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Forecasting US Exports: An Illustration Using Time Series and Econometric Models

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Forecasting exports efficiently enables policy makers to plan more appropriately and thus to help to improve the US balance of trade. Exports traditionally are forecast using econometric methods. This study focuses on a comparison of various simple time series models and an econometric model. The results show that simple time series techniques can forecast exports more accurately than can an econometric model. Future emphasis needs to be placed on complementary forecasting approaches, careful data analysis and understanding of the variables and forecasting environment.

Key words—forecasting, exports, time series, econometrics, accuracy, application

INTRODUCTION

EXPORTS ARE PLAYING an increasingly important role in the US economy. By the end of 1987, exports had reached a record value of $254 billion and in 1988 were expected to be worth $325 billion [34]. The export boom is having a highly favorable effect on the economy [33]. Exports are contributing to a lower US deficit, better economic growth and greater employment. The large contribution to economic growth is particularly significant because although exports accounted for only 6% of US gross national product (GNP), they directly accounted for a share of GNP growth in 1987 more than four times greater than previously. Thus, exports are compensating for sluggish growth in other GNP components like personal consumption, government spending and business investment. Exports also are contributing to higher corporate profits [33]. This confirms the positive and significant relationship between exports and profitability demonstrated by Pugel [32], for example.

Forecasting exports efficiently enables policy makers to plan more appropriately and help to improve the US trade balance and economic growth. While forecasting accuracy is one of the most decisive criteria in selecting a technique to forecast exports, other important criteria include cost and complexity of a method [2]. In a survey of forecasting accuracy [15] further empirical investigation was called for to confirm the superiority of simple forecasting methods over complex techniques. This issue is important in the context of forecasting macroeconomic variables like exports. In business, government and research, complex and costly econometric models are widely employed as tools for forecasting and policy analysis. Improvements in macroeconomic forecasting would be valuable to many public policy makers and managerial decision-makers.

Exports have usually been forecast using econometric methods. Nevertheless, some studies [5, 7, 21, 35] have shown that time series methods can also predict exports. Except for Thury's research, the methods studied have been sophisticated ones such as Box–Jenkins. Our study focuses on a comparison of various simpler models. Research [18] has indicated that simpler forecasting techniques can be more accurate than Box–Jenkins techniques.

Our purpose is to investigate the accuracy of simple time series methods for forecasting US exports and to compare the results to some econometric forecasting efforts. First, we review previous relevant work in the field. Next, we report the methodology and results of our study. Finally, we present conclusions and suggest further directions for research.

COMPARING THE PERFORMANCE OF ECONOMETRIC AND TIME SERIES MODELS

Many studies have compared the performance of econometric and time series forecasting models (see [10] for a thorough review). Research results have been contradictory. For example, some early studies [6, 29, 30] demonstrated the superiority of Box–Jenkins techniques over various econometric models in short term forecasting. Others (for example [3, 37]) found econometric forecasts to be better than simple extrapolation.

More recent research has not resolved these inconsistencies. Ahlers and Lakonishok [1] showed the value of simple statistical models as opposed to economists' consensus forecasts in a study of 10 economic indicators from 1947 to 1978. Llewellyn and Arai [14], however, found Organization for Economic Cooperation and Development forecasts of GNP and inflation to be superior to naive and ARIMA models. Regular evaluations of forecast accuracy for macroeconomic variables conducted by McNees [22–27] investigated various forecasting organizations and a range of variables, time periods and degrees of judgmental adjustment. In general, his results have supported the implementation of econometric models, especially in the long term. More recently, however, it was acknowledged [27] that Bayesian vector autoregression-generated forecasts [13] could present a strong challenge to conventional practice and serve as a powerful standard of comparison for other forecasts.

Three studies [5, 7, 21] have focused exclusively on forecasting exports. Each of these evaluated Box-Jenkins models. Coccari [5] identified a significant trend in quarterly US export data from 1960 to 1970 and a possible cyclical factor. His results implied that forecasts for exports could be obtained using information from the previous three quarters. Dale and Bailey [7] used univariate Box–Jenkins models and data from 1969 to 1979 to forecast US exports. Recognizing that economic conditions had changed since 1979, McCutchen [21] reexamined Dale and Bailey's work. He produced forecasts for the periods 1969–1979 and 1969–1982 and concluded that the Dale and Bailey approach was useful but if greater accuracy was desired it was necessary to update the models continuously.

