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CONSUMPTION AND INCOME IN FINLAND 1960-1983: A MULTIPLE TIME SERIES ANALYSIS

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CONSUMPTION AND INCOME IN FINLAND 1960-1983: A MULTIPLE TIME SERIES ANALYSIS*

Abstract

The aim of this paper is to find out whether there are gains with respect to forecasting from modelling consumption and income as a bivariate time series process rather than as univariate processes. It is found that consumption and income can be modelled best jointly through an $ARMA_2(2,1)$model. Income is found to be Granger causally prior to consumption.

CONTENTS

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INFORMATION: Seija Määttä, tel. 183 2519.

1. INTRODUCTION

The study of consumers' expenditure is of major concern to economists; neoclassical economics sees the delivery of individual consumption as the main object of the economic system. Furthermore, aggregate consumption accounts for a large share of national income so that fluctuations in behavior or "consumption chocks" have important consequences for output, employment, and the business cycle. Since Keynes' general theory, the relationship between consumption and income has played a central role in macroeconomics.

Standard consumption functions that had worked well into the early seventies seriously overpredicted aggregate consumption during the period of rapid inflation that followed the oil chocks. The consumption function was one of the examples Lucas (1976) singled out for his "critique". He pointed out that if consumption is determined by the discounted present value of expected future incomes, the response of consumption to a change in income is not well-defined until we know how expectations of income are formed. Each observed realization will cause a re-evaluation of future prospects in accordance with formulae that depend on the nature of the stochastic process governing income. if the nature of this process is changed (e.g. by a change in taxation) then the way in which information is processed will change. Thus new information about incomes will have different implications for future expectations and for future consumption.

Lucas' critique gave a whole new lease of life to the study of consumption. Generally, if expectations are important, there ought to be high returns to the simultaneous modelling of consumption and income. The first important step was taken by Hall (1978) who showed that, as an approximation, consumption of non durables should follow an AR(1) process if the life cycle-permanent income hypothesis is true. That is, no other lagged variable than consumption can increase the accuracy of prediction. The notable thing about this model is the apparent absence of any reference to income. However, the model does not predict that consumption should not respond to current income. Income can also appear through the error term if current income contains new information about its own value or about future values of income (as will generally be the case).

A considerable amount of effort has recently gone into testing Hall's proposition (see e.g. Hall (1986) and the references cited therein). On the whole the model does not seem to survive the tests so well; a simple (AR)1 representation does not characterize data well enough. Many explanations for the failure have been put forward, but the most direct generalization of Hall's model has been made by Mankiw (1982). He pointed out that while durable goods, non durable goods, and services differ only in their rate of depreciation, assuming a depreciation rate of zero may be unrealistic for any category of consumption. In particular, it may be that those items classified as non durables and services are pretty durable. When this is the case Mankiw shows that consumption will follow an ARMA(1,1) process. If, in addition, there are stock adjustment costs consumption should follow an ARMA(2,1) process (also see Bernanke (1985)).

The Hall-type models are attractive because they do not depend on the properties of the income process, and focus only on consumption and its lags. But robustness comes at the price of power, and later work has devoted considerable attention to the joint properties of consumption and income. A natural route to modeling is to find a representation of real income as a stochastic process, typically as an ARMA model (Deaton (1986)). Sargent (1978) was the first to investigate the problem of formulating optimal consumption behavior as a restriction on a general time series model of consumption and income. However, as pointed out by Flavin (1981), Sargent's version did not take into account that current savings finances future consumption. As a result, his model did not yield a satisfactory characterization of optimal consumption.

Campbell (1986) recognizes the possibility of time series feedback from lagged consumption to income, and models saving and the change in income as a bivariate VAR system in which each series is regressed on lagged values of both. He finds that the model is largely consistent with the time series evidence. Campbell's study indicates the potential gains from considering consumption and income jointly. Against this background the aim of this paper can be formulated.

The aim of this paper is to find out whether there are gains with respect to forecasting from modelling consumption and income as a bivariate time series process rather than as univariate processes. Though the emphasis is on forecasting the interpretation of the models will yield interesting information about the underlying economics in this problem. In particular we will be able to study the dynamic relationships among consumption and income. The emphasis on predictive power also serves the economic interpretation as one definition of causality is the degree of confidence in the predictions of a model.

