Structural testing of Business Cycles*

Esa Mangeloja†

Abstract

In this article, the predictability performance of certain classical business cycle theories are tested against contemporary statistical methods by using Finnish macroeconomic data. Keynesian multiplier-accelerator model derivatives and neo-classical real business cycle models are compared to statistical stochastic time-series methods. Some philosophical considerations on the scientific principles and macroeconomic analysis are extended for applied econometric practice. VAR and SUTSE models are estimated and compared against classical theory implications. It is found that in this case, SUTSE model has a superior forecasting ability and that pure statistical algorithms are the most efficient alternatives for predicting Finnish business cycle data.

1 Introduction

Economic theory concerning the modelling of the business cycles has not been emerging noteworthily since the early 1980s when the substantial body of literature was devoted to the "real business cycle" approach. As [4, p.436] has noted, the accuracy of the macroeconomic forecasts has not improved

*Keywords: Business Cycle, Real Business Cycle Theory, VAR, SUTSE, multiplier-acceleration

†University of Jyväskylä, School of Business and Economics, P.O.Box 35, FIN-40014 University of Jyväskylä, Finland

over the last 40 years, maybe because the descriptive statistics, used to measure the difficulty of forecasting over different time periods, may not capture the difficulty of preparing forecasts in any specific time period. A more appropriate approach is rather to consider performance relative to a suitable benchmark that has the potential to eliminate idiosyncratic effects which arise during each time period under analysis.

In this paper the reasoning follows Bayesian argumentation which treats uncertainty across theories as no conceptually different from stochastic elements of the theories themselves. Therefore alternative implications and forecasting power should be compared, not just between alternative theories, but also between classical theories and pure statistical methods [20, p.1599]. A focus on solving and calibrating models, rather than carefully fitting them to data, is reasonable at a stage where solving the models is by itself a major research task [21, p.112]. But when applicable theories have been advanced enough, more systematic collection and comparison of evidence cannot be avoided. As argued by McCloskey [11] and Sims [21], economics is definitely not physics. Economics is analyzing questions, which may always ultimately be returned to human behavior, and therefore does not achieve the clean successes and consensuses of the natural sciences. In economics, like in other social sciences, there can be disagreement not only about which theories are best, but also about which *modes of argument* are legitimate [21, p.119].

This paper follows the idea of the research by Fildes and Stekler (2002)[4], where they have analyzed the macroeconomic forecasting accuracy of macroeconomic models compared to their time series alternatives[1]. Previous qualitative results (see footnote) indicate that forecasters have made systematic errors in predicting several macroeconomic variables.These errors occurred when the economy was subject to major perturbations, just the times when accurate forecasts were most needed.

[1]for other related research see, Klein, 1991; Wallis, 1993; Bodkin et al.,1991; Daub, 1987; Smith, 1994; Den Butter and Morgan, 1998; Zarnowitz, 1992; McNees, 1992; Zarnowitz and Braun, 1992

Fildes and Stekler used US and UK data, and in this paper Finnish macroeconomic data is used instead. This gives interesting opportunity to test and compare their findings by using different data. They found that a comparison of the US and UK macroeconomic forecasts with times series predictions support the use of advanced statistical methods for improving the forecasting accuracy. By using different data, Finnish macroeconomic variables, that research is extended in this paper.

Traditional view of economic science was that the core issue in economics was to formulate testable hypotheses and confront them with data [18, p.21]. As Sims [21] has noted, that hypothesis oriented science is essentially dependent on the idea that there are true and false theories, when in reality the degree to which theories succeed in reducing data can be a continuum. As McCloskey [11] has argumented, still a large majority in economics (especially in macroeconomics) closely stick with traditional view of economic science [12, p.1320]. This is strange during the current time when most philosophers agree that strict logical positivism is dead [11, p.486].

The main forerunner in modernist economics were Samuelson and Friedman[2], which founded the modernist economic methodology. McCloskey labels Samuelson's use of mathematical problem formulations as scientific rhetoric, as a handy tool for persuasion and giving an impression of authority [11, p.500]. This is in contrast to Hicks, who pushed mathematics off into appendices. Most natural sciences give a much less important role to probability-based formal inference than does economics, but that is unavoidable, because there are few possibilities available for experimentation. But econometricians should remember to distinguish between the notions of pure statistical significance and economic significance [13, p.99], which apparently are not equal.

