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SPECIFYING A BAYESIAN VECTOR AUTOREGRESSION FOR SHORT-RUN MACROECONOMIC FORECASTING WITH AN APPLICATION TO FINLAND**

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ABSTRACT

The aim of this paper is to specify a small econometric model capable of generating adjustment-free, short-run forecasts of key macroeconomic variables on a monthly basis. The aim is carried out using the vector autoregression approach in conjunction with a Bayesian specification procedure. The Bayesian approach to forecasting is reviewed and applied using Finnish data from the 1980s. The out-of-sample forecasting performance of the model is found to be satisfactory.

CONTENTS

1. INTRODUCTION

The aim of this paper is to specify a small econometric model capable of generating adjustment-free, short-run forecasts of key macroeconomic variables on a monthly basis. The ability of real - time forecasting is, per se, valuable, but such forecasts may also be of value when assessing the reliability of preliminary economic statistics and in fixing starting values for econometric forecasting models operating on quarterly data. Furthermore, the adjustment-free forecasts can serve as a standard of comparison for other forecasts. In particular, comparison with forecasts which rely heavily on add factors may be of interest.

The aim is carried out using the vector autoregression (VAR) approach (Sims (1980)) in conjunction with a Bayesian specification procedure (Litterman (1979)). The Bayesian vector autoregression (BVAR) approach, has been found to yield macroeconometric models with reasonably accurate forecasts producable at low cost.[1] In particular, estimated BVAR models require no judgemental adjustment and forecasting can be done in minutes on a PC.[2]

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[1] Forecasts from BVAR models compared favorably with those of conventional macroeconometric models during the first half of the 1980s (Litterman (1986a), McNees (1986), Zarnowitz (1986)). The record of BVAR models has been somewhat less convincing during the latter half of the 1980s (McNees (1990)). See Friedman & Montgomery (1985) for theoretical work supporting the use of estimators like those used in BVAR models when forecasting.

[2] In a comparative study of the role of judgment in forecasting, McNees (1990) found that more often than not, forecasters could improve accuracy by placing less weight on their own adjustments relative to their mechanically generated model forecasts.

2. THE BVAR APPROACH

2.1 The specification problem

The conventional approach to specifying a macroeconometric model is to adopt one single paradigm within which each model equation is derived. Even if this procedure were appropriate for some particular type of economic activity, it seems far from guaranteed that the model as a whole will be a good approximation of the underlying complex, multifaceted structure of reality. In fact, using the positivist criterion for model adequacy (predictive power), the conventional approach typically fails as forecasters usually think of their models as not capable of unassisted forecasting. This comes about partly because conventional models are formulated conditional on exogenous variables and partly because they may behave peculiarly unless adjusted.

The conventional approach to specifying macroeconometric models came under heavy attack in the late 1970s. One line of attack was launched by Christopher Sims, who argued that the exclusion restrictions derived from imperfect economic theories used as identifying assumptions in conventional macroeconometric models are incredible (Sims (1980)). The critique put forward by Sims effectively implies that conventional exclusion restrictions may be a barrier to improved forecasting. This occurs because it seems quite reasonable to suppose that small bits of useful information concerning the aggregate economy are scattered through the data, and a narrowly focused approach is unlikely to find much useful information for forecasting purposes. As we see it, the problem of macroeconometric forecasting models hence becomes to extract as much of the information as possible from the data and to give each little bit an appropriate weight.

2.2 A Bayesian view of forecasting

From a Bayesian perspective, the view that the current state of macroeconomic theory leaves a great deal of uncertainty concerning which economic frameworks are useful for forecasting translates into

the following assertion. Economic theory allocates a small probability to a large number of economic structures, and each can be represented as an equation with a flat prior distribution over a wide range of parameter values. The parameters themselves are considered to be stochastic. Bayesian decision theory can then be used to revise the priors in the light of the evidence of the data in order to generate a filter for the optimal extraction of information from the data useful for forecasting.[3]

The Bayesian specification search developed by Litterman (1979) entails searching over a parameter-space with a certain fairly uncontroversial prior as a means of fine-tuning a filter for the optimal extraction of information from the data. In conjunction with the VAR approach of Sims (1980), this Bayesian approach allows one to generate a class of estimators that highlight the tradeoff between oversimplification and overparametrization of a forecasting multivariate autoregression. In other words, one is able to exploit the tradeoff between bias and variance. Out-of-sample prediction errors provide the metric for picking the optimal specification for forecasting purposes.

The issue of parsimony is, of course, particularly pressing in VAR models, and unrestricted VAR models are known to produce relatively large out-of-sample forecast errors. This simply suggests that spurious correlations in the data have been picked up by allowing too many channels of interaction between multicollinear, noisy variables. The use of priors reduces the risk of picking up misleading relationships and lessens the problem of noise in the data obscuring a weak signal.

In Bayesian time series models, parsimony is not achieved through exclusion restrictions like in conventional models. Exclusion of a variable amounts to full certainty that the parameters of the variable are exactly zero, but Bayesian decision theory questions such an absolute belief which is not given a chance to be revised by any amount

[3] The Bayesian approach dates back to the reverend Thomas Bayes and the 18th century (Bayes (1763)). See Zellner (1985) for an introduction to the Bayesian paradigm and its application to econometrics. See Harrison & Stevens (1971, 1976) for early applications of the Bayesian paradigm to short-run forecasting.

of historical evidence. The Bayesian procedure allows both the data and the beliefs of the modeler to bear on the results, and allows the modeler to flexibly control how much weight either consideration is to be given.

The way prior information and data are combined to yield a probability distribution for, say, a forecast is given by Bayes' theorem. Let $p(\boldsymbol{\theta})$ be the prior probability density function (pdf) for the parameter vector $\boldsymbol{\theta}$, $p(\boldsymbol{y}|\boldsymbol{\theta})$ the pdf for an observation vector $\boldsymbol{y}$, given $\boldsymbol{\theta}$ and the likelihood function, and $p(\boldsymbol{\theta}|\boldsymbol{y})$ the posterior pdf for $\boldsymbol{\theta}$ given $\boldsymbol{y}$ and the prior information. Then the joint pdf for $\boldsymbol{y}$ and $\boldsymbol{\theta}$ is

$$(1) \qquad p(\boldsymbol{y},\boldsymbol{\theta}) = p(\boldsymbol{\theta})\,p(\boldsymbol{y}|\boldsymbol{\theta}) = p(\boldsymbol{y})\,p(\boldsymbol{\theta}|\boldsymbol{y})$$

and

$$(2) \qquad p(\boldsymbol{\theta}|\boldsymbol{y}) = p(\boldsymbol{\theta})\,p(\boldsymbol{y}|\boldsymbol{\theta})/p(\boldsymbol{y}) \quad \alpha \; p(\boldsymbol{\theta})\,p(\boldsymbol{y}|\boldsymbol{\theta})$$

where α denotes proportionality. In words, Bayes' theorem (2) states that the posterior pdf is proportional to the prior pdf times the likelihood function. Also note that (2) provides an exact, finite sample posterior pdf for $\boldsymbol{\theta}$.

In order to obtain a point estimate like the posterior mean vector, we need to introduce an explicit loss function when solving

$$(3) \qquad \min_{\hat{\boldsymbol{\theta}}} \int L(\hat{\boldsymbol{\theta}},\boldsymbol{\theta})\,p(\boldsymbol{\theta}|\boldsymbol{y})\,d\boldsymbol{\theta}$$

where $L(\hat{\boldsymbol{\theta}},\boldsymbol{\theta})$ is the loss function and $\hat{\boldsymbol{\theta}} = \hat{\boldsymbol{\theta}}(\boldsymbol{y})$. For example, employing the quadratic loss function

$$(4) \qquad L(\hat{\boldsymbol{\theta}},\boldsymbol{\theta}) = (\boldsymbol{\theta}-\hat{\boldsymbol{\theta}})'Q(\boldsymbol{\theta}-\hat{\boldsymbol{\theta}})$$

where Q is a given, positive definite symmetric matrix, the problem (3) can be stated

$$(5) \qquad \min_{\hat{\boldsymbol{\theta}}} E\,L(\hat{\boldsymbol{\theta}},\boldsymbol{\theta})$$

where the expectation E is taken conditional on $\boldsymbol{\theta}$ in which

$$(6) \qquad E\,L(\hat{\boldsymbol{\theta}},\boldsymbol{\theta}) = E\,(\boldsymbol{\theta}-\overline{\boldsymbol{\theta}})'Q(\boldsymbol{\theta}-\overline{\boldsymbol{\theta}}) + (\hat{\boldsymbol{\theta}}-\overline{\boldsymbol{\theta}})'Q(\hat{\boldsymbol{\theta}}-\overline{\boldsymbol{\theta}})$$

where $\overline{\boldsymbol{\theta}} = E\,\boldsymbol{\theta}$ is the posterior mean vector. From (6) we see that taking $\hat{\boldsymbol{\theta}} = \overline{\boldsymbol{\theta}}$ leads to minimal expected loss. Thus the posterior mean is an optimal point estimate for a quadratic loss function in the sense that it minimizes expected loss. In the current work, we will use a readily computable approximation to this posterior mean vector relying on the mixed estimation technique of Theil (see Theil (1971), pp. 346–352).

In brief, the specification procedure developed by Robert Litterman for vector autoregression models consists of the following four steps.[4] Firstly, benchmark univariate autoregressive forecasting equations are estimated by ordinary least squares. The dimension of search is over the lag lengths of these univariate representations. The second step in the specification process consists of trying to improve the forecasting performance by allowing for multivariate interaction. The dimension of search includes the univariate specifications at one end and an unrestricted VAR model at the other.

In the third step of the specification procedure equation-specific priors are introduced into the multivariate autoregression. This search defines a dimension of more or less differentiation among variables; at one end all variables are treated symmetrically and at the other end equation-specific exclusion restrictions are obtained. The final step is to strike a balance between the oversimplification of a constant-coefficient specification and the overparametrization of a fully time-varying coefficient model. At each step in the specification process, out-of-sample forecast errors are generated using the Kalman filter, and forecasting performance is judged by, e.g., Theil's inequality coefficient.