Thury's [35] analysis of accuracy of macroeconomic forecasting in Austria included comparison of ARIMA and Holt-Winters exponential smoothing with econometric and judgmental forecasts. One of the variables Thury forecasted was exports. The best forecasts were obtained by applying Holt–Winters exponential smoothing. Thury noted the good performance of this method with respect to directional accuracy.

The performance variation of different forecasting methods (econometric, time series) in past studies has occurred for several reasons. These include the variable/series being forecast, the length of the forecast time horizon, whether or not the forecast is judgmentally adjusted and the nature of the study (*ex post* or *ex ante*). It is important to note that the purpose of econometric models is not purely forecasting. They also attempt to explain economic phenomena. From a *forecasting* point of view, however, questions concern whether any success of econometric models justifies their expense [20, 4]. Econometric model building is time consuming, expensive and requires expertise [10].

In the sixties and early seventies, economic forecasters favored econometric models. In the late seventies and eighties, various studies [5, 7, 21, 35] are indications of the recognition of the value of time series models during this period. Coccari [5] stresses that the identification of patterns over time is an asset to any forecasting analysis. The identification of trend, seasonal and cyclical components provides knowledge not given by traditional regression analysis. Comparative evaluations using time series techniques to analyze strengths and weaknesses of trade models may lead to a deeper understanding of the adequacy of the economic theories upon which present models are based [7]. It is true that economic structural relationships are changing, along with the increasing interdependence of nations. The recent US Department of Commerce report on trade performance in 1987 [36] observes that cause and effect relationships in the trade field have shifted. Earlier, it was accepted that trade flows determined capital flows, and, therefore, exchange rate levels. More recently, however, capital flows have very much been driven by forces other than trade flows and capital flows have in large measure set exchange rates, which in turn, affect trade flows. McNees [27], Zellner [38] and others have advocated the use of econometric and time series approaches as complementary forecasting tools instead of rivals. It is clear from a review of the literature that there is no "best" forecasting technique. Relatively little previous work has been done on the time series forecasting of exports. Time series methods may be useful, simple and inexpensive techniques for policy makers and business decision-makers if the techniques can be shown to have sufficient accuracy.

METHODOLOGY

Three data sets were used to forecast US exports. Series I [8] comprises quarterly US export data in millions of dollars from 1966:4 to 1988:3. Series II [31] represents monthly US exports in millions of dollars from January 1976 to December 1987. Series III [9] also represents quarterly export data, but is in billions of dollars and from 1979:1 to 1987:4. We selected two quarterly series for comparative purposes. Use of Series III permitted the comparison of our time series forecasts with published forecasts from the same database. The published forecasts based on Series III are generated using econometric techniques by the Research Seminar in Quantitative Economics (RSQE) at The University of Michigan. We recognize that Series III is rather short for time series analysis. We believe, however, that this is adequate for our present purposes of demonstrating any differences in the accuracy of techniques. Forecasts should be compared over identical time periods [28]. The consistency of data sources as well as time periods allows a valid comparison of different forecasting methodologies.

As mentioned earlier, our study focused on only the relatively less sophisticated time series models. The Box–Jenkins technique was not evaluated. The study includes the following methods: single exponential smoothing, Holt's, Winters, adaptive response rate, linear trend, Carbone–Makridakis [17] and classical decomposition. The accuracy measures used were Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). It is important to use more than one accuracy measure because there is no single universally accepted measure [11, 15]. Hence, in order to judge better the accuracy of the various forecasting methods in our study, we used three accuracy measures. The three were selected because of their wide use. Using a number of accuracy measures also permits illustration of the relative value of these different accuracy measures [16].