One implication from Lucas critique, not perhaps gained enough attention in economics, is his concluding sentence "econometric models are useless

[2]Friedman, M, "The Methodology of Positive Economics (1953) and Samuelson P.A. "The Foundations of Economic Analysis (1947)

for policy evaluation". The ultimate criterion for the validity of scientific theory should be the degree to which they help us order and summarize data. Classical Keynesian multiplier-accelerator models and RBC share the common interest into constructing and estimating of models, which Sims [21, p.115] labels as dynamic, stochastic, general-equilibrium (DSGE) models. But all too often these models, representing Kuhn's "normal science" in contemporary economics, are too stylized and remote to fit the data to provide a reliable guides to policy. That is the reason why several scholars, Sims [21] in forefront, demand that more stylized statistical time-series methods, like frequency domain analysis or other orthogonal decomposition VAR and SUTSE methods should be used as a standard part of any model (including especially RBC) evaluation. As Sims argues [21, p.118], usually a simple reduced form VAR(1) model gives a better fit than neoclassical RBC models. Therefore it is considerable interest in making comparisons between DSGE and alternative models, not to mention before any quantitative policy analysis is done.

2 Theoretical considerations

This chapter presents shortly the applied modelling alternatives for business cycle behavior. Models are explained only by extend relevant for the empirical purposes of this paper. More extensive analysis of the most important business cycle models can be found e.g. in collection by T.C. Mills[14].

2.1 The Samuelson Oscillator

The basic Samuelson (1939) business cycle model relies on simple Keynesian consumption function, which is appended by dynamic investment function to derive a classical multiplier-accelerator mechanism. His model represented a dynamic adjustment process, which is in contrast to classical static models [9]. The consumption function includes a Robertsonian lag of type

$$C_t = c_0 + cY_{t-1} \tag{1}$$

where present consumption is a function of past income. Investment function includes changes in consumption demand, according to the accelerator principle.

$$I_t = I_0 + \beta(C_t - C_{t-1}) \tag{2}$$

Government and foreign sector are assumed away, so the market identity closes the system with

$$Y_t = C_t + I_t$$

This system implies a second order linear difference equation:

$$Y_t - (1+\beta)cY_{t-1} + \beta\ cY_{t-2} = (c_0 + I_0) \tag{3}$$

The roots of this system determine the dynamics. It can be shown that they are the parameter regimes of β and c which yield the different dynamics, both complex and asymptotic. Only the apparently rare case of $c = \frac{1}{\beta}$ will produce constant and harmonic oscillation.

2.2 Hicks' trade cycle

Hicks' model (1950) is characterized by aiming to explain unstable oscillations and adding floors and ceilings to constrain them. Hicks applies simple Robertsonian consumption function as Samuelson, but replaces the accelerator by using past output differential. Therefore, the investment function becomes

$$I_t = I_0 + \beta(Y_{t-1} - Y_{t-2}) \tag{4}$$

while the consumption function remains identical to Samuelson model. The main implication is the different characteristic equation. Now the sufficient condition for constant oscillation behavior reduces to somewhat more simple case of $\beta = 1$, with no requirement for c. Nevertheless, any slight movement of β from unity will lead to explosive or damped behavior, making the model structurally unstable. The model adds also income ceiling and investment floor to the cyclical behavior [6, 435].

We should also note that the variations which induce investment are lagged one period. This means that some time must elapse in order that the new capital goods required to accommodate the increased demand can be produced. Hicks' model also shows that the linear dynamic models require exact model specification [2, 189-198].

The major difference between the Samuelsons' and Hicks' multiplier-accelerator models is, that in the Hicks' model the difference between the damped and explosive oscillation depends only on the accelerator β, while in Samuelsons' model this depends on β and c [5, 77].

