Economics Letters 146 (2016) 77–81

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

A note on the Cogley–Nason–Sims approach

Syed M. Hussain [a], Lin Liu [b,*]

[a] Department of Economics, Lahore University of Management Sciences, Lahore, Pakistan

[b] Management School, University of Liverpool, United Kingdom

ARTICLE INFO

Article history:
Received 23 October 2015
Received in revised form
13 April 2016
Accepted 30 June 2016
Available online 14 July 2016

JEL classification:
C32
E52

Keywords:
Cogley–Nason–Sims approach
Small sample properties
Structural Vector Auto-Regression
Identification
Monte-Carlo simulation

ABSTRACT

In evaluating an economic model with Structural Vector Auto-Regression (SVAR), the Cogley–Nason–Sims (CNS) approach compares impulse responses estimated from empirical data with those obtained from the identical SVAR run on model generated data. Using Monte-Carlo simulations, this paper examines small sample performance of the CNS approach.

1. Introduction

In macroeconomics, Impulse Responses Functions (IRFs) derived from Structural Vector Auto-Regression (SVAR), are often used to evaluate economic models. Invalid identifications, however, can result in quantitatively large discrepancies between identified and theoretical IRFs (see Carlstrom et al., 2009). The Cogley–Nason–Sims (CNS) approach[1] is meant to be immune to this problem. The reason is that it compares impulse responses estimated from empirical data with those obtained from the identical SVAR run on model generated data. As empirical and model generated data are treated symmetrically, the application of the CNS approach does not require identifications to be valid (see Kehoe, 2006).[2] It may therefore be tempting to use this approach for model evaluations.[3]

In this paper, we investigate and compare finite sample properties of the CNS approach in two scenarios—when identifications are either valid or invalid. We find that, for samples of the size commonly found in macroeconomic applications, when identifications are invalid, the resulting estimates contain considerable bias and are very sensitive to the amount of measurement error included. In particular, when the CNS approach is implemented for parameter estimation, the moments or the estimated IRFs are not informative about structural parameters to be estimated. The poor small sample properties of the CNS approach is due to the added uncertainty from other economic shocks, which in turn is a result of invalid identifications. This paper is a caution against the indiscriminate use of the CNS approach, as the results show that it can still go wrong, especially with invalid identifications.

* Corresponding author.
E-mail addresses: muhammad.hussain@lums.edu.pk (S.M. Hussain), Lin.Liu@liverpool.ac.uk (L. Liu).

1 It is advocated by Sims (1989) and applied by Cogley and Nason (1995). It is essentially an application of indirect inference.

2 The other approach used in macroeconomics is the common approach. It compares impulse responses estimated from empirical data with those directly derived from models. The application of this approach requires identifications to be valid. With Monte-Carlo simulations, Christiano et al. (2006) examines small sample properties of the common approach.

3 The CSN approach has been used in a number of studies: Dupaigne et al. (2007), Mertens and Ravn (2011), Barsky and Sims (2012), Le et al. (2011), Castelnuovo and Surico (2010) and etc.

http://dx.doi.org/10.1016/j.econlet.2016.06.036
0165-1765/

The paper is organized as follows: Section 2 describes the Monte-Carlo simulations; Section 3 presents results; Section 4 provides discussion and Section 5 concludes.

2. Monte-Carlo simulations

The data generating processes (DGP) used in the Monte-Carlo simulations are two variants of the New Keynesian (NK) models,[4] which only differ in the assumptions on monetary shocks. One is the standard textbook NK model, where monetary shocks have a contemporaneous effect on the economy (called 'the standard model'). The other adopts the assumption used in Christiano et al. (2005), where monetary shocks do not affect the economy contemporaneously (called 'the CEE model'). Then we derive impulse responses by estimating the three variable SVAR (output, price and interest rate) with the short-run recursive identification, that is, monetary shocks do not affect the current economy. Therefore, with the CEE model the identification is valid, while with the standard model the identification is invalid. We compare finite sample performance of the CNS approach in both of these scenarios.