To observe whether the accuracy of a method was consistent and stable over time (for example, when trends change), the data series were partitioned. For example, for Series I which included 88 data points, we used the first 64 data points to fit the model and used the estimated parameters to produce a forecast of eight periods ahead. We then added eight data points to the first 64 so 72 data points were used to refit the model and to forecast eight more data points ahead and so on. For Series II, the monthly series with 144 data points, we used the first 96 data points to fit the model and forecast ahead 12 months. We then included 12 more data points to refit the model and again forecast ahead 12 months and continued to do this until there were 132 data points. This data partitioning process was used for all the time series models. With Series III (36 data points), we used only 24 data points to fit the model and forecast ahead for four quarters and then included four more data points and forecast ahead for four more quarters. The accuracy of the fitted phases was compared to the accuracy of both the forecasted values provided by the group of time series models and the RQSE econometric forecast values. This was done for the three consecutive forecasting phases.

RESULTS

The results are given in Tables 1–3. Table 1 shows the accuracy of the time series models

Table 1. Summary of accuracy measures for selected forecasting methods—US exports (quarterly data in millions of dollars), Series I

Accuracy measure	Fitted phases data points			Forecasted phases data points			Average
	1–64	1–72	1–80	65–72	73–80	81–88	
			Single Exponential				
MPE	2.78	2.53	2.26	−6.27	0.81	20.60	5.05
MAPE	4.75	4.66	4.44	6.87	2.36	20.60	9.94
RMSE	510.79	549.77	556.12	1302.95	548.60	5982.38	2611.31
			Adaptive Response Rate				
MPE	4.04	3.51	3.25	−9.27	2.14	20.67	4.51
MAPE	5.90	5.83	5.52	9.27	2.77	20.67	10.90
RMSE	588.70	665.06	660.20	1762.37	654.26	5886.13	2767.59
			Holt's				
MPE	−0.34	−0.08	−0.09	6.21	−15.37	12.19	1.01
MAPE	7.76	6.91	6.05	8.91	15.37	12.34	12.21
RMSE	610.45	597.12	574.49	1961.67	3017.10	3899.23	2959.33
			Winters				
MPE	0.09	0.22	0.21	6.36	−16.65	12.87	0.86
MAPE	4.06	4.11	3.92	8.93	16.65	12.87	12.82
RMSE	438.03	491.16	511.57	1975.29	3264.12	4047.76	3095.72
			Classical Decomposition				
MPE	−0.20	−0.20	−0.18	−13.80	−16.67	2.02	−9.48
MAPE	1.87	1.90	1.87	13.80	16.67	9.73	13.40
RMSE	176.02	204.00	213.54	2403.04	3110.85	2651.81	2721.90
			Linear Trend				
MPE	2.42	0.58	−1.47	−13.97	−16.72	1.96	−9.58
MAPE	25.11	21.15	18.30	13.97	16.72	9.72	13.47
RMSE	1672.39	1703.49	1807.41	2432.66	3119.72	2647.60	2733.33
			Carbone-Makridakis				
MPE	−0.34	−0.08	−0.09	−8.15	−13.56	5.53	−5.39
MAPE	7.76	6.91	6.05	8.15	13.56	8.29	10.00
RMSE	610.45	597.12	574.49	1462.33	2626.83	2655.95	2248.37

Source: Economic indicators.

at the fitted and forecasted phases using Series I. Note that, as expected, for some methods accuracy improved as the length of the series increased. For example, observe the values of Mean Percentage Error (MPE) and Mean Absolute Percentage Error (MAPE) for single exponential smoothing at the first (1–64 data points), the second (1–72) and the third (1–80) fitted phases.