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[4] See Litterman (1979, 1986b) for details on the specification procedure. Doan et al. (1984) develop a similar, but more complex, procedure. The antecedents of these procedures are the work of Hoerl & Kennard (1970), Leamer (1972, 1978), Shiller (1973) and Stein (1974) on shrinkage estimation and its Bayesian interpretation.

2.3 The Minnesota prior

The prior used throughout the specification search has gained sufficient popularity among BVAR forecasters to merit a closer presentation. Since it was developed by researchers associated with the University of Minnesota and the Federal Reserve Bank of Minneapolis, it has been minted the Minnesota system of prior beliefs, or more briefly, the Minnesota prior.[5] This prior expresses, in the form of probabilities, which kind of a set of model parameter values will give the best forecasts. In particular, the Minnesota prior assumes that the joint probability distribution for the model parameters is multivariate normal.

The first moments of the model parameters are set according to the random walk hypothesis. As it is well known, a random walk component has proved to be very hard to reject in most macroeconomic time series. The prior second moments on own lag parameters are set to decay geometrically or harmonically with lag length. Cross lags get prior means of zero with the same downweighting of prior variances as own lags. Cross lag variances are also weighted by an own-versus-cross variance factor, which gives the cross prior variances units comparable to those of the own prior variances. The Minnesota system of priors is completed by specifying a prior on the absolute size of own and cross variances.[6]

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[5] The Minnesota prior is lucidly and at length presented by Todd (1984). The Minnesota prior is sometimes also referred to as the Litterman prior.

[6] Applications of the Minnesota prior include Amirizadeh & Todd (1984), Doan et al. (1984), Litterman (1984a, b), Kunst & Neusser (1986), Genberg & Salemi (1987), Cargill & Morus (1988), Raynauld (1988), Trevor & Thorp (1988), Trehan (1989), Artis & Zhang (1990) and Boero (1990).

3. AN APPLICATION TO THE FINNISH ECONOMY

3.1 Data and functional form

The choice of what variables to include into a VAR model depends on the aim and scope of the study. In our study we, in a sense, sidestep the problem by simply including those variables which have received most attention in the context of real time forecasting, when assessing the reliability of preliminary economic statistics and in fixing starting values for econometric forecasting models based on quarterly data. Of course, the resulting vector of variables will almost surely not be the entropy-minimizing vector. The Bayesian specification procedure allows us to balance bias and variance in the resulting model, but computational considerations limit the number of variables to include. Following earlier work designed for purposes similar to ours, we limit the number of variables to eight.[7]

All data are monthly and (where appropriate) seasonally adjusted and expressed in natural logarithms.[8] The variables are: an indicator of real gross domestic product (y), real industrial production (y_i), consumer prices (p), the short-term nominal interest rate (i), real exports (x), real imports (m), export prices (p_x) and import prices (p_m). We employ data from 1980M1 - 1990M9, using data from 1980M1 - 1989M9 to estimate the model from and leaving data from 1989M10 - 1990M9 for the assessment of forecasting performance. This choice of estimation period maximizes the difficulties of out-of-sample forecasting, since a major slowdown of the Finnish economy began at the end of the estimation period following a decade of stable growth. Data from the 1960s and the 1970s are not employed, since major structural changes took place during the latter part of the 1970s changing the short-run dynamics of the Finnish economy (Starck (1990)).

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[7] Studies with aims similar to ours include Litterman (1979, 1984a, 1986b), Doan et al. (1984), Kunst & Neusser (1986), Cargill & Morus (1988), Trevor & Thorp (1988), Artis & Zhang (1990) and Boero (1990).

[8] While the use of seasonally adjusted data may have its drawbacks (Sims (1974), Wallis (1974)), the use of sensible priors should mitigate these concerns.

The multivariate autoregression comprising the above variables is estimated in levels. By refraining from differencing we avoid distroying information about possible long-run (cointegration) relationships between the variables. We include intercepts in every equation, but refrain from using time trends. This is because an eight-variable VAR model can fit exactly an arbitrary set of very high-order polynomial time trends, while explicitly adding trend terms requires that forecasts with a linear time trend have standard errors of forecast not increasing at all as the forecast horizon lengthens. Including intercepts implies that our prior will not include a pure random walk, but a random walk with drift.[9]

3.2 Empirical results

Throughout the specification search, Theil's inequality coefficient U will be used in the evaluation of dynamic, out-of-sample forecasts. This metric will be reported for 1, 3, 6, 9 and 12 steps ahead forecasts. Theil's U is the ratio of the root mean square error of forecast to the corresponding error of a no-change forecast. This unit-free statistic is 0 for a perfect forecast, while a value in excess of 1 is discouraging in the sense that a naive no-change forecast would do better. A no-change forecast is the optimal forecast for a pure random walk, and it is reasonable to believe that our variables contain sizeable random walk components. All empirical results are relegated to the Appendix.

Results from the first step in the specification procedure - estimating univariate benchmark models - are presented in Table 1. Autoregressive models of order 1 through 12 are evaluated. Overall, very low-order - 1 and 2 lag - models forecast best. There seems to be no need to include more lags in order to increase the accuracy of forecasts for longer horizons. The best benchmark models outperform no-change models in practically all cases and at all forecast horizons. Nevertheless, the variables y, y_i, i, p_x and p_m appear to be closely approximated by

[9] Outliers are dealt with using the following dummy variables: 81M4 (i), 85M5 (x), 86M5 (y, y_i, m), 86M6 (m) and 86M8 (i).

random walks hence severely limiting the possibilities to improve forecasts for these variables. In particular, the best forecast for p_x is a no-change value at all forecast horizons. The data generating processes for p, x and m appear to be more elaborate than random walks thus leaving scope for improvement in forecasting.

In the second step of the specification process, we evaluate gains in forecasting performance from allowing for multivariate interaction between variables. A sixth-order VAR is chosen because of computational considerations. The second moments of the distributions for coefficients on lags vary as a function of the lag number, being tighter around lags further back. The tightening of second moments is harmonic with a unity decay parameter. The tightness of the prior around zero for each of the coefficients on variables other than own lags is parametrized by a number π_1. When $\pi_1 = 0$ a system of univariate equations is estimated and when $\pi_1 = 1$ a complete VAR model is considered. Constants and coefficients on dummy variables are given flat priors with zero means. Empirical findings are reported in Table 2.

The best forecast performance is in the majority of cases obtained by allowing for interaction between variables. In general, in the best models the variance around the first lag of other variables with prior mean zero is as high as 0.5 (aside from a scale factor). Some variation in the optimal value of π_1 is encountered depending on the forecast horizon. The variables y_i and p_x appear to be largely exogenous and difficult to forecast, however. Increases in forecasting accuracy relative to benchmark models are unanimous for p and x and partial for m and p_m. Allowing for unstructured multivariate interaction does not improve forecasts for y, y_i, i and p_x.

Having put priors on the variances of coefficients on variables other than own lags, we proceed by investigating the consequences for forecasting of varying the tightness of the prior around first own lags. Let π_2 determine prior own lag variances and maintain $\pi_1 = 0.5$ for other than own lag variances. The empirical evidence is given in Table 3. Results differ somewhat across variables and forecasting horizons, but a modest tightness ($\pi_2 = 0.15$) seems to be preferable, on the whole. Again, y_i and p_x resemble random walks, while clear improvements in forecasting are documented for p and x and some success is encountered in the cases of m and p_m. The evidence tends to suggest that the mean of the own first lag of x is less than unity.

Having found optimal degrees of tightness on prior variances ($\pi_1 = 0.5$ and $\pi_2 = 0.15$), we conclude the second step of the specification process by searching for the optimal type of tightening of variances by lag number. So far, a harmonic lag decay with decay parameter $\pi_3 = 1$ has been used. In Table 4 we report results using both harmonic and geometric decays for a variety of values of π_3.[10] As it happens, no overall best type of lag decay can be singled out. Most variables seem to require fairly tight decays, but m and p_x may benefit from relatively loose decays. Improvements in forecasting relative to benchmarks are found for p and x, and possibly for i and m. While the choice of lag decay pattern does not seem to be of overwhelming importance, we chose to tighten the decay somewhat in the subsequent analysis by employing a harmonic pattern with decay parameter $\pi_3 = 2$.

Moving on to the third step of the specification process, we introduce equation-specific priors. We suggest a tentative structure for the relationships between the variables in our model, but let the data override the prior if the historical evidence is strong enough. The relative weights used to impose an asymmetric structure on the model are given in Table 5. Let π_4 index how much weight the a priori structure is to have. When $\pi_4 = 1$ all variables are treated symmetrically, and as π_4 decreases, the limiting specification has zero restrictions with the relative weights displayed in Table 5.

Results from the search along a dimension of the prior allowing for varying amounts of asymmetric multivariate interaction are presented in Table 6. For most variables, a modest degree of asymmetric treatment ($\pi_4 = 0.2$) appears to be appropriate. In the case of y_i and p_x, tight adherance to the limiting specification is preferable. In all cases, allowing for a mild structure on the interactions in the model improves

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[10] Harmonic lag decay as a function of lag lenght l is imposed using the formula $l^{-\pi_3}$ and geometric decay is obtained using π_3^{l-1}.

forecasting performance relative to previous estimates. Moreover, the preferred model outperforms the benchmark models for p, x and m. All forecasts, except those for y_i and p_x, also outdo naive no-change forecasts for at least some forecast horizons.

The final step in the specification search is to evaluate whether gains in forecasting performance can be obtained by allowing for parameter variation. We let the parameters follow a random walk with variances proportional to their variances in the prior distribution. Let the factor of proportionality be π_5. When $\pi_5 = 0$ a constant-coefficient model is used and as π_5 increases more parameter variation is allowed. In this final search, the optimal parameter settings obtained above are, as in earlier searches, employed ($\pi_1 = 0.5$, $\pi_2 = 0.15$ and harmonic decay with $\pi_3 = 2$).[11] Empirical results are given in Table 7.