Hicks' model is intrinsically less stable than Samuelson's model. This is not surprising, since in the former induced investment depends on the variations in consumption demand, which are evidently smaller. According to Hicks, the accelerator coefficient is always greater than unity, and this puts the model in the unstable regions. The explosiveness of the model, however, is checked by some non-linearities built in the model in an ingenious way. These non-linearities are an upper limit and a lower limit to income, which check its otherwise explosive behavior and give rise to cycles of constant amplitude around the trend.

It is interesting to note that the presence of the limits reduces to a matter of secondary importance the problem whether the "free" movement (i.e. the movement that would occur in absence of the limits) is monotonic or oscillatory, since the rebound gainst the limits gives rise in any case to a fluctuating movement. The fluctuations in income are then contained between the two limits and so are of approximately constant amplitude in relative terms, i.e. when measured as relative deviations from the trend. In absolute value they are actually of increasing amplitude.

2.3 RBC, Real Business Cycle-theory

Formulating of RBC-theory meant the establishment of a new research methodology. This must be emphasized as one common mistake among RBC-critics is to only blame it as forgetting any substantive role of money in formulating business cycle behavior [3]. But that is an over-simplification of the underlying meaning of the theory, which has enabled a more inductive approach to systematic quantitative description of business cycle behavior. The theory has also been able to emphasize the importance of purely qualitative results, spreading to other economic applications as well. One important contribution of RBC to modern business cycle theory is that it implies that a model should be broad enough to explain also related economic findings.

One feature that differentiates alternative theories of the business cycle is the nature of the "shocks" (random events) that cause fluctuations in economic aggregates. For example, one popular theory, often identified with Milton Friedman, holds that shocks to monetary policy are the primary cause of business cycles. Another theory, one identified with John Maynard Keynes, maintains that sudden changes in the sentiments ("animal spirits") of entrepreneurs are the primary cause. Real business cycle theory focuses on the role played by fluctuations in the level of technology. Real Business Cycle models assume an economy which aggregates a large number of infinite-lived identical households [8], which at time t aim to maximize

$$E_t \left[\sum_{j=0}^{\infty} \beta^j u(c_{t+j}, l_{t+j}) \right]. \tag{5}$$

Representative consumption and leisure decisions are denoted by c_t and l_t, respectively. Parameter β can be interpreted as a discount factor $(0 < \beta < 1)$ which reflects a current over future consumption preference.

Households are assumed to face a homogenous of degree one production function

$$y_t = z_t f(n_t^d, k_t^d), \tag{6}$$

where n_t^d and k_t^d denote production inputs of labor and capital. The variable z_t is a random variable that implies the state of technology in period t and follows a Markov class process. Capital is assumed to disappear via depreciation by the fraction δ. Household's budget constraint in period t depends also on wage and rental rates w_t and q_t, which are assumed to be derived from competitive labor and capital services markets.

$$c_t + k_{t+1} = z_t f(n_t^d, k_t^d) + (1-\delta)k_t - w_t(n_t^d - n_t) - q_t(k_t^d - k_t). \qquad (7)$$

RBC model assumes rational expectations. Market equilibrium, holding for periods $t = 1, 2, \ldots,$ is characterized by the following equalities:

$$c_t + k_{t+1} = z_t f(n_t, k_t) + (1-\delta)k_t \qquad (8)$$

$$u_1(c_t, 1-n_t) - \lambda_t = 0 \qquad (9)$$

$$u_2(c_t, 1-n_t) = \lambda_t z_t f_1(n_t, k_t) \qquad (10)$$

$$\lambda_t = E_t \; \beta\lambda_{t+1}[z_{t+1} f_2(n_{t+1}, k_{t+1}) + 1 - \delta] \qquad (11)$$

Empirical problem with RBC models is that there are very few functional forms for u and f which will permit derivation of explicit closed-form solutions for k_{t+1}, c_t and n_t. Nevertheless, one combination involves a log-linear specification for u and a Cobb-Douglas form for f, implying:

$$u(c_t, 1-n_t) = \theta log c_t + (1-\theta) log(1-n_t), \qquad (12)$$

$$z_t f(n_t, k_t) = z_t n_t^{\alpha} k_t^{1-\alpha} \qquad (13)$$

That special case requires $\delta = 1$, that is complete depreciation of capital during a single period. It has been shown that in this depreciation case and using AR(1) technology shocks, quantity variables have the time series properties of AR(2) process. Usually detrended quarterly macroeconomic data series for the logs of various aggregate factors are well described by

AR(2) type models. Empirically that is important, because we can now estimate the RBC model by using:

$$log\ c_t = (1-\alpha+\rho)log\ c_{t-1} - (1-\alpha)\rho\ log\ c_{t-2} + \alpha(1-\rho)\phi_1 + (1-\alpha)(1-\rho)\phi_0 + \epsilon_t \tag{14}$$

Another interesting property of equation 14 is that the average product of labor is positively correlated with the level of total output.