Although we provide the average of the accuracy measures for the forecasted phases, one should be careful in judging the performance of a particular method solely on the basis of the average for the three different periods. For example, the average value of MAPE (9.94) for the three forecasted phases indicates that single exponential smoothing ranks first in terms of accuracy (see Table 1). Examining the

Table 2. Summary of accuracy measures for selected forecasting methods—US exports (monthly data in millions of dollars), Series II

Accuracy measure	Fitted phases data points				Forecasted phases data points				Average
	1–96	1–108	1–120	1–132	97–108	109–120	121–132	133–144	
				Single Exponential					
MPE	0.74	0.86	0.67	0.69	5.62	−4.98	0.96	7.95	2.39
MAPE	3.16	3.21	3.17	3.15	5.62	5.54	2.91	9.92	6.00
RMSE	582.97	616.05	612.36	628.58	1238.29	1055.79	652.76	2492.08	1359.73
				Adaptive Response Rate					
MPE	0.85	1.16	0.91	0.83	7.25	−4.54	0.73	9.03	3.12
MAPE	3.35	3.35	3.37	3.26	7.25	5.12	3.17	11.00	6.64
RMSE	619.34	645.72	652.06	644.94	1496.10	984.36	704.27	2689.30	1468.51
				Holt's					
MPE	−0.06	0.00	−0.12	−0.04	3.73	−12.08	6.87	6.19	1.18
MAPE	3.14	3.24	3.36	3.42	3.88	12.55	7.05	8.34	7.96
RMSE	560.00	595.93	616.17	645.78	917.74	2377.34	1510.31	2108.54	1728.48
				Carbone-Makridakis					
MPE	−0.05	0.01	−0.10	−0.03	3.21	−10.92	5.99	6.10	1.20
MAPE	3.11	3.26	3.26	3.26	3.63	11.94	7.30	8.11	7.64
RMSE	559.00	594.83	610.15	649.39	911.65	2236.63	1429.63	2101.38	1669.82

Source: OECD Department of Economics and Statistics, Monthly Statistics of Foreign Trade, Paris.

Table 3. Comparative analysis between time series and econometric models of forcasting—US exports (quarterly data in billions of dollars), Series III

Accuracy measure	Fitted phases data points			Forecasted phases data points			Average
	1–24	1–28	1–32	25–29	29–32	33–36	
			Single Exponential				
MPE	1.67	1.14	1.28	−6.80	3.55	14.40	3.72
MAPE	3.88	3.61	3.45	6.90	3.67	14.40	8.32
RMSE	16.15	15.73	15.17	25.84	16.23	77.97	40.01
			Holt's				
MPE	−0.19	−0.50	−0.10	−7.70	4.59	12.24	3.04
MAPE	5.43	5.08	4.75	7.70	4.59	12.24	8.18
RMSE	23.54	23.24	67.66	28.74	19.68	67.66	38.69
			Adaptive Response Rate				
MPE	2.52	2.05	2.17	0.15	2.72	17.60	6.82
MAPE	6.49	5.97	5.67	2.06	3.03	17.60	7.56
RMSE	28.74	26.98	25.91	9.22	14.65	89.27	37.71
			Classical Decomposition				
MPE	0.07	0.21	0.06	−6.30	−1.90	14.29	2.03
MAPE	1.35	1.28	1.22	6.30	2.90	14.29	7.83
RMSE	5.45	5.45	5.30	24.45	12.27	75.09	37.27
			Linear Trend				
MPE	−1.26	−0.99	−1.00	−6.47	−1.97	14.31	1.96
MAPE	9.84	8.94	8.19	7.20	3.33	14.31	8.28
RMSE	37.40	35.54	33.51	28.26	12.73	73.91	38.30
			Carbone-Makridakis				
MPE	−0.19	−0.50	−0.19	−7.75	−1.03	−7.75	−5.51
MAPE	5.43	5.08	5.43	7.75	1.95	7.75	5.82
RMSE	23.54	23.24	23.54	28.96	7.88	28.96	21.93
			Econometric Method[a]				
MPE				−19.35	−23.96	2.82	−13.50
MAPE				19.35	30.36	5.25	18.32
RMSE				26.56	28.30	25.40	26.75

Source: Economic Outlook, USA.
[a]Generated by the Research Seminar in Quantative Economics (RSQE), University of Michigan.

individual values of MAPE for each of the forecasted phases, shows that single exponential smoothing is indeed the most accurate method for the first two phases. Yet at the third phase, the value of MAPE is 20.60 and single exponential smoothing ranks sixth out of seven in terms of accuracy. The most accurate method at the third forecasted phase is the Carbone–Makridakis method. Clearly, different forecasting methods perform differently over various time periods and it is important to examine this variation in performance.