2. DATA

The natural log of quarterly seasonally adjusted real per capita personal consumption of nondurables and services was used as the measure of consumption, and this series will be referred to as CON. CON is constructed from three quarterly, seasonally adjusted (unfortunately the data were available in adjusted form only) series from the National Accounts of Finland. The series are personal consumption of nondurables and services at current prices (FIM 1000000), the implicit deflator of consumption of nondurables and services (unitless), and population (1000 persons). CON covers the period 1960.I - 1983.IV and thus contains 96 observations. The series clearly is nonstationary (it seems to contain a stochastic, downward sloping trend), and its variance is .179. Observations 7, 16 and 21 look like additive outliers.

As a measure of income, denoted INC, the natural log of quarterly seasonally adjusted real per capita personal disposable income was used. INC is constructed from the series personal disposable income at current prices (FIM 1000000) in a similar way as CON is constructed. INC also covers the period 1960.I - 1983.IV and contains 96 observations. The series clearly is nonstationary (it has a nearly linear upward sloping trend), and its variance is .044. Observations 64,67 and 72 look like additive outliers.

3. STATISTICAL ANALYSIS

A univariate representation for CON:

Tentative specification;

As the series is highly autocorrelated the sample ACF (autocorrelation function) and PACF (partial autocorrelation function) do not reveal much more than the pronounced AR(1) component.[1] However, the EACF (extended autocorrelation function; see Tsay & Tiao (1984)) clearly hints at the existence of a MA(2) component in addition to the autoregressive component. Based on the EACF's the first models to consider would be ARMA(1,2) and ARIMA (1,1,2).[2]

Estimation;

All estimations in this paper were carried out by maximizations of the "exact" maximum likelihood function due to Hillmer & Tiao (1979). In the first iteration of the modelling process the following results were obtained:

(1) $(1 - .994B)CON_t = (1 + .315B + .312B^2)a_t \quad \sigma^2 = .373 \times 10^{-3}$

(2) $(1 - .923B)(1 - B)CON_t = (1 - .631B + .087B^2)a_t \quad \sigma^2 = .369 \times 10^{-3}$

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[1]An extensive appendix (the contents of which is listed in the appendix to this paper) containing detailed computer printout documenting all reported results of this paper is available from the author upon request.

[2]No signs of seasonality are present; in this respect the seasonal adjustment has been successful.

Here a_t is the noise term and σ^2 its estimated variance.

Diagnostic checking;

Judgind by the estimated ACF and PACF of the output of (1) a_t is white noise. Apart from significantly nonzero autocorrelations and partial autocorrelations at lag 6 the same holds for model (2).

Forecasting;

All forecasts in this paper were made for the observations 85-96. Model (1) consequently overpredicts CON, and the one-step ahead forecast error variance at observation 96 is $\sigma^2_{96} = .101$. Model (2) predicts very well, and $\sigma^2_{96} = .182$.

Alternative models;

Several alternative models were estimated. Among these were e.g.,

(3) $(1 - 1.847B + .848B^2)CON_t = (1 - .569B)a_t \quad \sigma^2 = .354 \times 10^{-3}$

which yielded white noise residuals apart from significantly nonzero autocorrelations and partial autocorrelations at lag 6. Furthermore, (3) produced the most accurate and precise ($\sigma^2_{96} = .130$) forecasts of all considered models. The pure autoregression

(4) $(1 - 1.270B - .043B^2 + .315B^3)CON_t = a_t \quad \sigma^2 = .359 \times 10^{-3}$

also yielded clean output and accurate and precise ($\sigma^2_{96} = .131$) forecasts. Fitting the model of Hall (1978) yielded

(5) $(1 - 1.015B)CON_t = -.050 + a_t \quad \sigma^2 = .507 \times 10^{-3}$

which produced residuals clearly different from white noise and poor although precise ($\sigma^2_{96} = .085$) forecasts.

Outliers and intervention analysis;

Utilizing the techniques described in Hillmer et al. (1983) and Chang & Tiao (1985) observation 16 (1963.IV) was identified as an additive outlier. Modifying e.g. model (1) to take into account the outlier and estimating the modified model gives

$$(6)\quad (1 - .996B)CON_t = .054D_t^{16} + (1 + .180B + .316B^2)a_t \quad \sigma^2 = .455 \times 10^{-3}$$

where D^{16} is a dummy variable that equals one for observation 16 and is zero for all other observations. This model produces white noise residuals but markedly overpredicts consumption now with $\sigma_{96}^2 = .455 \times 10^{-3}$.