In the case of y, p, x and m improvements in forecasting performance cannot be obtained by allowing parameter variation. A very small amount of time variation may be beneficial for y_i, i and p_x. Allowing the parameters in the equation for p_m to change clearly would improve out-of-sample forecasts. The last result stems from the occurrence of the latest oil-shock (see Figure 1h of the Appendix), which, obviously, cannot be accounted for by the other model variables.

On the whole, we favor the use of a fixed-coefficient model for the following reasons. Firstly, half of the variables do not benefit from varying parameter specifications. Secondly, the computational burden is massive for varying parameter models. Thirdly, the parameter drift for those variables that could benefit from it is of negligible magnitude, in particular in comparison to sampling error. The implied standard error of the change in the first own lag is roughly 0.001 around a prior mean of 1. Lastly, the fact that simple random walks forecast as well as they do even 12 steps ahead (Table 1) is inconsistent with large amounts of parameter variability. In addition, we should remember that data spanning a decade only are used thus lessening the magnitude of possible true parameter drift.

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[11] Because of computational difficulties, asymmetric multivariate interaction is not employed in the last step of the specification search. Likewise, the models are estimated without dummy variables.

We conclude the illustration of the Bayesian specification scheme by scrutinizing the forecasting ability of our final model. A selection of model evaluation statistics is presented in Table 8 where the best benchmark models are contrasted with the best multivariate model. With respect to in-sample fit, the final model outperforms all benchmark models. In out-of-sample forecasting, consistent improvements are documented for p, x and m. For y and i, only minor improvements are found. No gains relative to a no-change forecast are achieved in the case of y_i, p_x and p_m. In fact, within our vector of variables, no model was found to beat a no-change forecast of p_x.

The forecasting performance of the final model is presented graphically in Figure 1 of the Appendix. With regard to y and y_i, the trend is picked up, but the slowdown at the very end of our sample period is not tracked. Using our disparate set of variables, it seems, not too surprisingly, to be impossible to account for the recent, pronounced slowdown in the production variables.[12] The model tracks p well, and picks up the fundamental movements in i. Likewise, x is well forecasted while some difficulties in predicting the slowdown in m show up. The forecast for p_x is nonsensical and modest success is met with in the case of p_m.

[12] As it is well known, VAR models typically contain only a little information not in conventional econometric macromodels while conventional models may contain information not in VAR models (Fair & Shiller (1989, 1990)).

4. CONCLUDING REMARKS

In this paper, we have reviewed a Bayesian approach to multivariate time series modeling for short-run forecasting, illustrating it with data from the Finnish economy. A vector autoregression model with Bayesian priors was specified, which yields adjustment-free, low-cost forecasts of key macroeconomic variables on a monthly basis. The model is estimated using data from the 1980s only, and the out-of-sample forecasting performance is found to be reasonable for some of the model variables. Since our variables are characterized by only small amounts of comovement, and the specification period differs from the forecasting period, our application would tend to speak favourably of the Bayesian approach to specifying multivariate time series models.

APPENDIX

TABLE 1 UNIVARIATE AUTOREGRESSION FORECAST PERFORMANCE AS MEASURED BY THEIL'S U

	Number of steps ahead forecasted				
1	1	3	6	9	12
	Real gross domestic product				
1	1.007	1.008	.655	.482	.777
2	.852	.971	.539	1.069	1.875
3	.933	.981	.612	1.374	2.212
4	.935	1.012	.725	1.713	2.739
5	1.031	1.139	1.087	2.387	3.679
6	1.052	1.192	1.151	2.566	3.902
7	1.148	1.238	1.270	2.756	4.142
8	1.124	1.227	1.221	2.622	3.946
9	1.188	1.314	1.343	2.771	4.156
10	1.104	1.173	1.150	2.538	3.842
11	1.114	1.202	1.200	2.597	2.873
12	1.130	1.258	1.280	2.706	4.055
	Real industrial production				
1	.988	.971	.978	.818	.732
2	1.002	1.055	1.052	1.476	1.469
3	1.249	1.124	1.163	2.104	1.880
4	1.323	1.147	1.194	2.292	1.985
5	1.474	1.186	1.283	2.635	2.165
6	1.455	1.185	1.248	2.543	2.171
7	1.499	1.226	1.324	2.696	2.294
8	1.467	1.206	1.446	2.870	2.341
9	1.474	1.206	1.431	2.887	2.350
10	1.507	1.240	1.496	2.985	2.414
11	1.434	1.172	1.399	2.239	2.381
12	1.413	1.154	1.379	2.821	2.377
	Consumer prices				
1	.684	.527	.477	.469	.421
2	.670	.508	.452	.442	.385
3	.669	.508	.451	.440	.381
4	.677	.517	.455	.441	.381
5	.609	.469	.405	.398	.327
6	.602	.487	.434	.430	.361
7	.602	.507	.476	.464	.417
8	.628	.519	.495	.477	.443
9	.620	.498	.470	.450	.414
10	.582	.449	.421	.402	.370
11	.615	.492	.466	.449	.422
12	.603	.423	.384	.373	.344
	Short-term nominal interest rate				
1	1.022	.931	.648	.234	590
2	1.285	1.040	.780	.367	912
3	1.382	1.085	.846	.438	991
4	1.429	1.119	.854	.442	1060
5	1.415	1.097	.859	.472	1100
6	1.496	1.142	.931	.561	1070
7	1.487	1.142	.882	.511	1300
8	1.391	1.101	.891	.537	1140
9	1.393	1.091	.859	.519	1170
10	1.308	1.059	.916	.620	1100
11	1.300	1.053	.932	.652	1180
12	1.271	1.035	.954	.741	1120

TABLE 1 (continued)

	Real exports				
1	.943	1.066	1.368	1.013	.899
2	.868	.905	1.186	.897	.781
3	.796	.814	1.047	.815	.695
4	.780	.785	1.007	.784	.657
5	.761	.753	.960	.767	.645
6	.755	.743	.939	.749	.614
7	.749	.733	.912	.727	.579
8	.725	.720	.909	.734	.547
9	.756	.748	.916	.759	.460
10	.765	.755	.932	.773	.484
11	.791	.765	.956	.834	.514
12	.741	.725	.913	.800	.508
	Real imports				
1	1.157	1.068	2.263	.839	.292
2	.997	.803	1.316	.632	.191
3	1.116	.832	1.020	.746	.679
4	1.138	.828	1.094	.845	.887
5	1.170	.846	1.347	1.026	1.177
6	1.132	.807	1.516	1.143	1.386
7	1.135	.802	1.488	1.120	1.348
8	1.163	.834	1.679	1.128	1.466
9	1.220	.882	1.859	1.183	1.560
10	1.242	.895	1.889	1.188	1.584
11	1.300	.939	1.977	1.239	1.650
12	1.287	.928	1.961	1.246	1.627
	Export prices				
1	1.035	1.124	1.237	1.356	1.490
2	1.070	1.142	1.284	1.384	1.784
3	1.112	1.318	1.625	1.937	2.551
4	1.121	1.326	1.634	1.949	2.561
5	1.125	1.284	1.550	1.789	2.357
6	1.151	1.292	1.554	1.740	2.321
7	1.096	1.305	1.601	1.816	2.380
8	1.123	1.252	1.435	1.309	1.627
9	1.132	1.218	1.369	1.112	1.373
10	1.119	1.211	1.341	1.040	1.244
11	1.112	1.225	1.374	1.114	1.327
12	1.115	1.201	1.338	1.025	1.202
	Import prices				
1	.997	.980	.992	.969	.922
2	.899	.980	1.030	.980	.957
3	.897	.985	1.034	.974	.946
4	.897	.998	1.041	.966	.940
5	.892	1.002	1.048	.971	.964
6	.878	.983	1.045	1.010	.995
7	.881	.983	1.042	1.010	1.009
8	.911	1.027	1.083	1.041	1.131
9	.894	1.006	1.061	1.055	1.079
10	.896	1.002	1.063	1.064	1.064
11	.891	1.003	1.102	1.065	.965
12	.892	1.003	1.114	1.068	.949

TABLE 2 FORECAST PERFORMANCE MEASURED BY THEIL'S U FROM A SEARCH ALONG A DIMENSION OF THE PRIOR ALLOWING VARYING AMOUNTS OF MULTIVARIATE INTERACTION

π_1	Number of steps ahead forecasted				
	1	3	6	9	12
	Real gross domestic product				
0.001	.965	1.105	.947	2.111	3.365
0.01	.963	1.098	.932	2.068	3.298
0.05	.949	1.037	.799	1.638	2.658
0.1	.946	1.017	.738	1.308	2.206
0.5	.968	1.072	.648	1.053	2.035
1	.988	1.048	.631	1.235	2.332
	Real industrial production				
0.001	1.070	1.078	1.084	1.877	1.705
0.01	1.073	1.082	1.094	1.894	1.700
0.05	1.113	1.127	1.201	2.047	1.685
0.1	1.161	1.191	1.302	2.192	1.735
0.5	1.299	1.358	1.559	2.760	2.065
1	1.331	1.359	1.631	2.987	2.178
	Consumer prices				
0.001	.671	.510	.461	.457	.403
0.01	.671	.509	.459	.456	.401
0.05	.665	.493	.436	.426	.364
0.01	.655	.461	.388	.369	.291
0.05	.673	.387	.244	.177	.009
1	.721	.415	.247	.170	.098
	Short-term nominal interest rate				
0.001	1.256	1.068	.947	.785	197
0.01	1.264	1.061	.873	.558	576
0.05	1.323	1.096	.809	.458	1250
0.1	1.327	1.098	.806	.469	1260
0.5	1.296	.993	.688	.422	727
1	1.304	.973	.723	.582	529
	Real exports				
0.001	.918	1.014	1.462	1.174	1.122
0.01	.880	.922	1.265	.998	.916
0.05	.760	.703	.869	.674	.475
0.1	.740	.683	.833	.646	.405
0.5	.713	.664	.799	.632	.326
1	.703	.636	.812	.643	.319
	Real imports				
0.001	.977	.787	1.025	.712	.200
0.01	.978	.774	1.075	.688	.379
0.05	.992	.751	1.242	.649	.747
0.1	1.007	.757	1.299	.631	.818
0.5	.970	.741	1.251	.629	.955
1	.907	.706	1.187	.636	1.020
	Export prices				
0.001	1.078	1.244	1.474	1.688	2.114
0.01	1.079	1.249	1.483	1.705	2.138
0.05	1.105	1.332	1.627	1.942	2.458
0.01	1.147	1.459	1.839	2.247	2.832
0.5	1.400	2.090	2.857	3.615	4.347
1	1.460	2.294	3.236	4.098	5.004
	Import prices				
0.001	.942	.978	1.016	.957	.902
0.01	.945	.989	1.022	.969	.938
0.05	.951	1.016	1.052	.955	.960
0.1	.951	1.036	1.129	.890	.792
0.5	.942	1.164	1.745	1.456	.090
1	.896	1.104	1.841	1.642	.071

