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Multivariate autoregressive models for forecasting seaborne trade flows

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Abstract

This paper contributes to the literature on forecasting seaborne trade flows by presenting multivariate autoregressive time series models that can be used to produce long-term forecasts. The models are applied to forecasting the trade flows of four commodity markets (crude oil, iron ore, grain and coal) on major trade routes. The empirical results indicate that the models can produce long-term seaborne trade flow estimates that have relatively small forecast errors. © 2001 Elsevier Science Ltd. All rights reserved.

Keywords: Seaborne trade flows; Forecasting; Vector autoregressive models

1. Introduction

Tinbergen (1959) was the first to recognise that seaborne trade flow data can be interpreted as observed demand for seaborne transport. The demand for shipping has been investigated in detail by Eriksen (1982). His approach consists of constructing "relative demand" functions, as he calls them, which incorporate only that part of demand that is influenced by prices (freight rates and commodity prices). An alternative analysis is presented by Kavussanos (1996). He estimates a flexible functional form cost model, using bilateral seaborne trade flow data.

These approaches have a number of problems. Being structural in nature, these efforts have serious drawbacks either in the determination of the economic structures, or in the estimation of the parameters. Furthermore, it is often difficult to formulate a complete system of equations representing the demand for shipping services that is completely identified in terms of exogeneity and endogeneity of its variables. Sims (1980) suggests an alternative approach, i.e. multivariate

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time series models. While structural models in shipping, in general, are used to produce short-to-medium-term forecasts of seaborne trade flows, with typical horizons of three to five years, a multivariate time series model can be used to produce medium- to long-term forecasts.

This paper contributes to the literature on forecasting seaborne trade flows by presenting multivariate time series models that can be used to produce long-term forecasts. An application of the models indicates that they can produce long-term seaborne trade flow estimates that have relatively small forecast errors.

2. Trade flow data

The analysis is based on four bulk commodities, i.e. crude oil, iron ore, grain and coal. For the latter three, trade flow matrices were obtained from the Fearnleys publication *World Bulk Trades*, for the period 1962–1995. A crude oil trade matrix was obtained from the British Petroleum's Statistical Review of World Energy, for the period 1963–1995. The trade flow matrices provide total yearly trade volumes by major exporting and importing countries. The data are available in both metric tons and ton-miles. However, given the occasional unreliability and incompleteness of the data in ton-miles, trade flows in tons are used in the paper.

From the trade matrices, major routes are selected to reduce the number of variables in the model. These routes are reported in Table 1, together with the results of the Augmented Dickey-Fuller (ADF) tests. The natural logarithms of the original series have been used in order to reduce the possibility of heteroskedasticity and to make the series more comparable.

With the exception of Australia–Japan (coal) and S. America–Japan (iron ore), all route series in Table 1 are non-stationary of the first-order. A closer look at the two exceptional routes above shows that stationarity there is the result of the existence of outliers in the beginning of the sample period. If these observations are excluded, the two series are non-stationary too and thus all series in the model can be treated as non-stationary of the first-order.

3. The vector autoregressive model

As its name suggests, a vector autoregressive (VAR) model is a multivariate time-series model whose general mathematical form is given by:

$$\boldsymbol{X}_t = \Phi(0) + \sum_{i=1}^{p} \Phi(i)\boldsymbol{X}_{t-i} + \boldsymbol{u}_t, \qquad (1)$$

where $\Phi(i)$ is the ith order parameter matrix of the proper dimensions, p the order of the VAR, $\boldsymbol{X}$ the column vector of trade flows and $\boldsymbol{u}$ is a residual error-term.

The unrestricted VAR model used in this paper could be seen as another formulation of a vector error-correction (VEC) model. In the latter type of models, the error-correction mechanism can be estimated on the basis of co-integration tests. Like the VAR, VEC models can also contain lagged variables. The error-correction mechanism term is lagged one period only. Since the co-integration relations, and thus the error-correction mechanism, are assumed to contain the

Table 1
Results of the ADF stationarity test (series in logarithms)[a]

Commodity/route	ADF statistic	Stationarity
Grain		
USG–Europe	−1.25	No
USG–Japan	−2.67	No
USG–Far East	−1.39	No
USG–SA	−1.29	No
Coal		
Australia–Europe	−1.85	No
Australia–Japan	−14.82	Yes
US–Europe	−1.80	No
US–Japan	−2.39	No
Iron Ore		
Australia–Europe	−2.55	No
Australia–Japan	−2.99	No
SA–Europe	−1.92	No
SA–Japan	−5.31	Yes
Crude oil		
Caribbean–United States	−2.40	No
Middle East–Europe	−0.80	No
Middle East–Far East	−0.40	No
Middle East–Japan	−3.09	No
Middle East–United States	−1.40	No
North Africa–Europe	−2.21	No