2.4 VAR forecasting

Forecasting is quite obvious use for VAR systems. The optimal forecast in this context is the conditional expectation given all information up to the period when forecast was made. Optimality implies minimizing the forecast mean square error (MSE) of each variable. If the generation process is a known VAR(p) for variable y_t with independent white noise errors v_t, the conditional expectation $y_T(h)$ of y_{T+h} given $y_T, y_{T-1}, \ldots,$ is straightforward to determine. Denoting by E_T the conditional expectation operator given $y_T, y_{T-1}, \ldots,$.

$$\begin{aligned} y_T(h) = E_T[y_{T+h}] &= v + \Theta_1 E_T[y_{T+h-1}] + \ldots + \Theta_p E_T[y_{T+h-p}] \\ &= v + \Theta_1 y_T(h-1) + \ldots + \Theta_p y_T(h-p) \end{aligned} \tag{15}$$

where $y_t(h-1) = y_{T+h-i}$ for $i \geq h$ and $E_T[v_{T+h}] = 0$ has been used. This equation can be applied repeatedly for recursively computing h-step-forecasts for $h = 1, 2, \ldots$.

2.5 Seemingly unrelated time series equations modelling (SUTSE)

Seemingly unrelated time series equation modelling estimates Beveridge-Nelson[1] type decomposition of multivariate time series in an unobserved components framework. Vector of observations are linked together through the correlations of the disturbances driving unobservable components. All the series are assumed to have the same dynamic properties[22]. SUTSE is an alternative to VAR approaches and its appeal lies in its transparency and structural character. The basic SUTSE model parsimoniously nests a large set of common trend and common cycle restrictions. If the cyclical component has a sufficiently rich serial correlation pattern, all covariance terms of the trend and cycle innovations are identified[17]. Tests for common trends are based on a method developed by Nyblom and Harvey[16] and hypotheses on common cycles are tested using likelihood ratio statistics with standard distributions.

SUTSE models offer insights in the dynamic relations between variables as well as the identification of innovation sources. Individual pieces like trend, cycle, seasonal and possible exogenous and endogenous explanatory variables can be modeled separately and subsequently combined in the state-space model. Unobserved components approach also enables modeling common factor restrictions in a transparent way. Possible common factor restrictions include long-run restrictions imposed by common trends and short-run restrictions by common cycles [22].

The basic SUTSE representation is a state-space model that serves as a basis to estimate the Beveridge-Nelson decompositions as the sum of two unobserved components, which consists of k common stochastic trends, $\gamma\tau_t$, and l common cycles, $\tilde{\gamma}c_t$ [17]. No restrictions are imposed on the covariances of the error terms (as is done in unobserved components models (UC)). It is assumed that the cyclical component is described by a stationary VAR(p) process. This implies

$$y_t = \gamma\tau_t + \tilde{\gamma}c_t \tag{16}$$

$$\tau_t = \tau_{t-1} + \eta_t \tag{17}$$

$$\Phi(L)c_t = \epsilon_t \tag{18}$$

where η_t and ϵ_t are the trend and cycle innovations, and $\Phi(L)$ is a l-dimensional lag polynomial of order p. Basic model allow for a wide range of formulations [15, p.3]. The model can be cast into state space form by defining the measurement equation as (16) and the state vector as equation (17) with present and past values of the cycle being generated by equation (18). The parameters are estimated by maximum likelihood using the prediction error decomposition [10].

3 Empirical results

Empirical testing is done by using Finnish macroeconomic data, which covers years 1975-2002. The quarterly time-series are seasonally adjusted and presented in figure 1.