The problem of using the average value of the accuracy measure over the three forecasted phases is compounded when MPE is used because of the offsetting of the negative and positive signs of the errors. This is an inherent disadvantage of MPE [16]. The average of MPE over three forecasted phases for Series I shows that Winters' method is most accurate (see Table 1). For Series II (see Table 2), Holt's and for Series III (see Table 3), the linear trend are the most accurate according to the average value of MPE. To avoid reaching misleading conclusions about accuracy, forecasters should also examine MAPE or RMSE.

Judging the accuracy of the forecasting methods on the bases of the averages of MAPE or RMSE reveals different results from those suggested by the MPE averages. For example, in Table 1, selecting the most accurate methods on the basis of MAPE or RMSE indicates that the classical decomposition method is the most accurate at the fitted phases. On the basis of the average value of MAPE or RMSE, single exponential smoothing and Carbone–Makridakis are the two most accurate methods at the forecasted phases. Hence different methods perform differently at the fitted versus forecasted phases. This is consistent with other empirical evidence [18] which shows that good fit does not necessarily lead to good forecasting *ex ante*. Makridakis and Gardner [19] comment that quality of fit is not even closely correlated with forecasting accuracy *ex ante*. One reason for the difference in performance between the fitted and forecasted phases is the inability of a particular method to capture changes in the data pattern. In this study, when the data in Series I exhibited a trend (over the period represented by data points 81–88), the linear trend and the Carbone–Makridakis methods were most

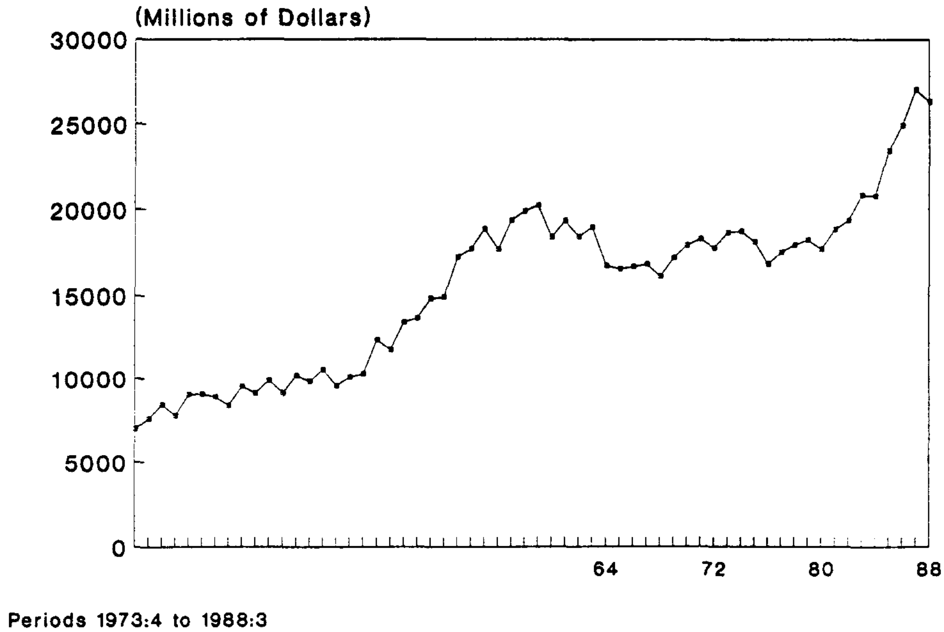

Fig. 1. US exports quarterly data (Series I).

capable of capturing the data pattern (see Fig. 1).

Also, certain methods were more appropriate for the data pattern of the monthly series, Series II: single exponential smoothing, Holt's adaptive response rate and Carbone–Makridakis (see Table 2). Holt's and the Carbone–Makridakis methods were superior in terms of MPE and MAPE at the fitted phases. There were mixed results at the forecasted phases. For example, the single exponential smoothing and adaptive response rate methods did well in the third forecasting phase. Holt's and Carbone–Makridakis were better in the first and fourth forecasting phases. These methods performed relatively poorly in the second forecasting phase, however, because of their inability to capture the smoothness in the data pattern during that time period.