TABLE 3 FORECAST PERFORMANCE MEASURED BY THEIL'S U FROM A SEARCH ALONG A DIMENSION OF THE PRIOR ALLOWING VARYING AMOUNTS OF TIGHTNESS OF A RANDOM WALK SPECIFICATION FOR OWN LAGS

π_2	Number of steps ahead forecasted				
	1	3	6	9	12
	Real gross domestic product				
1	1.024	1.183	.929	2.196	3.455
0.2	.965	1.067	.652	1.218	2.271
0.15	.968	1.072	.648	1.053	2.035
0.1	.987	1.091	.707	.957	1.836
0.05	1.019	1.128	.842	1.193	2.002
0.01	1.048	1.235	1.114	2.208	3.517
	Real industrial production				
1	1.487	1.281	1.673	3.607	2.534
0.2	1.369	1.370	1.589	2.921	2.162
0.15	1.299	1.358	1.559	2.760	2.065
0.1	1.202	1.317	1.528	2.559	1.944
0.05	1.093	1.218	1.437	2.205	1.801
0.01	1.053	1.160	1.335	2.053	1.918
	Consumer prices				
1	.862	.523	.315	.223	.305
0.2	.688	.393	.238	.166	.050
0.15	.673	.387	.244	.177	.009
0.1	.658	.388	.263	.206	.057
0.05	.650	.422	.329	.293	.195
0.01	.669	.496	.437	.424	.367
	Short-term nominal interest rate				
1	1.552	1.149	1.203	1.458	118
0.2	1.340	.995	.728	.530	654
0.15	1.296	.993	.688	.422	727
0.1	1.231	1.000	.664	.335	872
0.05	1.124	1.006	.699	.394	1140
0.01	1.030	1.011	.890	.620	1010
	Real exports				
1	.599	.631	.810	.696	.168
0.2	.676	.666	.798	.629	.289
0.15	.712	.664	.799	.632	.326
0.1	.783	.683	.813	.649	.387
0.05	.915	.830	.910	.769	.594
0.01	1.013	1.042	1.127	1.144	1.279
	Real imports				
1	.930	.591	1.122	.704	1.123
0.2	.978	.728	1.225	.637	.983
0.15	.970	.741	1.251	.628	.955
0.1	.954	.761	1.277	.629	.946
0.05	.959	.853	1.214	.721	1.105
0.01	1.037	1.157	1.873	1.659	2.268
	Export prices				
1	1.617	2.686	3.889	5.023	6.635
0.2	1.408	2.174	3.011	3.805	4.533
0.15	1.380	2.090	2.857	3.615	4.347
0.1	1.338	1.970	2.645	3.347	4.091
0.05	1.251	1.742	2.276	2.863	3.569
0.01	1.144	1.457	1.825	2.230	2.747
	Import prices				
1	.824	1.035	2.047	2.163	.524
0.2	.913	1.148	1.808	1.539	.038
0.15	.942	1.164	1.745	1.456	.090
0.1	.972	1.152	1.589	1.269	.231
0.05	.995	1.077	1.216	.896	.672
0.01	1.030	1.067	1.073	1.196	1.327

TABLE 4 FORECAST PERFORMANCE MEASURED BY THEIL'S U FROM A SEARCH ALONG A DIMENSION OF THE PRIOR ALLOWING VARYING AMOUNTS OF TIGHTNESS IN LAG DECAY

π_3		Number of steps ahead forecasted				
		1	3	6	9	12
		Real gross domestic product				
0.5	(harmonic)	1.028	1.134	.833	1.658	2.694
1	(harmonic)	.968	1.072	.648	1.053	2.035
2	(harmonic)	.961	1.081	.642	.641	1.528
0.75	(geometric)	.983	1.079	.692	1.352	2.462
0.5	(geometric)	.945	1.068	.607	.691	1.662
0.25	(geometric)	.960	1.084	.651	.617	1.496
		Real industrial production				
0.5	(harmonic)	1.313	1.310	1.540	2.961	2.238
1	(harmonic)	1.299	1.358	1.559	2.760	2.065
2	(harmonic)	1.279	1.422	1.611	2.640	1.927
0.75	(geometric)	1.304	1.306	1.525	2.863	2.183
0.5	(geometric)	1.299	1.401	1.559	2.669	1.981
0.25	(geometric)	1.279	1.434	1.629	2.643	1.919
		Consumer prices				
0.5	(harmonic)	.685	.389	.233	.147	.072
1	(harmonic)	.677	.387	.244	.177	.009
2	(harmonic)	.666	.382	.250	.189	.024
0.75	(geometric)	.682	.395	.240	.160	.058
0.5	(geometric)	.670	.391	.255	.193	.008
0.25	(geometric)	.666	.382	.251	.189	.025
		Short-term nominal interest rate				
0.5	(harmonic)	1.342	1.047	.843	.711	627
1	(harmonic)	1.296	.993	.688	.422	727
2	(harmonic)	1.310	1.014	.603	.294	897
0.75	(geometric)	1.303	1.018	.835	.738	563
0.5	(geometric)	1.274	.971	.638	.340	734
0.25	(geometric)	1.315	1.023	.610	.316	909
		Real exports				
0.5	(harmonic)	.714	.671	.798	.638	.307
1	(harmonic)	.712	.664	.799	.632	.326
2	(harmonic)	.727	.675	.821	.637	.351
0.75	(geometric)	.707	.670	.798	.636	.299
0.5	(geometric)	.711	.661	.804	.632	.333
0.25	(geometric)	.728	.676	.822	.637	.352
		Real imports				
0.5	(harmonic)	.951	.710	1.173	.653	1.015
1	(harmonic)	.970	.741	1.251	.628	.955
2	(harmonic)	.981	.752	1.311	.633	.934
0.75	(geometric)	.959	.726	1.209	.634	.980
0.5	(geometric)	.972	.752	1.295	.620	.921
0.25	(geometric)	.980	.752	1.318	.636	.934
		Export prices				
0.5	(harmonic)	1.407	2.206	3.101	3.914	4.652
1	(harmonic)	1.380	2.090	2.857	3.615	4.347
2	(harmonic)	1.395	2.071	2.734	3.502	4.343
0.75	(geometric)	1.401	2.203	3.058	3.872	4.594
0.5	(geometric)	1.395	2.109	2.820	3.589	4.399
0.25	(geometric)	1.401	2.078	2.734	3.512	4.374
		Import prices				
0.5	(harmonic)	.905	1.156	1.926	1.690	.029
1	(harmonic)	.942	1.164	1.745	1.456	.090
2	(harmonic)	.996	1.150	1.566	1.266	.198
0.75	(geometric)	.917	1.172	1.876	1.627	.004
0.5	(geometric)	.963	1.176	1.689	1.397	.102
0.25	(geometric)	1.003	1.150	1.555	1.258	.201

TABLE 5 RELATIVE WEIGHTS OF VARIABLES IN DIFFERENT EQUATIONS

Equation	Variable							
	y	y_i	p	i	x	m	p_x	p_m
y	2.0	0.2	0.1	0.2	0.5	0.8	0.1	0.8
y_i	0.5	2.0	0.1	0.2	0.2	0.2	0.1	0.2
p	0.8	0.1	2.0	0.2	0.8	0.1	0.2	0.2
i	0.5	0.2	0.5	1.0	0.2	0.1	0.2	0.1
x	0.2	0.5	0.1	0.5	1.0	0.2	0.8	0.2
m	0.8	0.2	0.2	0.1	0.1	1.0	0.2	0.5
p_x	0.8	0.1	0.5	0.1	0.1	0.1	2.0	0.8
p_m	0.2	0.2	0.8	0.5	0.2	0.5	0.2	2.0

TABLE 6 FORECAST PERFORMANCE MEASURED BY THEIL'S U FROM A SEARCH ALONG A DIMENSION OF THE PRIOR ALLOWING VARYING AMOUNTS OF ASYMMETRIC TREATMENT OF VARIABLES IN DIFFERENT EQUATIONS