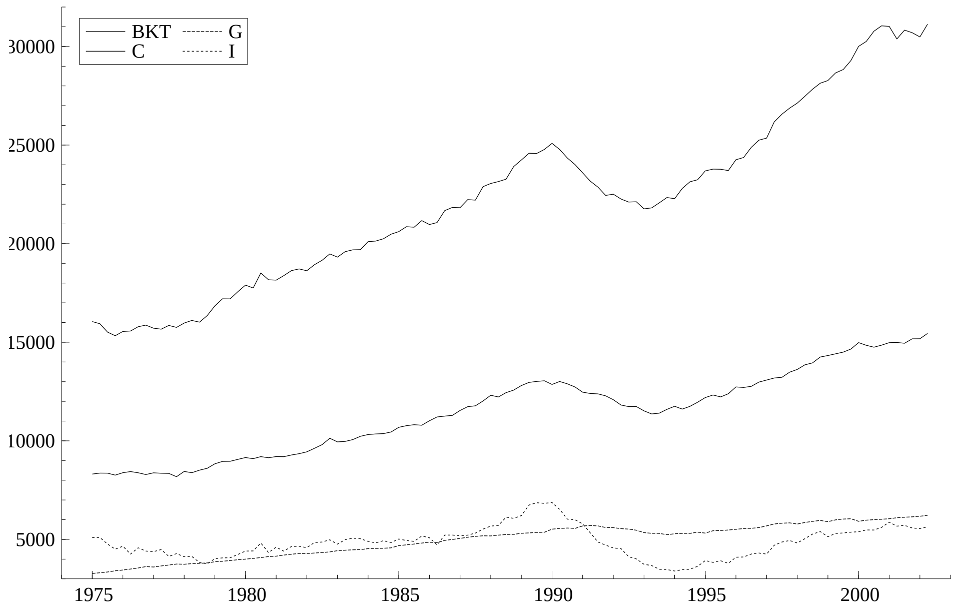

Figure 1: Macroeconomic data used for Finland

The well-behaving residual requirements and stability conditions for the estimations are guaranteed by using usual diagnostic procedures. Statistical properties of Finnish business cycle are presented in table 1. The statistics support the usual understanding that investment fluctuates much more than output or consumption (about 4 times)[3]. Detrended variables do not present significant autocorrelation.

Variable	(a)	(b)	(c)	(d)	(e)
Output	0.13	1.00	1.00	0.11	0.23
Consumption	0.13	0.99	0.46	0.17	0.14
Investment	0.51	3.85	0.62	-0.09	0.30

Table 1: Statistical properties of Finland Business Cycle

Note: Explanation of columns: (a) standard deviation, s.d.; (b) s.d. relative to output; (c) correlation with output; (d) ar(1); (e) ar(2)

Measuring forecasting accuracy and estimating it statistically would be straightforward, if we would knew the true probabilistic structure which generates these prediction errors, but in measuring macroeconomic forecasts we have no definite idea of how to measure the welfare losses of incorrect predictions or the stochastic structure [19, p.226]. Under these circumstances, ranking of forecasting ability is done here only by using the first two moments of calculated forecasting errors.

Business cycle models of Samuelson and Hick's were estimated by using simultaneous multiple-equation FIML technique applied to the system of macroeconomic variables. Each system was built according to equations found in section 2. Dynamic (ex ante) 1-step forecasts were calculated for four (inside the data) periods. Parameter constancy was also tested. Estimation diagnostics are found in table 2.

Econometric modelling requires a testing of unit root property. Variables were found to be $I(1)$, but no co-integration was found in test. Co-integration was analyzed following Johansen's method in VAR context and tested for the VAR estimation purposes. The co-integration test results are found in

[3]Results are derived from detrended seasonally adjusted data, ADF tests were done for each time-series, which were uniformly found to be $I(1)$

Model	(a)	(b)	(c)	(d)	(e)
Samuelson	0.13	0.25	1.93	287.12	16.07
Hick's	0.13	0.25	14.97	295.62	10.21
RBC	0.13	0.13	0.52	64.89	4.45
VAR	0.12	0.12	0.44	557.61	6.87