To avoid from any confusion, some terminologies are clarified here. There are two types of monetary shocks: one is the monetary shocks that appears in the Taylor rule, which we call the *exogenous monetary shocks*, and the other is the monetary shocks recovered using the short-run identification, which we call the *identified shocks*. These two shocks generally are different, and so are their impulse responses. Moreover, there are three types of impulse response functions (IRFs):

- The *theoretical IRFs* give the effects of the exogenous monetary shocks. They are derived directly from models (see Christiano et al., 2005);
- The *population IRFs* describe the effects of the identified shocks in the population, which are immune from random sampling uncertainties. In the standard model, the population IRFs are obtained from the analytical VAR representation of model dynamics with the short-run identification (see Carlstrom et al., 2009). In the CEE model, the population IRFs are obtained by applying SVAR with the short-run identification on model generated data with sufficiently large sample size and number of lags.[5]
- The *estimated IRFs* describe the effects of the identified shocks in finite samples. They are estimated by applying the SVAR with the short-run identification to model generated data with sample size commonly found in macroeconomic applications. Since the length of simulated data sets are limited, they suffer from finite sample problem (see Christiano et al., 2006).

Carlstrom et al. (2009) examines the difference between the theoretical and population IRFs, due to the mis-identification of monetary shocks. In this paper, we investigate the difference between the estimated and population IRFs, due to small sample size.

3. Results

In this section, we evaluate finite sample performance of the CNS approach with two estimators — estimated IRFs and estimated model parameter. Throughout the paper, all the responses are normalized so that the initial rise in interest rate is 25 basis points, and here we only report results for output responses.[6]

3.1. Estimated IRFs

In each scenario, we generate $N = 500$ simulated data sets, with length equal to 180 periods each. To derive the estimated IRFs, we apply SVAR with short-run recursive assumption to each data set. Then we obtain N sets of estimated IRFs of the identified shocks.

The first row in Fig. 1 presents the mean estimated IRFs for both scenarios—the average of all the estimated responses, along with the population IRFs for easy comparison. Since the population IRFs are not subject to sampling uncertainties, they provide us criteria for evaluating the estimated IRFs. We find that, for the CEE model, the mean estimated IRFs are very close to the population IRFs, while for the standard model, the mean responses are markedly different from the population IRFs. Furthermore, in order to show the magnitudes of sampling uncertainties associated with the estimated IRFs, in the second row of Fig. 1 we look at both sample probability intervals and confidence intervals.[7] We can see that for both models the confidence bands and probability intervals are very similar. This confirms the findings in Christiano et al. (2006) that confidence intervals correctly reveal the amount of sampling uncertainties contained in probability intervals. However, we find that for the CEE model, the bands are very narrow at the initial few periods, suggesting that the drop in output is statistically significant. In contrast, for the standard model, the bands are too wide to provide any useful inference. In other words, they support a broad range of empirical results, and are not very informative.

3.2. Estimated parameter

The CNS approach is often used to estimate model parameters by matching impulse responses derived from empirical observations and model generated data. We choose the auto-correlation of monetary shocks as the targeted parameter to be estimated.[8] The true parameter value is 0.5. To proceed, for each scenario, with the true persistence we simulate one data set from which we estimate the impulse responses. These are treated as the empirical IRFs, and the parameter is then estimated by the simulated method of moments. We repeat this procedure for 500 times, and obtain a series of estimates.

The third row in Fig. 1 plots the probability density functions for the parameter estimates. Clearly, the estimates of the CEE model center around the true parameter value. The mean of

[4] The NK model setup closely follows Carlstrom et al. (2009). Please refer to Appendix (see Appendix A) for more details.

[5] Since the CEE model does not have a pure finite VAR representation, we could not derive the population IRFs analytically. So we derive the population IRFs with sufficiently large sample size and number of lags. As shown in Figure B.1 in the Appendix, for the CEE model, the population IRFs match closely with the theoretical IRFs, which does not suffer from finite sample problems. Moreover, it implies that the SVAR with short-run identification can correctly identify the exogenous monetary shocks in the CEE model.

[6] Please refer to the Appendix (see Appendix A) for the full sets of results.

[7] Probability intervals are those estimated IRFs that are two standard deviations away from the mean. They describe the extent of uncertainties associated with random realization of economic shocks. Moreover, for each data set we derive 95% confidence intervals of its estimated IRFs. The average of all these confidence intervals are the confidence bands presented in Fig. 1.

[8] We could have chosen to estimate more parameters or some other parameters. The reason we choose to estimate auto-correlation of monetary shocks is that it is one of the key determinant factors for the impulse responses of the identified shocks in both models. By concentrating on estimating this parameter, on the one hand we want to give the CNS approach its best shot in uncovering the true parameter value, and on the other hand the results are easily comparable between the two models.