π_4	Number of steps ahead forecasted				
	1	3	6	9	12
			Real gross domestic product		
1	1.017	1.205	1.062	1.985	3.083
0.2	.918	1.058	.641	.936	1.902
0.15	.922	1.051	.622	.928	1.882
0.1	.943	1.050	.624	1.003	1.906
0.05	.988	1.062	.673	1.167	1.924
0.01	1.023	1.099	.772	1.360	2.223
			Real industrial production		
1	1.661	1.461	1.901	3.570	2.503
0.2	1.430	1.435	1.649	2.825	2.020
0.15	1.340	1.398	1.605	2.743	1.965
0.1	1.198	1.302	1.508	2.583	1.870
0.05	1.040	1.110	1.236	1.996	1.566
0.01	1.015	1.045	1.076	1.312	1.297
			Consumer prices		
1	.693	.373	.221	.155	.140
0.2	.643	.360	.231	.171	.035
0.15	.641	.369	.248	.193	.074
0.1	.642	.390	.282	.235	.137
0.05	.652	.439	.356	.325	.255
0.01	.675	.508	.453	.442	.390
			Short-term nominal interest rate		
1	1.423	1.000	.739	.527	631
0.2	1.294	1.035	.641	.377	1050
0.15	1.262	1.047	.657	.446	1140
0.1	1.211	1.052	.682	.522	1260
0.05	1.125	1.029	.705	.528	1390
0.01	1.028	1.008	.883	.607	989
			Real exports		
1	.636	.708	.830	.639	.176
0.2	.713	.690	.818	.627	.316
0.15	.747	.706	.834	.634	.335
0.1	.813	.750	.876	.656	.377
0.05	.933	.885	1.022	.805	.609
0.01	1.012	1.036	1.155	1.157	1.299
			Real imports		
1	1.034	.717	1.266	.721	1.110
0.2	.970	.730	1.321	.666	1.004
0.15	.946	.730	1.324	.670	1.012
0.1	.920	.742	1.325	.693	1.045
0.05	.944	.854	1.306	.827	1.221
0.01	1.024	1.109	1.617	1.477	1.912
			Export prices		
1	1.434	2.047	2.774	3.426	4.423
0.2	1.270	1.806	2.376	3.009	4.111
0.15	1.263	1.797	2.372	3.045	4.226
0.1	1.262	1.799	2.392	3.119	4.353
0.05	1.241	1.740	2.307	2.993	4.021
0.01	1.148	1.465	1.832	2.230	2.740
			Import prices		
1	.818	1.056	1.638	1.269	.237
0.2	.945	1.189	1.544	1.145	.344
0.15	.967	1.178	1.464	1.050	.444
0.1	.987	1.136	1.306	.900	.630
0.05	1.002	1.059	1.066	.852	.943
0.01	1.028	1.055	1.057	1.158	1.270

TABLE 7 FORECAST PERFORMANCE MEASURED BY THEIL'S U FROM A SEARCH ALONG A DIMENSION OF THE PRIOR ALLOWING VARYING AMOUNTS OF TIME-VARIATION IN COEFFICIENTS

π_5	Number of steps ahead forecasted				
	1	3	6	9	12
			Real gross domestic product		
0	1.246	1.741	1.556	3.696	5.660
1×10^{-8}	1.329	2.005	2.492	4.570	7.579
1×10^{-7}	1.719	3.131	5.751	14.622	6.531
1×10^{-6}	2.180	4.531	8.442	9.987	19.783
1×10^{-5}	2.201	4.114	7.295	6.293	9.050
1×10^{-4}	1.934	3.472	5.758	6.242	5.399
			Real industrial production		
0	1.344	1.255	1.629	3.313	2.622
1×10^{-8}	1.253	1.168	1.638	1.289	3.004
1×10^{-7}	1.501	1.890	4.858	14.804	7.411
1×10^{-6}	1.788	2.854	7.796	28.400	8.260
1×10^{-5}	1.663	2.324	5.026	6.740	1.835
1×10^{-4}	1.552	1.687	3.419	3.854	1.729
			Consumer prices		
0	.886	.576	.337	.174	.217
1×10^{-8}	.987	.794	.696	.679	.220
1×10^{-7}	1.064	.954	.985	.914	.826
1×10^{-6}	1.081	1.101	1.150	.945	1.446
1×10^{-5}	.954	1.011	1.069	.932	1.239
1×10^{-4}	.908	1.004	1.075	.854	1.204
			Short-term nominal interest rate		
0	1.872	1.354	1.190	1.111	466
1×10^{-8}	1.593	1.354	1.483	2.139	1190
1×10^{-7}	1.502	1.809	3.023	8.238	4310
1×10^{-6}	1.538	2.395	4.655	15.766	2870
1×10^{-5}	1.227	1.911	3.005	6.268	2340
1×10^{-4}	.883	1.348	2.114	4.706	2420
			Real exports		
0	.846	.674	.932	.734	.187
1×10^{-8}	1.009	.734	.837	.849	.467
1×10^{-7}	1.304	1.637	2.119	4.162	1.436
1×10^{-6}	1.612	3.167	7.981	13.992	7.318
1×10^{-5}	1.692	3.116	6.194	7.533	9.264
1×10^{-4}	1.686	3.004	5.114	6.649	7.623
			Real imports		
0	1.069	.497	1.415	.742	1.297
1×10^{-8}	1.197	.651	1.386	1.038	1.044
1×10^{-7}	1.461	1.518	4.101	5.224	2.069
1×10^{-6}	1.675	2.615	13.011	14.129	3.611
1×10^{-5}	1.718	2.484	8.598	7.298	12.611
1×10^{-4}	1.659	2.354	6.605	4.935	8.723
			Export prices		
0	2.152	3.384	4.763	6.297	8.231
1×10^{-8}	1.653	2.294	3.076	3.721	6.584
1×10^{-7}	1.649	2.288	2.892	3.166	6.073
1×10^{-6}	1.707	2.527	3.577	3.736	7.031
1×10^{-5}	1.633	2.450	3.680	3.464	7.949
1×10^{-4}	1.493	2.301	3.664	3.523	8.045
			Import prices		
0	1.071	1.444	3.122	4.060	1.487
1×10^{-8}	1.081	1.655	2.675	2.691	.288
1×10^{-7}	1.017	1.684	3.140	4.122	.485
1×10^{-6}	.951	1.677	3.505	6.184	.449
1×10^{-5}	.834	1.357	2.496	2.570	.108
1×10^{-4}	.811	1.159	2.010	1.137	1.171

TABLE 8 COMPARISON OF INITIAL UNIVARIATE AND FINAL MULTIVARIATE MODELS

Statistic	Variable							
	y	y_i	p	i	x	m	p_x	p_m
	initial/ final	initial/ final	initial/ final	initial/ final	initial/ final	initial/ final	initial/ final	initial/ final
l	2 / 6	1 / 6	12 / 6	1 / 6	8 / 6	2 / 6	1 / 6	1 / 6
$\bar{R}^2$	0.9815 / 0.9851	0.9403 / 0.9636	0.9990 / 0.9993	0.8757 / 0.9180	0.5800 / 0.6435	0.6326 / 0.7929	0.9950 / 0.9958	0.9681 / 0.9739
SEE	0.0112 / 0.0101	0.0218 / 0.0170	0.0045 / 0.0041	0.0088 / 0.0072	0.0717 / 0.0662	0.0957 / 0.0719	0.0065 / 0.0060	0.0122 / 0.0110
Q	0.0000 / 0.0000	0.0000 / 0.0029	0.4125 / 0.0000	0.0224 / 0.0590	0.4977 / 0.0097	0.0005 / 0.0015	0.0010 / 0.0850	0.2654 / 0.4806
U(1)	0.8518 / 0.9175	0.9880 / 1.4295	0.6033 / 0.6427	1.0219 / 1.2940	0.7254 / 0.7132	0.9969 / 0.9695	1.0352 / 1.2704	0.9974 / 0.9454
U(3)	0.9713 / 1.0581	0.9706 / 1.4352	0.4229 / 0.3595	0.9313 / 1.0349	0.7201 / 0.6895	0.8030 / 0.7298	1.1237 / 1.8064	0.9796 / 1.1890
U(6)	0.5394 / 0.6405	0.9777 / 1.6486	0.3844 / 0.2307	0.6479 / 0.6407	0.9086 / 0.8178	1.3156 / 1.3208	1.2373 / 2.3756	0.9921 / 1.5440
U(9)	1.0694 / 0.9362	0.8183 / 2.8254	0.3729 / 0.1712	0.2342 / 0.3774	0.7339 / 0.6269	0.6315 / 0.6655	1.3558 / 3.0092	0.9688 / 1.1448
U(12)	1.8751 / 1.9019	0.7316 / 2.0201	0.3444 / 0.0353	590 / 1048	0.5467 / 0.3157	0.1906 / 1.0043	1.4901 / 4.1112	0.9222 / 0.3441
U(wa)	0.9541 / 0.9985	0.9305 / 1.7432	0.4540 / 0.3580	0.8412 / 0.9940	0.7441 / 0.6755	0.8767 / 0.8473	1.1913 / 2.1703	0.9801 / 1.0958

l is lag length, $\bar{R}^2$ is the degrees-of-freedom-corrected squared multiple correlation coefficient, Q is the Ljung-Box portmanteau statistic based on 30 autocorrelations, U(n) is Theil's U at forecast horizon n, n = 1, 3, 6, 9, 12 and U(wa) is a weighted average of the U(n) with weights (at forecast horizon n) 0.30 (1), 0.25 (3), 0.20 (6), 0.15 (9) and 0.10 (12). In the case of the variable i, U(12) is ignored in the calculation of U(wa) using the weights (at forecast horizon n) 0.40 (1), 0.30 (3), 0.20 (6), 0.10 (9) and 0.00 (12).

FIGURE 1 TIME SERIES AND FORECASTS
Actual ____
Forecast ......