Table 2: Estimation diagnostics of Keynesian multiplier-accelerator, RBC and VAR models

Note: Explanation of columns: (a) σ for output eq; (b) σ for consumption eq; (c) σ for investment eq; (d) $-\frac{T}{2}\log|\widehat{\Omega}|$ of system; (e) parameter constancy forecast χ^2 test using Ω

table 3. Because no co-integration property was found, VAR model was estimated using first differences of the variables and the appropriate lag value ($k = 4$) was found using general-to-specific reduction algorithm enabling well-behaving residuals with no autocorrelation property. Also VAR model estimation diagnostics are included in table 2. VAR model seems to produce best fit for the data used, even when VAR model was estimated in first difference form, which may weaken the forecasting ability contra error-correction VAR representation alternatives.

H_0:rank $\leq$	λ_{trace}	p-value	eigenvalue
0	18.091	[0.569]	0.10112
1	6.8969	[0.596]	0.049536
2	1.5624	[0.211]	0.014770

Table 3: Co-integration test results

SUTSE model estimation enables using common factor representation, if disturbance vectors have less than N elements. Recognition of common factors yields models which may not only have an interesting interpretation, but may also produce more efficient inferences and forecasts[7], but as Johansen's co-integration test implied, this is not an valid alternative in this case. Therefore one important alternative modelling option is here absent. Nevertheless, in basic SUTSE representation applied, several components can be included into multivariate model. In this case, one common cycle (amplitude estimated as being 13 periods) and a stationary AR(1) process are appended, producing the following estimation diagnostics found in table 4.

	Output	Consumption	Investment
s.d.	0.1195	0.1192	0.4062
$Q(12,6)$	11.750	22.812	17.866
Final state coefficients			
η	106.70	106.60	100.91
τ	0.0870	0.0699	0.0794
c_1	0.0528	-0.0487	0.1442
c_2	-0.0262	0.0242	-0.0716
ar(1)	-0.1356	-0.0585	0.1435
s.d. of disturbances (q-ratio)			
η (10^{-2})	4.9038 (1.0000)	7.6753 (1.0000)	30.388 (1.0000)
τ (10^{-2})	2.2309 (0.4733)	2.7244 (0.3550)	8.3033 (0.2732)
c_t (10^{-2})	1.2520 (0.2349)	1.0634 (0.1385)	3.1463 (0.1035)
ar(1) (10^{-2})	8.2498 (1.6823)	3.06360 (0.3956)	4.5312 (0.1491)
Cycle amplitude	0.0590	0.0544	0.1610
Cycle % of trend	5.8954	5.4421	16.1023

Table 4: SUTSE model diagnostics

In the presented table 5 the mean values and standard deviations of the forecast errors are presented, for the GNP, consumption and investment forecasts (scaled for base 10^{-2}). In predicting output behavior, SUTSE model (including common cycles and AR(1) process) gave superior forecasts. Nevertheless, the result was not much better than with using simple VAR(4) estimation. Classical multiplier-accelerator models were giving clearly worst predictions. Compared to those, RBC succeeded better. A little surprise was that RBC models gave the best predictions in estimating consumption behavior and with that time series, statistical VAR and SUTSE models did not succeed significantly better than theoretical applications. Nevertheless, the differences are not wide. In investment forecasts, SUTSE model was a clear winner, but VAR(4) performance was not far away behind.

These results seem to support the idea that pure a-theoretical alternatives for business cycle modelling are not awkward alternatives against more theoretically grounded classical models. It also suggests that frequency domain analysis or other standard methods of orthogonal decomposition of macroeconomic time series data, as VAR impulse responses or SUTSE common component analysis, ought to be a standard part of RBC model evaluation.

