrik Baard, Henrik Carlsen, Karin Edvardsson Björnberg and Maria Vredin Johansson	Scenarios and Sustainability. A Swedish Case Study of Adaptation Tools for Local Decision-Makers	2011
125	Hansson, Sven Ove, Karin Edvardsson Björnberg and Maria Vredin Johansson	Making Climate Policy Efficient Implementing a Model for Environmental Policy Efficiency	2011
126	Antipin, Jan-Erik, Farid Jimmy Boumediene and Pär Österholm	Forecasting Inflation Using Constant Gain Least Squares	2012
127	Meredith Beechey, Pär Österholm	Policy Interest Rate Expectations in Sweden: A Forecast Evaluation	2012
128	Meredith Beechey, Pär Österholm	Central Bank Forecasts of Policy Interest Rates: An Evaluation of the First Years	2013
129	Jan-Erik Antipin, Farid Jimmy Boumediene, Pär Österholm	On the Usefulness of Constant Gain Least Squares when Forecasting the Unemployment Rate	2013

**National Institute of Economic Research, Kungsgatan 12-14, Box 3116, SE-103 62 Stockholm, Sweden
Phone: +46 8 453 59 00, Fax: +46 8 453 59 80, E-mail: ki@konj.se, Website: www.konj.se**

ISSN 1100-7818