FIGURE 1a Real gross domestic product

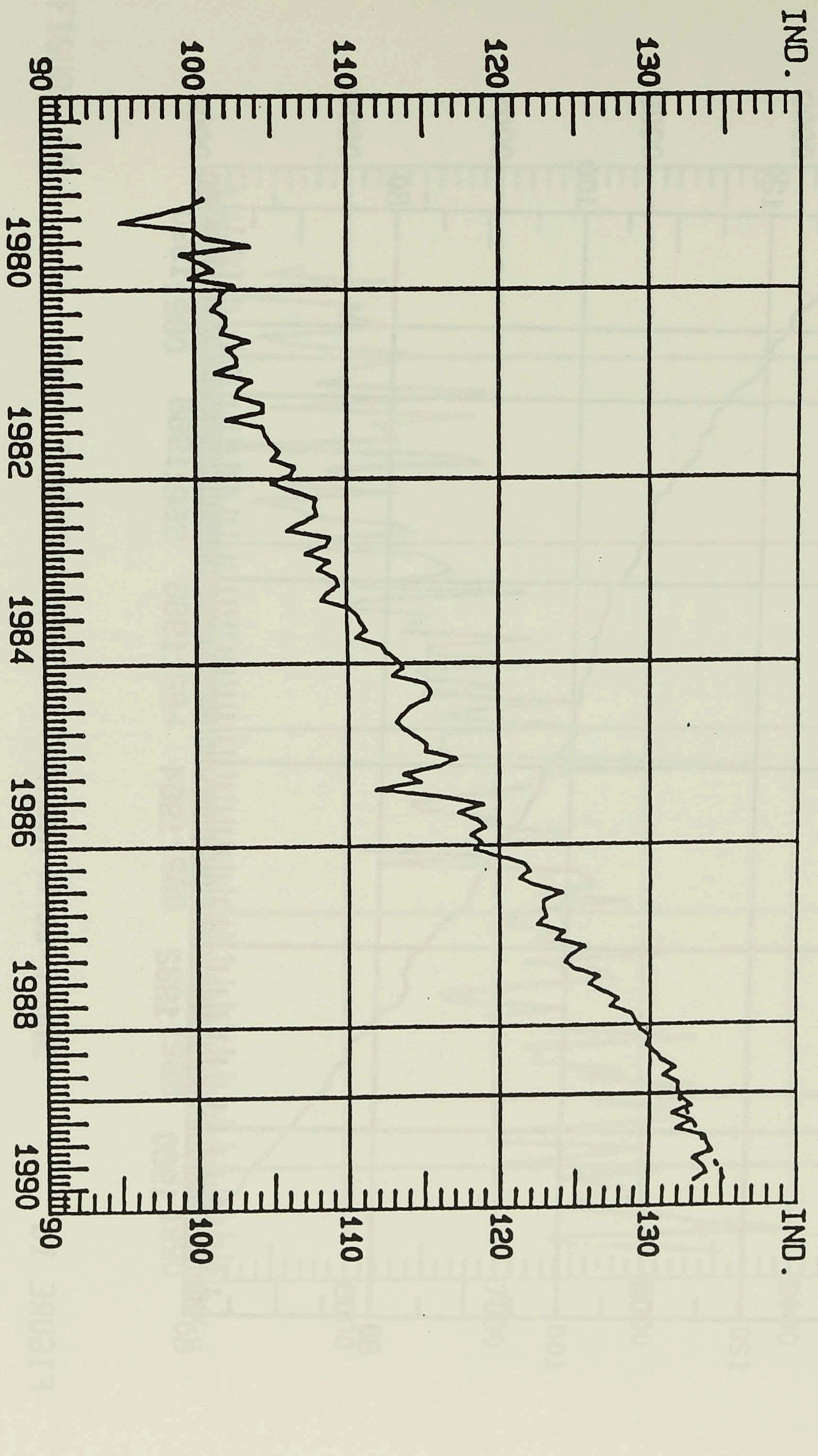


FIGURE 1b Real industrial production

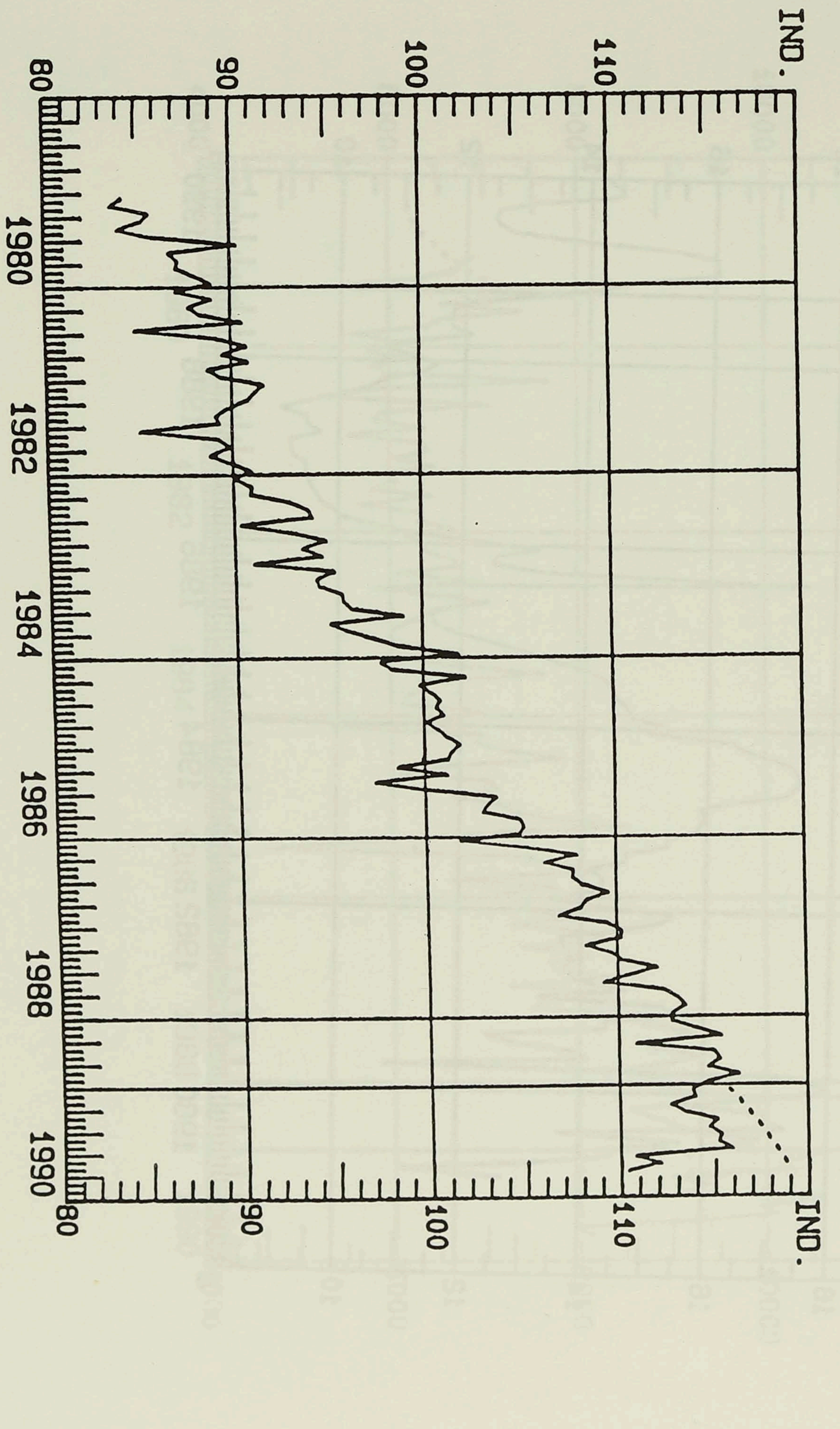


FIGURE 1c Consumer prices

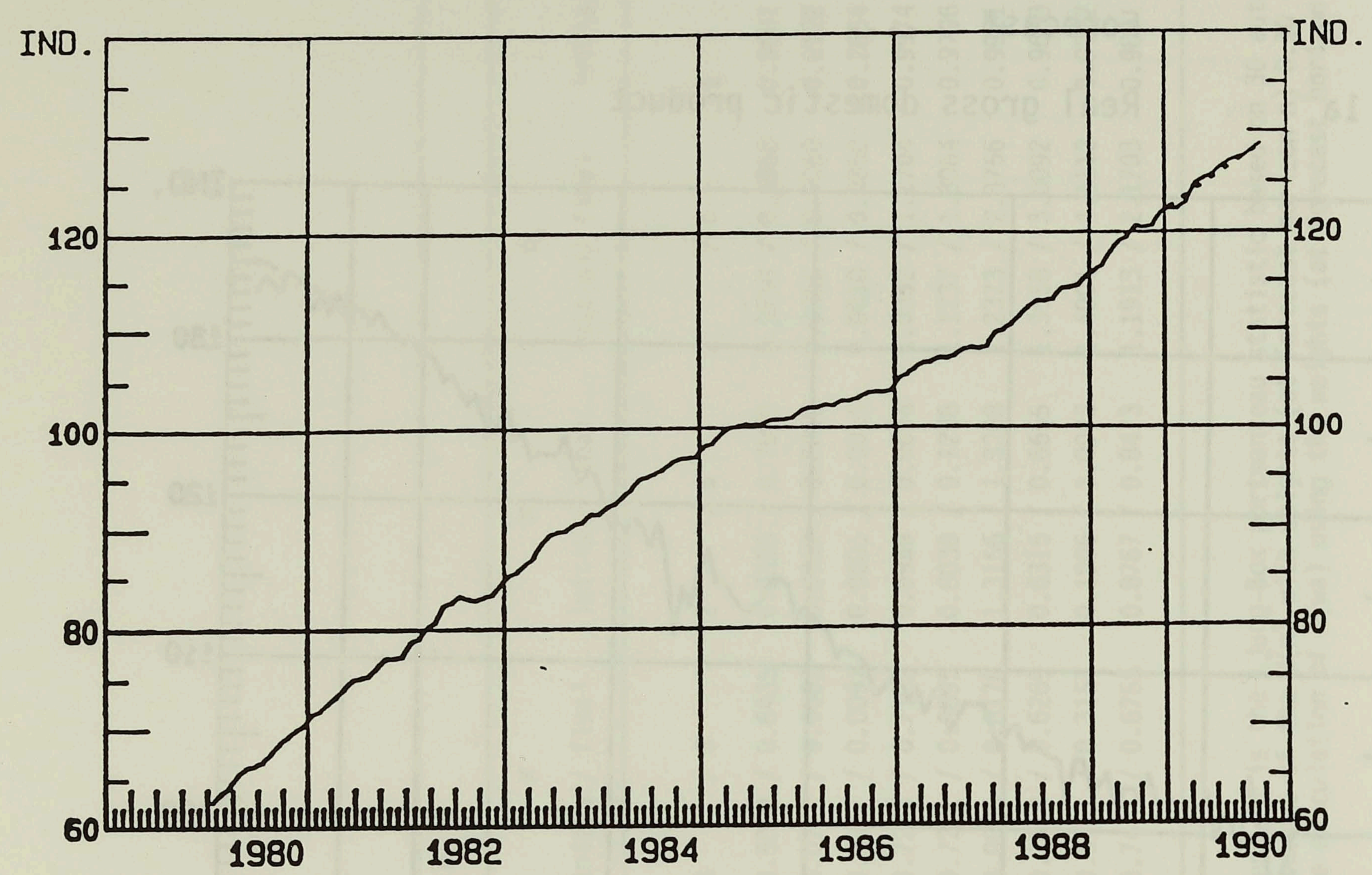