A univariate representation for INC:

Tentative specification;

As the series is highly autocorrelated the sample ACF and PACF do not reveal much more than the pronounced AR(1) component. The EACF does not give an easily interpretable result, but the first models to consider would be ARMA(1,2) and ARMA(2,1).[3]

Estimation;

$$(7)\quad (1 - 1.005B)INC_t = (1 - .299B + .330B^2)a_t \quad \sigma^2 = .420 \times 10^{-3}.$$

$$(8)\quad (1 - .729B - .278B^2)INC_t = (1 + .008B)a_t \quad \sigma^2 = .445 \times 10^{-3}.$$

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[3]No signs of seasonality are present; in this respect the seasonal adjustment has been successful.

Diagnostic checking;

Judging by the estimated ACF's and PACF's of the output of (7) and (8) the a_t's are white noise.

Forecasting;

Both model (7) and model (8) overpredicts INC, with $\sigma^2_{96} = .074$ and $\sigma^2_{96} = .061$ respectively.

Alternative models;

Several alternative models were estimated. Among these were e.g. the random walk with drift model

$$(9) \quad (1 - .980B)INC_t = .044 + a_t \quad \sigma^2 = .902 \times 10^{-3}$$

which, however, yielded residuals that were far from clean. The model underpredicts income slightly, and $\sigma^2_{96} = .093$. Fitting the model that seems to fit U.S. data best (see e.g. Deaton (1986)) gives

$$(10) \quad (1 - .465B - .340B^2)INC_t = .288 + .134T_t + a_t$$

$$\sigma^2 = .695 \times 10^{-3}.$$

where T is a linear time trend (1 = .01, 2 = .02, ...). However, when fitted to Finnish data model (10) does not yield clean residuals although the forecasts are rather accurate and very precise ($\sigma^2_{96} = .039$).

Outliers and intervention analysis;

Observations 64(1975.IV), 67(1976.III), 72(1977.IV) and 77(1979.I) were identified as additive outliers. Modifying e.g. model (7) to take into account the outliers and estimating the modified model gives

$$(11)\quad (1 - 1.005B)INC_t = .092D_t^{64} + .070D_t^{67} - .080D_t^{72} + 037D_t^{77}$$

$$+ (1 - .274B + .293B^2)a_t \quad \sigma^2 = .400 \times 10^{-3}.$$

This model produces white noise residuals but overpredicts income with $\sigma_{96}^2 = .071$. However, model (11) overpredicts income slightly less than model (7) does.

A bivariate representation for CON and INC:

Tentative specification;

As both series are highly autocorrelated and cross correlated (the estimated sample cross correlation at lag zero is -.88) the estimated cross correlation matrices are of no use in determining the order of the moving average part in the bivariate model. Similarly, the partial autoregression matrices and the AIC give little information about the order of the autoregressive part. However, the chi-square statistic of Tiao & Box (1981) suggests a maximum autoregressive order of three.[4]

To resolve the identification problem a smallest canonical correlation analysis (SCAN) was performed as developed in Tsay & Tiao (1985). The analysis suggests a bivariate model of maximum dimensions $ARMA_2$ (2,2) or $ARMA_2$(2,1). These models will be estimated in the first round of the modelling process.

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[4]As the difficulties in identification may stem from the nonstationarity of the vector series the same identification procedures where performed on once differenced data. However, results where as uninformative as before (the chi-square statistic now suggests a maximum autoregressive order of two).

Estimation;

$$(12)\qquad \left(I - \begin{bmatrix} .495 & .306 \\ -.046 & .122 \end{bmatrix} B - \begin{bmatrix} .523 & -.344 \\ -.056 & .870 \end{bmatrix} B^2 \right) \underset{\sim}{z}_t =$$

$$\left(I - \begin{bmatrix} -.536 & .224 \\ -.172 & -.359 \end{bmatrix} B - \begin{bmatrix} -.207 & -.292 \\ -.374 & .486 \end{bmatrix} B^2 \right) \underset{\sim}{a}_t$$

$$\Sigma = \begin{bmatrix} .425 \times 10^{-3} & \\ .177 \times 10^{-3} & .676 \times 10^{-3} \end{bmatrix}$$

$$(13)\qquad \left(I - \begin{bmatrix} .736 & -.300 \\ .929 & 1.178 \end{bmatrix} B - \begin{bmatrix} .281 & .266 \\ -.937 & -.156 \end{bmatrix} B^2 \right) \underset{\sim}{z}_t =$$

$$\left(I - \begin{bmatrix} -.131 & -.530 \\ .771 & .795 \end{bmatrix} B \right) \underset{\sim}{a}_t$$

$$\Sigma = \begin{bmatrix} .484 \times 10^{-3} & \\ .211 \times 10^{-3} & .680 \times 10^{-3} \end{bmatrix}$$

$\underset{\sim}{z}_t$ denotes the vector time series, $\underset{\sim}{a}_t$ the vector of estimated residuals, and Σ the estimated error covariance matrix.