[a] The test regression contains a constant and no trend. The null hypothesis is that the series is non-stationary. This hypothesis is rejected if the statistic is larger in absolute value than the critical values. Critical values for the ADF test are −3.67, −2.96 and −2.62 for the 1%, 5% and 10% level, respectively. The sample is 1962–1995 for Coal, Iron ore and grain and 1963–1995 for crude oil. 'USG' – US Gulf and 'SA' – South America.

long-run information required to yield good forecasts, there is no a priori need to extend the VAR model beyond the first-order. However, the Schwarz criterion may indicate a higher order, and in that case this is taken as the order of the VAR. The VAR model in VEC form, including the error-correction component, is:

$$\Delta \boldsymbol{X}_t = \Phi(0) + \sum_{i=1}^{p-1} \Psi(i)\Delta \boldsymbol{X}_{t-i} + \alpha\beta' \mathbf{X}_{t-1} + \boldsymbol{u}_t, \tag{2}$$

where $\Phi(0), \Psi(i)$, α, and β are parameter matrices and the other variables are as above. This model is obtained by subtracting $\boldsymbol{X}_t$ from both sides of (1). All terms and parameter matrices are then rearranged to obtain the expression in $\Delta\boldsymbol{X}_{t-i}$ and $\boldsymbol{X}_{t-1}$. Furthermore, the parameter matrix of the term $\boldsymbol{X}_{t-1}$ is expressed as $\alpha\beta'$ in such a way that the estimated co-integration relations are included in $\beta'\boldsymbol{X}_t$.

The estimation of VAR models requires a two-step procedure. The first step is the estimation of the co-integration parameters. Calculated co-integration relations are subsequently included as variables in the VAR model. In the second step, each equation is estimated by ordinary least squares (OLS) (Lütkepohl, 1993).

4. Empirical results

The econometric packages EVIEWS and TSP for Windows were used for the estimations, simulations and forecasts. The Schwarz criterion selected an order of three for the coal, iron ore and grain models, and an order of two for the crude oil model.

The testing procedure for co-integration relations is the Johansen (1990) test. This part of the data analysis is crucial since the co-integration relations in a set of time series can be assumed to include long run information on the development of the time series (see Engle and Granger, 1987). To establish the order of the VAR testing model, the Schwarz criterion was applied to the unrestricted VAR (Lütkepohl, 1993, p. 133).

Tables 2 and 3 present the existing co-integration relations. In general, the results indicate that commodity trades on different routes are fairly closely related, to the extent that they might be viewed as comprising a homogeneous market. For coal, iron ore and grain, the maximum number of co-integration relations (three) is achieved.

In the six crude oil series, three co-integration relations seem to exist, involving all six series. The markedly different co-integration structure of the crude oil series can be seen as an indication that the structure of the crude oil market is also different from that of the dry bulk markets.

With the structure of the co-integration relations established, the complete VAR model can be estimated with OLS. It is generally very difficult to interpret individual coefficients of VAR

Table 2
Results of the Johansen co-integration test; dry bulk (series in logarithms)[a]

Coal			
US–Europe	US–Japan	Australia–Japan	Australia–Europe
1			−1.07
	1		0.01
		1	−0.96
Grain			
US Gulf–Europe	US Gulf–Japan	US Gulf–Far East	US Gulf–South America
1			−1.41
	1		−1.01
		1	−0.75
Iron ore			
US–Europe	US–Japan	Australia–Japan	Australia–Europe
1			−1.59
	1		−0.07
		1	−0.08

[a] All co-integration relations include a non-zero constant not shown in the table. The test model contains an unrestricted intercept and no trend. The sample is 1962–1991 for coal and grain and 1972–1995 for iron ore.

Table 3
Results of the Johansen co-integration test; crude oil (series in logarithms)[a]

Caribbean–US	N. Africa–E	M. East–US	M. East–E	M. East–Japan	M. East–FE
1			−0.082	−0.001	−0.230
	1		0.080	−1.872	0.659
		1	−2.188	2.268	−2.210

[a] The co-integration relations include a non-zero constant not shown in the table. The test model contains an unrestricted intercept and no trend. The sample is 1963–1995. 'US' – United States, 'N. Africa' – North Africa, 'E' – Europe, 'M. East' – Middle East and 'FE' – Far East.

models. Neither the value of the coefficient nor its statistical significance can provide a good basis for inferences about the model. A second problem is that forecasting models are commonly tested by comparing in-sample forecasts with the actual values. This means that some observations in the sample should be reserved for this purpose. However, the sample size of a maximum of 34 observations (yearly data for 1962–1995) is rather small for such a test. Model estimation with fewer observations may lead to quite different parameter estimates. It was therefore preferred to estimate the model on the largest possible data set. As a consequence, this paper will not report the estimation results for the VAR models.