FIGURE 1d Short-term nominal interest rate

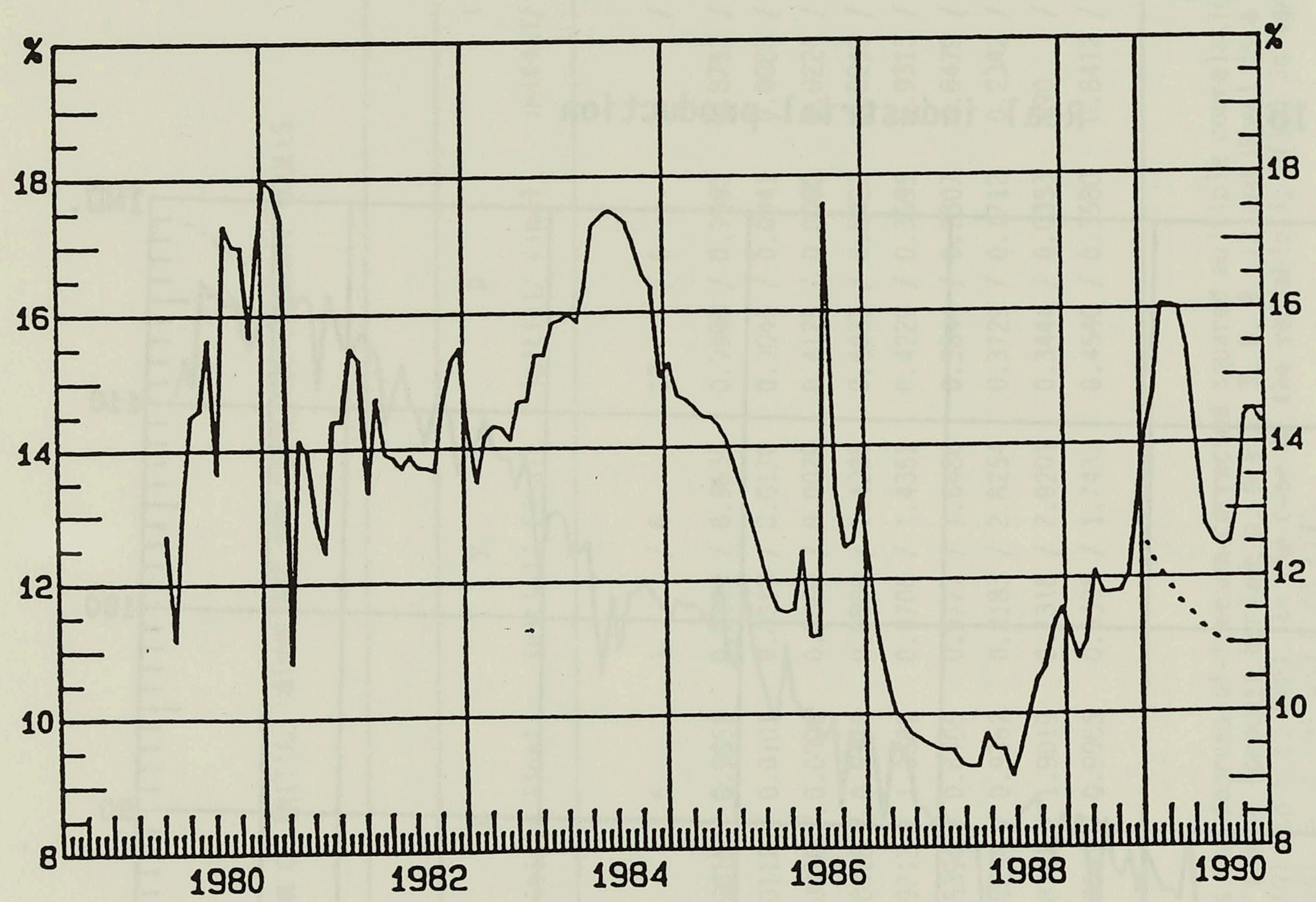


FIGURE 1e Real exports

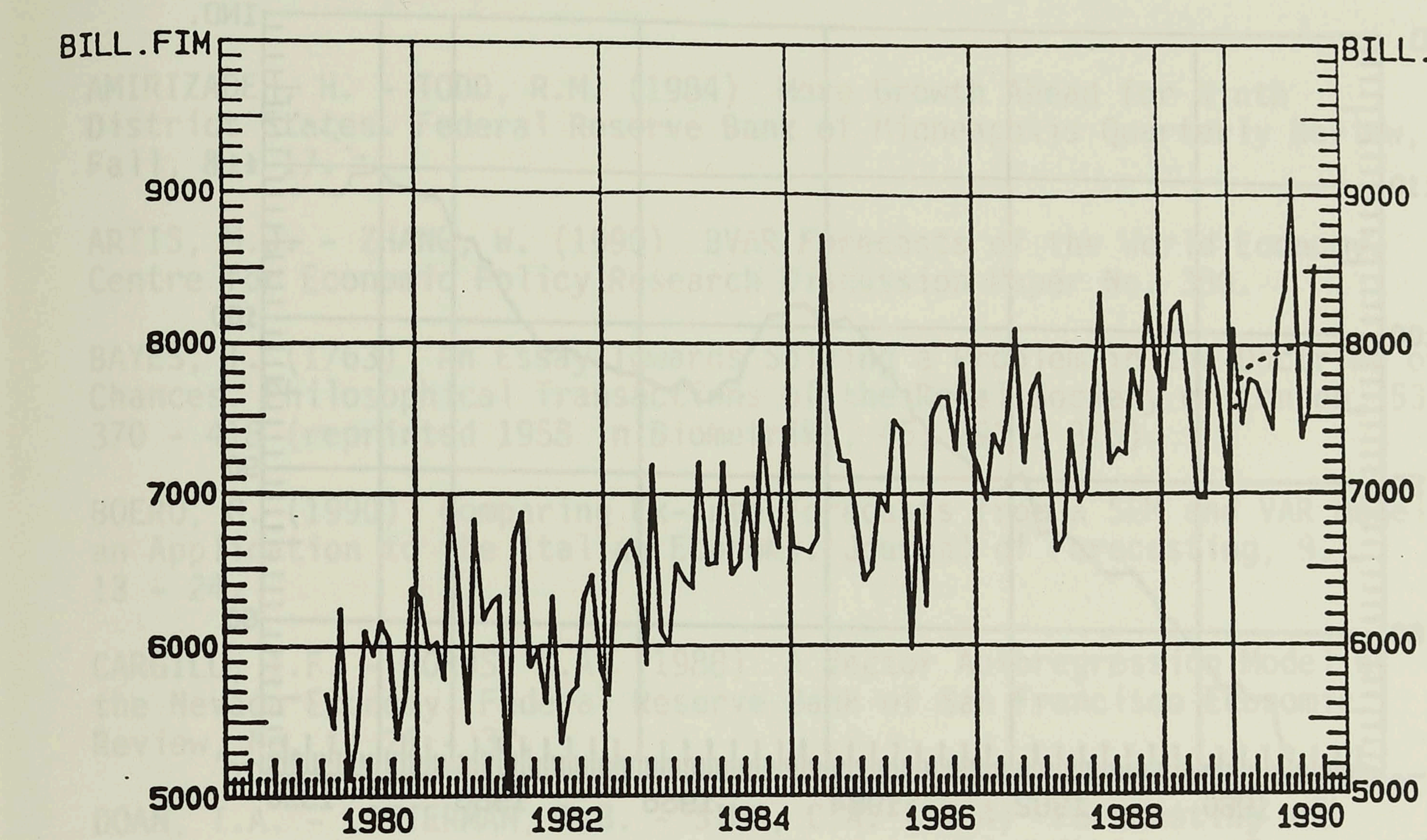


FIGURE 1f Real imports