Variable	Samuelson	Hicks	RBC	VAR(4)	SUTSE
Output $\bar{x}$	0,71	2,18	-0,14	-0,11	-0,02
σ	9,74	10,00	8,77	8,30	8,24
Consumption $\bar{x}$	37,93	30,01	5,28	-4,74	2,63
σ	8,25	7,55	5,54	8,12	7,51
Investment $\bar{x}$	-188,01	-194,22	33,39	-21,43	30,55
σ	41,75	14,83	26,25	14,32	13,40

Table 5: Moments of macroeconomic forecast errors

But the methodological and philosophical aspects should not be neglected in macroeconomic modelling. Econometric modelling is not separate entity from economic science. Pure statistical inference does not imply anything on economic significance. Pure statistical significance does not *per se* reveal any new information on the business cycle formation or behavior. The economic meaning and content should be given with theoretically solid argumentation, not just using significance level. That task is relevant for any economist and should not be neglected or left to statisticians or mathematics. Therefore, these results imply that more emphasis should now be put on developing better business cycle models with clear and solid economic reasoning, using statistical tools, but not forgetting the basic scientific aim of revealing real behavior of human economics.

4 Conclusion

By comparing the forecasting ability of several business cycle modelling alternatives, it was found that pure statistical algorithms were the most successful. Keynesian multiplier-accelerator models and real business cycle models failed to give additional forecasting accuracy compared to VAR or SUTSE models, except in forecasting the consumption variable, where RBC model seemed to give the best predictions. Nevertheless, the overall predicting ability was superior using SUTSE modelling. This finding is thus in line with previous findings by Fildes and Stekler (2002), where similar analysis was done by using the macroeconomic data of US and UK. This raises important questions to be asked in future macroeconomic empirical modelling. VAR and SUTSE models are considered as valid alternative for macroeconomic and business cycle forecasting if appended with theoretical foundations. SUTSE models can be seen as wide applications of time-series statistics, which encompasses the other methods tested, which can be seen as special case restricted alternatives. This supports the notion that common factor models yield more efficient inferences and forecasts[10]. As each component is modelled separately by an appropriate stochastic process, this technique enables the econometrician to identify specific stable relationships between time series.

Previous research on macroeconomic forecasting states[4], that there exists one result about where there is general agreement, namely that no one forecasting method or one model or one individual does best all of the time. Both theoretical and empirical studies have shown economic forecasting to be potentially valuable. Contemporary macroeconomic models provide a rigorous theoretical basis for macroeconomic analysis. These theoretical developments have been matched by statistical innovations. The comparison of model forecasts with those generated by time series has led to improved specifications as well as a more refined evaluation methodology based on structural time series modelling. These approaches abandon the premise that there is a "correct" model that is stable over time.

Considerable intellectual activity is devoted to forecasting major economic variables. Improved macroeconomic forecasting may also require a thorough understanding of the intellectual or cognitive processes that forecasters use in making forecasts and adjusting their models. In order to obtain the understanding of forecasting processes, it would be necessary to build and test models of forecaster behavior. Use of various methods and techniques would give an enchanted forecasting power for different situations where conventional procedures are not any more the optimal choices. Increasing use of common component and SUTSE models would improve also the macroeconomic forecasting performance. While there is considerable research resource spent in developing macroeconomic theory and to a lesser extent, statistical models, little attention has been given to the evaluation and improvement of forecasting performance. A success in widening use of structural time series models would also lead to an improved understanding of macroeconomic processes.

References

[1] S. Beveridge and C. Nelson. A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the business cycle. *Journal of Monetary Economics*, 7:151–174, 1981.

[2] J.M. Blatt. *Dynamic Economic Systems.* New York, 1983.

[3] J.P Danthine and J.B. Donaldson. Methodological and empirical issues in real business cycle theory. *European Economic Review*, 37:1–35, 1993.

[4] R. Fildes and H. Stekler. The state of macroeconomic forecasting. *Journal of Macroeconomics*, 24:435–468, 2002.

[5] G. Gandolfo. *Economic Dynamics; Methods and Models.* Netherlands, 2 edition, 1983.

[6] C.H. Hommes. A reconsideration of hicks' non-linear trade cycle model. *Structural Change and Economic Dynamics*, 6:435–459, 1995.

[7] S.J. Koopman, A.C. Harvey, J.A. Doornik, and N. Shephard. *Stamp. Structural Time Series analyser, modeller and predictor.* Timberlake Consultants Ltd, 1995.

[8] F.E. Kydland and E.C. Prescott. Time to build and aggregate fluctuations. *Econometrica*, 50(6):1345–1370, November 1982.