A solution to evaluate both the fit of the model and its forecasting potential is to use the model to generate a series over the sample period and observe how well these simulated series match the actual data. The fit across the series and commodities is evaluated by the standard mean squared and percentage forecast errors.

It should be mentioned that the simulation exercise is only a partial test of forecasting performance. It leans heavily on the assumption that the statistical structure of the model will not change substantially in the future. However, since the analysis is statistical in nature, the addition of observations to the data set will inevitably change the statistical structure of the model. If in the future longer data series are available, the evaluation of in-sample forecasts is recommended.

The model in (2) is used as the simulation equation. The process is quite straightforward: The initial (first and second year) observations in the sample are fed in the model as starting values for the calculation of $\Delta \boldsymbol{X}$. Adding the latter to the starting values gives the simulated $\boldsymbol{X}$ values for the third year in the sample. The process is repeated for each year in the sample period. Comparison of the simulated $\boldsymbol{X}$ values with the actual trade flow data provides a first indication of goodness-of-fit and of the forecasting potential of the model. In the same way, out-of-sample forecasts can also be calculated from (2) by using as starting values the last known values of the time series. The forecasts can in principle be extended to a time horizon of any length. Here, a 10-year forecasting horizon is used.

The forecasts are presented in logarithms. The transformation of the series from logarithms back to levels is not straightforward. Arino and Franses (1996) calculate the transformation that has to be applied in the context of VAR models. Further investigation for seaborne trade flows will be undertaken in a future paper.

Note that the simulations start much later in the iron ore case because some of the iron ore series represent fast growing trades in the period 1963–1974, while others are much more smooth. Such significant differences in growth are undesirable if the series are to be modelled in a VAR context.

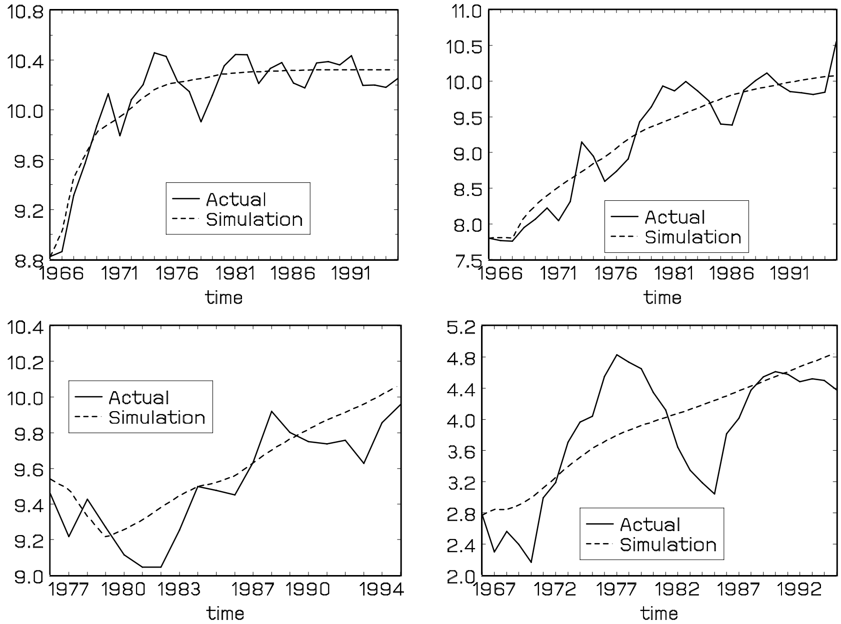

Fig. 1. Simulation results. The upper left window depicts the trade for coal, United States–Japan, and the other windows are, clockwise, grain United States–Far East, crude oil Middle East–United States, and iron ore Australia–Europe. The simulations for coal, grain and iron ore are based on a third-order VAR model. In the case of crude oil, the order of the VAR is two. The starting year for the simulations of the coal and grain series is 1965, 1966 for crude oil and 1975 for iron ore.