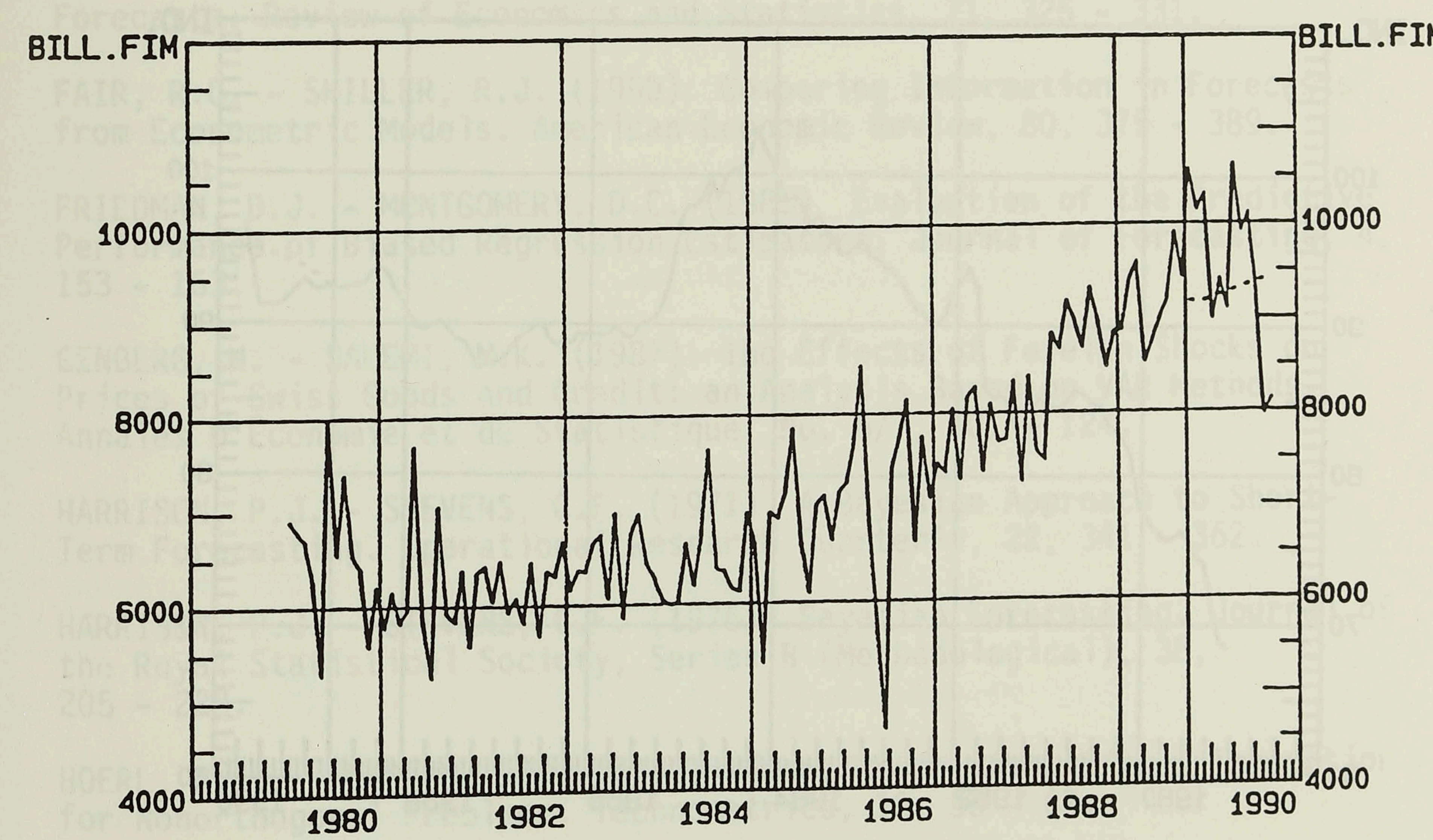


FIGURE 1g Export prices

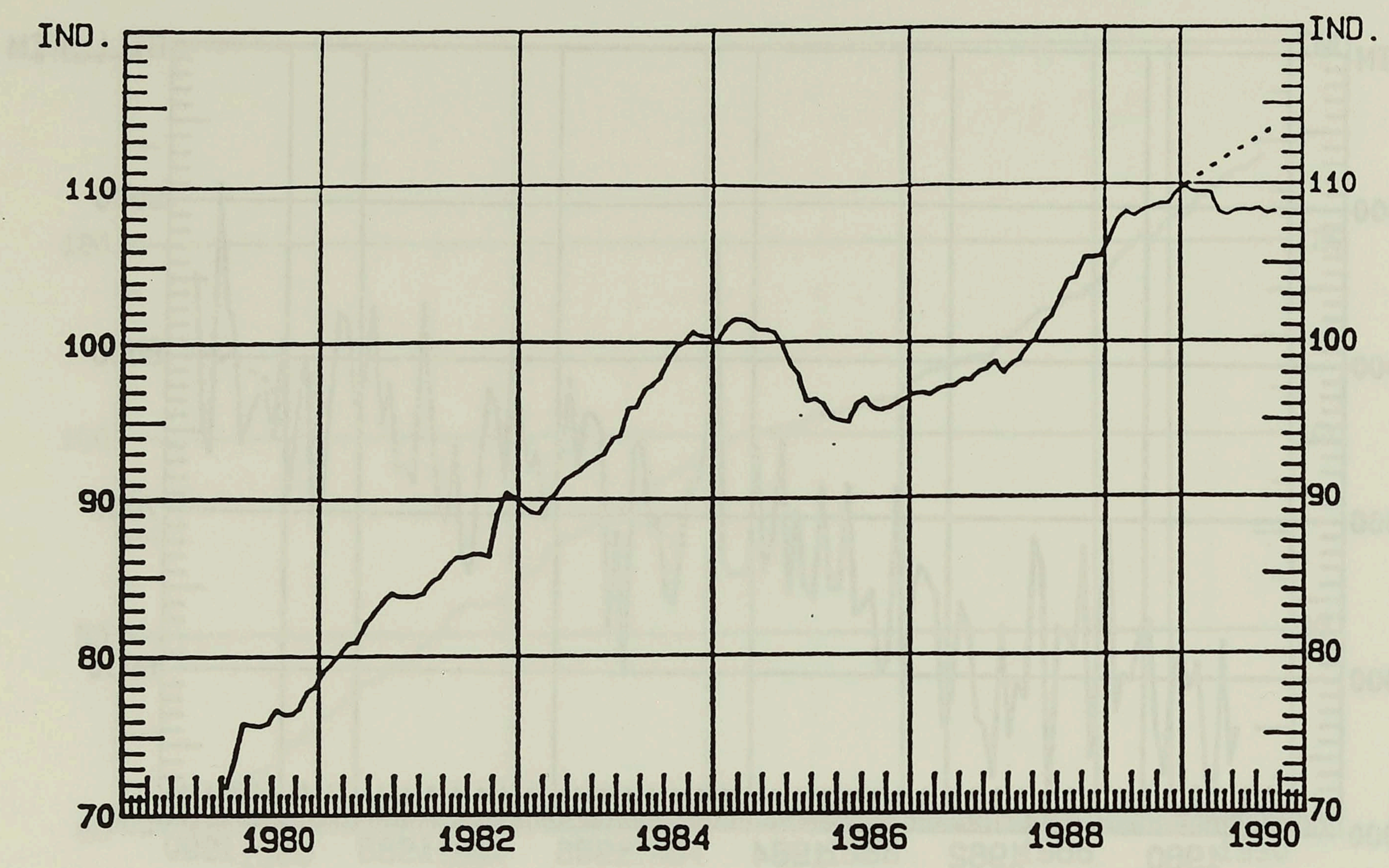
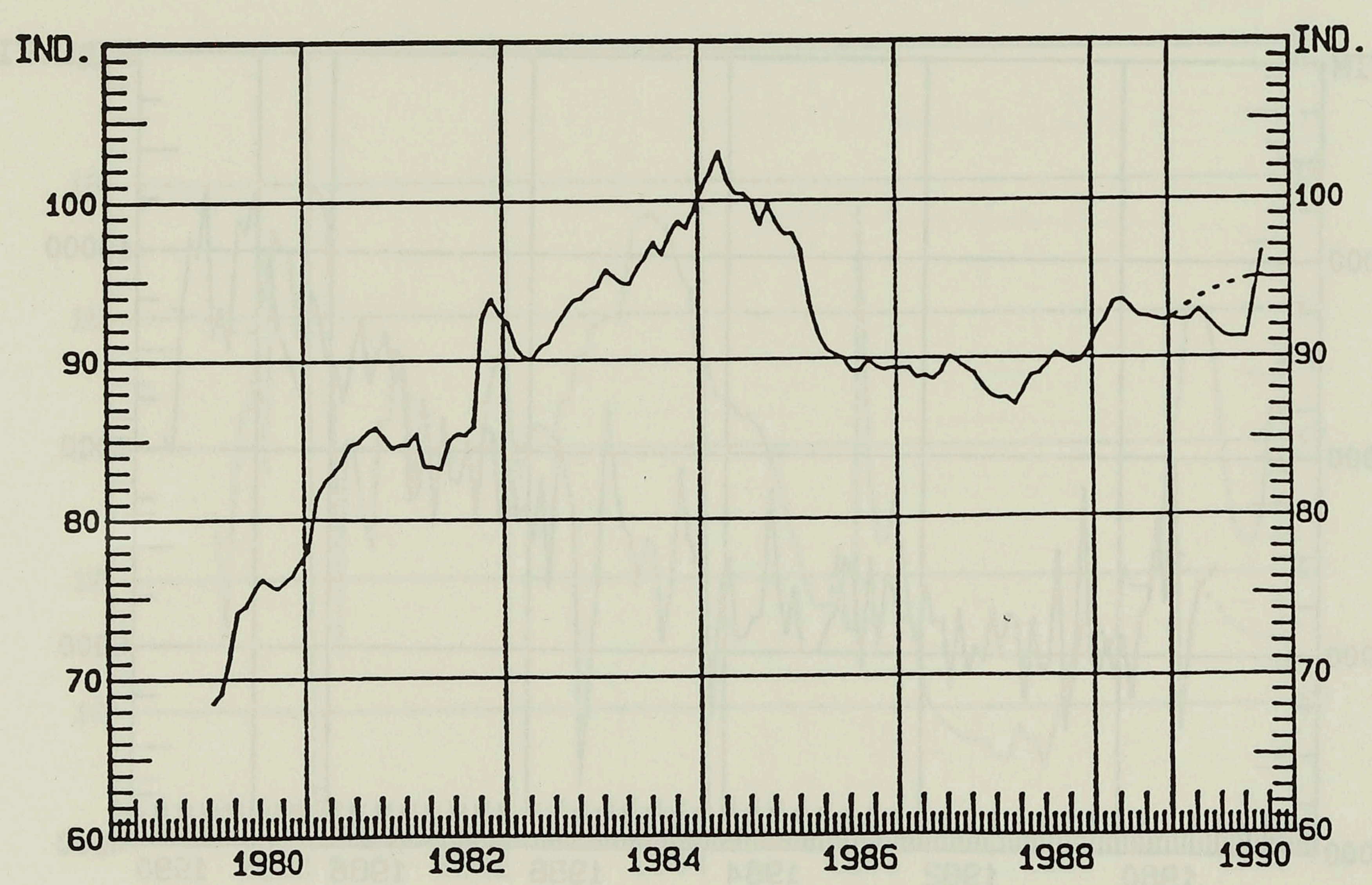


FIGURE 1h Import prices



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