Diagnostic checking;

Judging by the estimated cross correlation matrices of the residual vectors both models yield practically clean residuals.

Forecasting;

Model (12) underpredicts both CON (σ^2_{96}= .090) and INC (σ^2_{96} = .056). Model (13) underpredicts CON (σ^2_{96} = .080) but predicts INC fairly well (σ^2_{96} = .057).

Alternative models;

Several alternative models were estimated. Among these were e.g.

$$(14) \qquad \left(I - \begin{bmatrix} 1.013 & -.027 \\ .006 & .996 \end{bmatrix} B \right) \underset{\sim}{z}_t$$

$$= \left(I - \begin{bmatrix} .116 & -.210 \\ -.219 & .676 \end{bmatrix} B - \begin{bmatrix} -.242 & -.098 \\ -.029 & .290 \end{bmatrix} B^2 \right) \underset{\sim}{a}_t$$

$$\Sigma = \begin{bmatrix} .448 \times 10^{-3} & \\ .174 \times 10^{-3} & .694 \times 10^{-3} \end{bmatrix}$$

which produced clean residuals, but underpredicted both CON (to a considerable extent, $\sigma^2_{96} = .092$) and INC ($\sigma^2_{96} = .064$). The model

$$(15) \qquad \left(I - \begin{bmatrix} 1.013 & -.027 \\ .005 & .997 \end{bmatrix} B \right) \underset{\sim}{z}_t$$

$$= \left(I - \begin{bmatrix} .106 & -.205 \\ -.122 & .529 \end{bmatrix} B \right) \underset{\sim}{a}_t$$

$$\Sigma = \begin{bmatrix} .505 \times 10^{-3} & \\ .183 \times 10^{-3} & .707 \times 10^{-3} \end{bmatrix}$$

also produced practically clean residuals, and underpredicted both series less than model (14) ($\sigma^2_{96} = .078$, $\sigma^2_{96} = .053$, respectively). Imposing a first-order VAR on CON and INC produced

$$(16) \qquad \left(I - \begin{bmatrix} 1.013 & -.026 \\ .007 & .994 \end{bmatrix} B \right) \underset{\sim}{z}_t = \underset{\sim}{a}_t$$

$$\Sigma = \begin{bmatrix} .485 \times 10^{-3} & \\ .104 \times 10^{-3} & .916 \times 10^{-3} \end{bmatrix}$$

This filter worked reasonably well apart from the fact that the residual of INC was far from white noise. The model also underpredicted both consumption ($\sigma^2_{96} = .079$) and income ($\sigma^2_{96} = .103$). A third-order VAR

$$\left(I - \begin{bmatrix} .928 & .148 \\ .175 & .400 \end{bmatrix} B - \begin{bmatrix} .373 & -.055 \\ .132 & .241 \end{bmatrix} B^2 - \begin{bmatrix} -.293 & -.113 \\ -.304 & .365 \end{bmatrix} B^3 \right) \underset{\sim}{z}_t = \underset{\sim}{a}_t$$

$$\Sigma = \begin{bmatrix} .456 \times 10^{-3} & \\ .157 \times 10^{-3} & .644 \times 10^{-3} \end{bmatrix}$$

was required to produce essentially clean residuals, but this model underpredicted both consumption ($\sigma^2_{96} = .102$) and income ($\sigma^2_{96} = .063$) severely.[5]

Eigenvalue - eigenvector analyses;

In order to check for the existence of exact (or approximate) contemporaneous linear relationships between real per capita consumption and income the eigenvalues in the estimate of the lag zero cross covariance matrix of the original (i.e. nonlogarithmic) series were computed (see Tiao & Box (1981)). As the smaller one was .186 contemporaneous linear relationships are not an issue in our analysis. Nevertheless, the cross correlation function peaks at lag zero.

To further analyze the relationship between CON and INC a canonical analysis based on model (3) was performed (see Box & Tiao (1977) and Tsay & Tiao (1985)). As one eigenvalue was .9984 there seems to be a near nonstationary space of dimension one accounting for the overall dynamic change generating factors in the series.