The simulations in Fig. 1 are a sample of a total of 18 simulations that were performed. [1] Most of the simulations follow the long-term development of the actual series rather closely. The results of the simulations highlight also the importance of the co-integration relations in achieving satisfactory results. The case of crude oil, with less than the maximum number of co-integration relations, shows clearly weaker simulation results.

This picture is supported by the forecast errors presented in Table 4. The results show that the simulation errors, mean squared error and mean percentage error, for the dry bulk commodities (coal, grain and iron ore) range from 0.06 to 0.44 and from 0.45% to 3.41%, respectively. For the crude oil series, however, the errors are generally higher.

Eq. (2) has been used to calculate the ex ante forecasts depicted in Fig. 2. The vertical axis measures logarithms of the trade flow volumes (in tons) and the horizontal axis displays years. The vertical line indicates the point in time where the actual series turns into forecasts.

Most of the forecasts seem to be reasonable, predicting a steady increase compatible with general expectations of world-wide economic growth. Of particular interest is the forecast for Australia–Europe coal shipments, suggesting a considerable decrease in the next 10 years and stabilisation thereafter.

[1] Space limitations do not allow inclusion of all simulations here but the graphs are available from the authors upon request.

Table 4
Forecast errors in simulations[a]

Coal	US–Europe	US–Japan	Australia–Japan	Australia–Europe		
MSE	0.44	0.08	0.31	0.14		
% error	2.68	0.60	2.40	1.13		
Grain	US Gulf–Europe	US Gulf–Japan	US Gulf–Far East	US Gulf–South America		
MSE	0.37	0.26	0.18	0.39		
% error	3.41	2.37	1.58	3.01		
Iron ore	US–Europe	US–Japan	Australia–Japan	Australia–Europe		
MSE	0.16	0.07	0.10	0.06		
% error	1.36	0.47	0.71	0.45		
Crude oil	Caribbean–US	N. Africa–Europe	M. East–US	M. East–Europe	M. East–Japan	M. East–Far East
MSE	0.13	0.42	0.49	0.38	0.54	0.24
% error	2.33	6.53	8.29	6.39	12.05	4.36

[a] MSE denotes mean squared error. It is calculated as MSE $= \sqrt{(\Sigma(x_i - x_i^*)/n)}$, where x_i are the actual values, x_i^* the simulated values, n is the length of the simulation period. % error is the mean percentage error. This is calculated as the mean share of absolute difference between actual and simulated values with respect to the actual values.

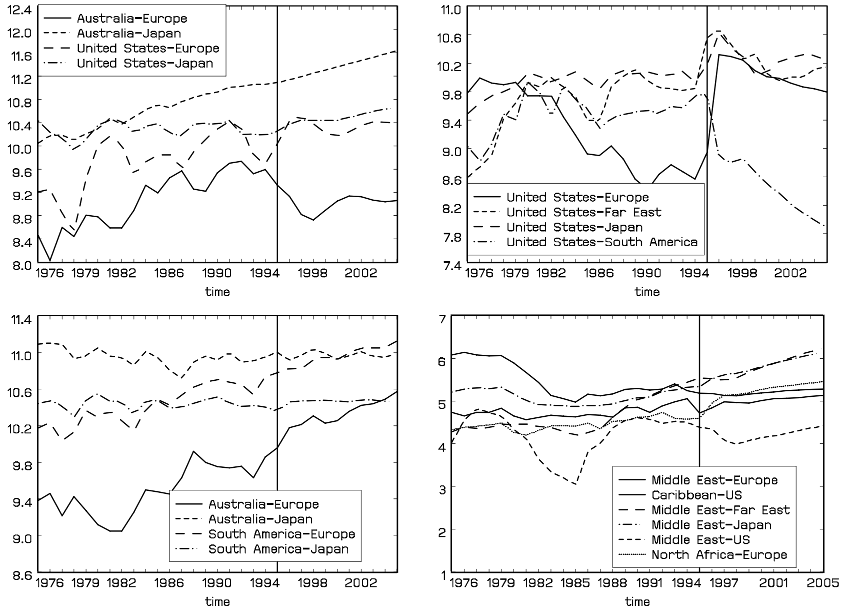

Fig. 2. Forecasted series. The upper left window depicts the forecasts for coal, and the other windows are, clockwise, grain, crude oil and iron ore.

5. Conclusion

The paper has presented multivariate autoregressive time series models that can be used to produce long-term forecasts of seaborne trade flows. Trade flow data of dry bulk and crude oil commodities over main trade routes were used in an application of the models. The empirical results indicate that the models can produce long-term seaborne trade flow estimates that have relatively small forecast errors.

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