[9] R.E.Jr Lucas. Methods and problems in business cycle theory. *Journal of Money, Credit and Banking*, 12:271–297, 1980.

[10] R. Luginbuhl and S.J. Koopman. The common converging trend-cycle model: Estimation, modeling and an application to european convergence. 2002.

[11] D.N. McCloskey. The rhetoric of economics. *Journal of Economic Literature*, 21(2):481–517, 1983.

[12] D.N. McCloskey. Modern epistemology against analytic philosophy: A reply to mäki. *Journal of Economic Literature*, 33(3):1319–1323, September 1995.

[13] D.N. McCloskey and S.T. Ziliak. The standard error of regressions. *Journal of Economic Literature*, 34(1):97–114, March 1996.

[14] T.C. Mills. *Long term trends and Business Cycles*, volume 1 and 2 of *The International Library of critical writings in Economics*. Edward Elgar Reference Collection, 2002.

[15] F. Moauro and G. Savio. Disaggregation of time series using common components model. *Greta, working paper*, (10.09), November 2001.

[16] J. Nyblom and A. Harvey. Tests of common stochastic trends. *Econometric Theory*, 16:176–199, 2000.

[17] C. Schleicher. Structural time series models with common trends and common cycles. University of British Columbia, November 2002.

[18] J.J. Siegfried, R.L. Bartlett, W.L. Hansen, A.C. Kelley, D.N. McCloskey, and T.H. Tietenberg. The economics major: Can and should we do better than a b-. *The American Economic Review*, 81(2):20–25, May 1991.

[19] Christopher A. Sims. Evaluating short-term macroeconomic forecasts: The dutch performance. *The Review of Economics and Statistics*, 49(2):225–236, May 1967.

[20] Christopher A. Sims. Understanding unit rooters: A helicopter tour. *Econometrica*, 59(6):1591–1599, Nov 1991.

[21] Christopher A. Sims. Macroeconomics and methodology. *The Journal of Economic Perspectives*, 10(1):105–120, Winter 1996.

[22] F. Vahid and R.F. Engle. Common trends and common cycles. *Journal of Applied Econometrics*, 8:341–360, 1993.

A SUTSE estimation results

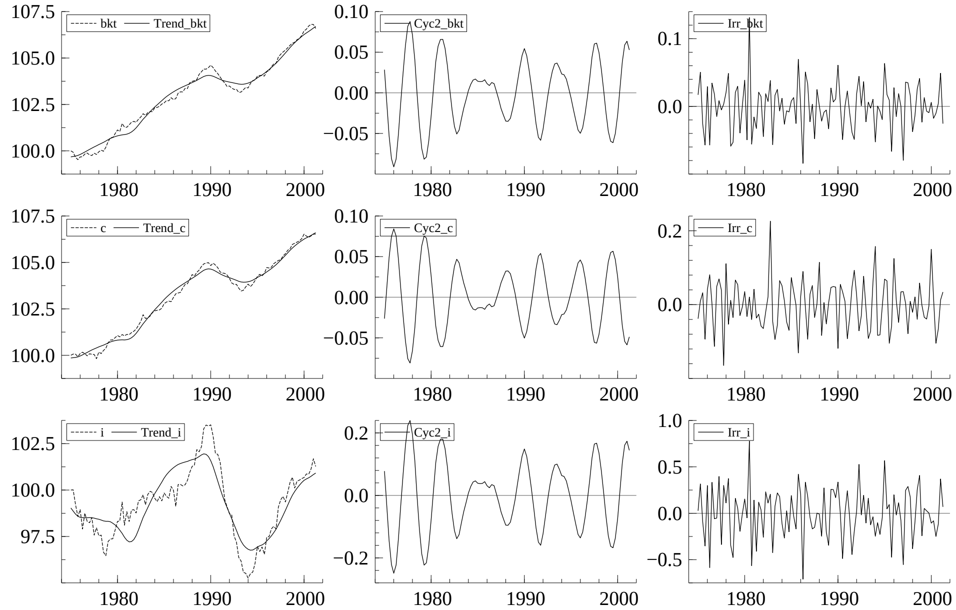

Figure 2: SUTSE components; Trend, cycle, irrational