4. INTERPRETATION AND COMMENTS

Univariate models;

Using filtering ability and forecasting performance as main criteria for model identification it was found that both CON and INC well could be characterized by ARMA(2,1) models (see models (3) and (8)). We recall that Mankiw (1982) showed that this model is consistent with durability and adjustment costs in consumption. The income process also is compatible with what one in general would expect to find (see e.g. Deaton (1986)). Both models forecast reasonably well; the forecasts for consumption are accurate while income is slightly overpredicted.

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[5]The systematic prediction errors of many models may, in part, be attributable to the omission of e.g. the interest rate from the VAR.

It is interesting to note that the simple random walk with drift models for consumption and income clearly did not capture the characteristics of the data well. However, the estimates of the first-order autoregressive coefficients were very close to unity (similar results have been obtained by several authors; see e.g. Nelson & Plosser (1982), Harvey (1985) and Wasserfallen (1986)).

Furthermore, it should be mentioned that, although the dimension of the models seem to be invariant through the sample, the parameters governing the processes have changed over time.[6] This is exactly what the Lucas critique leads one to expect. Thus the parameter values are better thought of as averages of the true, drifting parameters. The impact of outliers on the parameter values (and on over-all model performance for that matter) was minor.

Bivariate models;

By the criteria for model selection adopted in this paper consumption and income can be modelled best jointly through an $ARMA_2(2,1)$ model. When identified and estimated for Finnish data from the period 1960.I - 1980.IV this model slightly underpredicted consumption for the period 1981.I - 1983.IV whereas the predictions for income were fairly accurate. Comparing one-step ahead forecast error variances from the univariate models with those obtained from the bivariate model gives the main finding of this study: **modelling consumption and income jointly as opposed to separately decreases the forecast error variance for both series.**

The bivariate model (13) tells us that consumption depends on lagged consumption with decreasing weights, but also hints at a dynamic interaction with income. Income is determined in an analogous manner. However, sums of the coefficients on income in the consumption process and vice versa are very close to zero. The lack

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[6]Although no formal tests for parameter constancy were performed simple estimation of a model for different subsets of observations yielded significant but different parameter estimates.

of precision in these estimates makes it hazardous to draw firm conclusions about the interactions.

Instead, focusig on the $AR_2(1)$ representation (16) gives a more clear-cut picture. The coefficient matrix with estimated standard errors in parentheses is

$$\begin{bmatrix} 1.013 & -.026 \\ (.004) & (.006 \\ .007 & .994 \\ (.006) & (.008) \end{bmatrix}$$

As the coefficient matrix is upper triangular INC is Granger causally prior to CON. In other words, both CON and INC depend on their own history and in addition CON depends on the one quarter lag of INC (whereas INC does not depend on lagged CON).[7] This conclusion is robust with respect to estimation period, and it can be interpreted as arising from nonseparability of consumption and leisure in the utility function (see e.g. Nelson (1985)) or from taste shocks to consumption and leisure (Hayashi (1985)). It could also arise e.g. if liquidity constraints are important, and because of many other factors (the interested reader is referred to Deaton (1986) and Hall (1986) for extensive discussion and references).

On the other hand, some caveats to the finding that past income matters for current consumption but not vice versa should be mentioned. A spurious correlation may occur because of the temporal aggregation problem (Tiao & Wei (1976)) or because our tests are done with nonstationary variables (Fuller (1985), Mankiw & Shapiro

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[7]According to standard t-tests we can reject the hypothesis that the autoregression coefficient for CON equals one while the autoregression coefficient for INC is indistinquishable from one. As pointed out by Campbell & Mankiw (1986) the closer to an unit root we are the more shock persistence we have.

(1986)).[8] It may also arise because we use seasonally adjusted data (Wallis (1978)) or because of measurement errors in the data (Newbold (1978)). Nevertheless, there is a growing concensus in the literature that past income in practice matters for current consumption (see e.g. Hall (1986)).

The economics behind the findings of the canonical analysis is congruent with, i.a., the life cycle - permanent income hypothesis insofar as the principal component is permanent income (i.e. a function of wealth).

[8]It is worth noting that for univariate series, the use of a stationarity-inducing operator such as the difference operator certainly may be useful. However, when considering two nonstationary series jointly, it may not be necessary nor advisable to difference the series. In some situations differencing may lead to unnecessary complexity in the model (see e.g. Hillmer & Tiao (1979) and Tiao & Tsay (1983); also see footnote 4).

APPENDIX

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