Analysis using Series III permitted comparison between simple time series methods and the RSQE econometric method. In the third forecasted phase (33–36 data points) the econometric method was the most accurate. Its performance at the earlier forecasting phases, however, was inferior to the record of the time series methods. While more data and more information are needed to provide more substantive evidence, our results show that an econometric method is not superior to time series methods in forecasting US exports.

CONCLUSIONS AND IMPLICATIONS

Our findings suggest that time series methods can provide as accurate if not more accurate forecasts than an econometric approach. This confirms earlier research [5, 7, 21, 35]: time series forecasting techniques can be used to predict exports. This is so for relatively simple methods. Thus, our findings are also consistent with Makridakis *et al.* [18].

McCutchen [21] found that there was a need to update his Box–Jenkins model over time. Through the data partitioning approach used in this study, we demonstrated that forecasters should continually consider other models that might provide better forecasts for particular time periods. The forecaster should also try to identify the optimal value of the parameter(s) that minimizes MAPE, MPE or RMSE. It is important to reserve some data points to check the accuracy of a given method over time before deciding on the use of such a method as a basis for policy making. The results show clearly the importance of recognizing data patterns and interpreting the data structure. Levenbach and Cleary [12] emphasize data analysis as the key to successful forecasting. In this way, they observe, practitioners will stay away from the mechanistic execution of computer programs.

Judgmental input is also crucial. Forecasters should exercise considerable judgment to select forecasting methods. This selection should proceed according to expectations about the movement of the data. Forecasters should work closely with policy makers and analysts to understand the forecasting environment and the variables of interest. Our study demonstrates the value of certain time series models for different data structures at various time periods. Econometric models, through their explanatory capabilities, help policy makers to understand relationships between variables. Therefore, time series, econometrics and judgment should be seen as complementary approaches to forecasting economic variables like exports. Time series models, because of their relatively low costs, less time required and simplicity, can play an important role. Formally combining forecasts may be a helpful alternative. Previous research on time series methods suggests that combining different forecasting methods leads to improved performance [18].

Future research should focus closely on the reasons for the different levels of accuracy achieved by the different time series methods and econometric methods when forecasting exports. In order to do this it will be necessary to examine other export series from different sources and according to various classifications such as end use of products. This study included one econometric approach only. For results to be more widely applicable, it is imperative that more econometric forecasts be tested.

REFERENCES

1. Ahlers D and Lakonishok J (1983) A study of economists' consensus forecasts. *Mgmt Sci.* **29**, 113–125.
2. Carbone R and Armstrong JS (1982) Evaluation of extrapolative forecasting methods: Results of a survey of academicians and practitioners. *J. Forecasting* **1**, 215–217.
3. Christ CF (1975) Judging the performance of econometric models of the US economy. *Int. Econ. Rev.* **16**, 54–74.
4. Cicarelli J and Narayan J (1980) The performance of eleven economic forecasting models in the 1970s. *Bus. Econ.* **15**, 12–16.
5. Coccari RL (1978) Alternative models for forecasting US exports. *J. Int. Bus. Stud.* Spring/Summer, 73–84.
6. Cooper RL (1972) The prediction performance of quarterly econometric models of the US. In *Econometric Models of Cyclical Behavior* (Edited by Hickman BG). Columbia Univ. Press, NY.
7. Dale C and Bailey VE (1982) A Box–Jenkins model for forecasting US merchandise exports. *J. Int. Bus. Stud.* Spring/Summer, 101–108.
8. *Economic Indicators*, monthly publication of the Executive Office of the President, Council of Economic Advisors, Washington, DC.
9. *Economic Outlook USA*, University of Michigan Institute for Social Research, Survey Research Center, Ann Arbor, MI.
10. Fildes R (1985) Quantitative forecasting. The state of the art: econometric models. *J. Opl Res. Soc.* **36**, 549–580.
11. Gardner ES and Dannenbring (1980) Forecasting with exponential smoothing: Some guidelines for model selection. *Decis. Sci.* **11**(2), 370–383.
12. Levenbach H and Cleary JP (1984) *The Modern Forecaster, The Forecasting Process through Data Analysis.* Van Nostrand, Princetown, New York.
13. Litterman RB (1986) Forecasting with Bayesian vector autoregressions—Five years of experience. *J. Bus. Econ. Statist.* **4**(1), 25–37.
14. Llewellyn J and Arai H (1984) International aspects of forecasting accuracy. *OECD Econ. Stud.* **3**, 73–117.
15. Mahmoud E (1984) Accuracy in forecasting. *J Forecasting* **3**, 139–160.
16. Mahmoud E (1987) The evaluation of forecasts. In *The Handbook of Forecasting A Manager's Guide* (Edited by Makridakis S and Wheelwright SC), 2nd edn. Wiley NY.
17. Makridakis S (1986) The art and science of forecasting: An assessment and future directions. *Int. J. Forecasting* **2**(1), 15–40.
18. Makridakis S, Andersen A, Carbone R, Fildes R, Hibon M, Lewandowski R, Newton J, Parzen E and Winkler R (1982) The accuracy of extrapolation (time series) methods. *J. Forecasting* **1**(2), 111–154.
19. Makridakis S and Gardner ES (1988) The future of forecasting, *Int. J. Forecasting* **4**, 325–330.
20. Makridakis S and Wheelwright SC (1977) Forecasting issues and challenges for marketing management. *J. Mktg* 24–38.
21. McCutchen WW (1984) The use of Box Jenkins techniques for forecasting US merchandise exports: An update and extension. *Q. J. Bus. Econ.* **23**(4), 64–75.
22. McNees SK (1974) How accurate are economic forecasts? *New England Econ. Rev.* November–December, 2–19.
23. McNees SK (1975) An evaluation of economic forecasts. *New England Econ. Rev.* November–December, 3–39.
24. McNees SK (1979) The forecasting record for the 1970s. *New England Econ. Rev.* September–October, 33–53.
25. McNees SK (1981) The recent record of thirteen forecasters. *New England Econ. Rev.* September–October
26. McNees SK (1982) The role of macroeconometric models in forecasting and policy analysis in the US. *J. Forecasting* **1**, 37–48.
27. McNees SK (1986) Forecasting accuracy of alternative techniques: A comparison of US macroeconomic forecasts. *J. Bus. Econ. Statist.* **4**, 5–15.
28. McNees SK (1988) On the future of macroeconomic forecasting. *Int. J. Forecasting* **4**, 359–362.
29. Nelson CR (1972) The prediction performance of the FRB-MIT-PENN model of the US economy. *Am. Econ. Rev.* **62**, 902–917.
30. Nelson CR (1973) *Applied Time Series Analysis for Managerial Forecasting.* Holden–Day, San Francisco, CA.
31. OECD Department of Economics and Statistics. *Monthly Statistics of Foreign Trade*, Paris, France.
32. Pugel TA (1978) *International Market Linkages and US Manufacturing.* Ballinger, Cambridge, MA.
33. Teske GR (1988) The US export boom: Causes and effects. *Bus. Am.* October 24, 7–11.
34. Teske GR and Davis LA (1989) The US export boom and economic growth. *US Ind. Outlook 1989*, 12–15.

35. Thury G (1985) Macroeconomic forecasting in Austria. An analysis of accuracy. *Int. J. Forecasting* **1**, 111–121.
36. US Department of Commerce (1988) *US Trade Performance in 1987.* US Department of Commerce International Trade Administration, Washington, DC
37. Zarnowitz V (1978) On the accuracy and properties of recent macroeconomic forecasts. *Am. Econ. Rev.* **68**, 313–319.
38. Zellner A (1977) Comments on time series analysis and causal concepts in business cycle research. In *New Methods in Business Cycle Research: Proceedings from a Conference* (Edited by Sims CA). Federal Reserve Bank of Minneapolis.

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