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A FREQUENCY DECOMPOSITION APPROACH TO EXCHANGE RATE FORECASTING

by

BRUCE TABAKMAN

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1985

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Abstract

A FREQUENCY DECOMPOSITION APPROACH TO EXCHANGE RATE FORECASTING

by

Bruce Tabakman

Advisor: Professor Salih Neftci

Using the tools of spectral analysis, the exchange rate between the Deutshe mark and dollar is decomposed into a high frequency component and a high frequency filtered component. It is hypothesized that an econometric model, utilizing exchange rate "fundamentals", for the filtered component combined with a time series or econometric model for the high frequency component can out-predict a similar economic model for the undecomposed series.

After a review of the economic fundamentals that determine exchange rates, several candidate models to explain the frequency decomposed time series are explored. Three variants of the monetary version of the purchasing power parity model, popular in the late seventies, are estimated and rejected as candidates for the high frequency filtered series. Additionally, two different specifications of a Vector Autoregressive system for the filtered data combined with first an ARIMA model and second a random walk specification for the high frequency component are likewise rejected. A single equation model incorporating "long run" fundamentals is finally adopted for the filtered series. For the high frequency series, an ordinary least squares model is fit using a "short run" fundamental and the lagged dependent variable. Comparing ex-post forecasting ability of these two equations, utilizing actual right hand side data, with a fundamentals-based equation for the original exchange rate reveals that the frequency decomposition based models do marginally better at horizons of two to three years.

Acknowledgements

The completion of the doctoral dissertation is never the work of a single individual. I would like to thank Professors Neftci, Anderson and Grossman for their thoughtful comments and guidance. Martin Gerra, my manager at IBM, provided me with the time, resources and encouragement to finish the doctorate. For this, I am very grateful. To Marguerite Lian and Tom Orzell, also of IBM, I owe uncountable thank yous for their expert help in software installation and debugging. Finally, my family. A big thanks to my parents. To my wife, Shelley, and sons, Keith and Scott, whose understanding and patience were truly remarkable, I dedicate this degree.

Bruce Tabakman

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1.0 Introduction

The introduction, to economics, of time series analysis in the "frequency domain", attributable to Engle (1976), has touched off a rash of literature that seeks to test classic long run economic relationships. Such papers as Lucas (1980), Geweke (1983) and Summers (1983) focus on the low frequency components of time series, which is claimed, is analagous to the "long run".[1] Lucas uses frequency filtered data to test the proposition that a change in the growth rate of an economy's money supply will induce an equal change in the inflation rate. Summers' paper reexamines the Fisher effect: an increase in interest rates owing to a like increase in the rate of inflation. Finally, Geweke uses frequency domain analysis to explore the neutrality of money.

It is the intent of this paper to expand the use of frequency domain analysis - not simply to test theory (though this may occur as a by-product) but to utilize the decomposition by frequency for forecasting. The instrument to be examined here is the exchange rate. The exchange rate seems to be a perfect candidate because it has a well established and documented theory to its long run determination (i.e. the purchasing power parity[2]) but it is subject to various severe short term shocks that make its predictability difficult. The existence of these shocks is exemplified in the following quotation from the December 14, 1983 Wall Street Journal.

> In fact, sages have predicted all year that the rise of the dollar against major currencies would finally end in the face of a booming U.S. trade deficit, lower domestic interest rates and other major economic factors.

---

1 McCallum (1984) presents evidence that the association of low frequency time series statistics with long run economic propositions are not generally warranted.

2 See Officer (1976) for a review article.

But no. Instead of weakening, the dollar is showing almost unprecedented strength.... Why the continued strength ? It seems to be the result of a potent mixture of economics and psychology.

High U.S. interest rates tend to attract foreign investors into dollar denominated investments, strengthening the dollar. And even though U.S. interest rates have declined in the past 18 months, they're still high compared with those of other industrialized countries. What's more many currency traders are convinced that heavy federal borrowing to finance the big budget deficits will keep interest rates relatively high.

The dollar also appears to have replaced gold as the "safe haven" that investors seek in times of international political unrest. The dollar has even spurted when the U.S. has been involved in international incidents, such as the recent U.S. bombing of Syrian positions in Lebanon. Investors apparently believe that is the worst comes, the U.S. is the best place to have stashed money.

In addition, the bull market on Wall Street has attracted foreign investors which also helps the dollar.... Another factor adding to the dollar's recent strength has been demand from corporations, especially multinationals.... They have finally had to give up waiting for a weaker dollar and get into the market.... That has created an increased demand for dollars in what would normally have been a fairly thin yearend market.

Local factors are also affecting the dollar's strength against other currencies. Fears that Britain will lower the price of its North Sea oil have helped to depress the pound, while concern about the policies of France's Socialist government has hurt the franc.

Further, to demonstrate the problems in exchange rate forecasting one can turn to Richard Levich. In his annual review article in Euromoney in which he compares foreign exchange forecasting services he concludes that, "track records of professional currency forecasting services are deteriorating" and "this year's study concludes that forecasting expertise does not exist in general across the sample of forecasters".[3]

While Levich's sample includes econometric as well as non-econometric services, Chapter 3 of this paper will detail the out-of-sample failure of classical exchange rate forecasting models. This chapter will borrow heavily from the work of Meese and Rogoff (1983).

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3 Levich (1983) p. 140 and p. 144

It will be argued in this paper that forecasting accuracy[4] can be improved by applying exchange rate fundamental-type econometric models to the exchange rate stripped of its high frequency volatility. For this purpose a representative exchange rate, that between Germany and the U.S. - denoted DM/$, will be used. The high frequency (or short term) components of the DM/$ will be assumed to follow an ARIMA process of the type introduced in Box and Jenkins (1970). It is important to note at the outset that the bi-modal methodology for exchange rate forecasting to be presented here is justifiable in terms of causality. The long term determination of the exchange rate is a phenomenon of economic reasoning, while short term movements are due to shifting perceptions, politics and not in the least government intervention.[5]

The remainder of this paper will be divided up as follows. Chapter 2 will explain the accomplishment of the frequency decomposition. The aforementioned Chapter 3 will present the empirical embodiments of theories of the seventies and their failures to adequately predict the exchange rates in the late seventies and early eighties. The first part of Chapter 4 will describe the "fundamentals" model and the ARIMA model that are to be used for forecasting. The second part of the chapter will be devoted to their empirical results. Concluding remarks will be made in Chapter 5.

---

4 Generally speaking accuracy will be judged using the Root Mean Square Error (RMSE).

5 See Beenstock (1983) for the effects of intervention on the exchange rate.

2.0 Frequency Decomposition of DM/$

The first step in decomposing a time series into its relative frequencies is to look at its spectrum (more correctly, its periodogram, which is the estimate of the spectrum).[6] Engle defines the spectrum as follows:

> The spectrum provides another way of characterizing time series. In this case we think of a series as being made up of a great number of sine and cosine waves of different frequencies which have just the right (random) amplitudes to make up the original series. Thus the list of how much of each frequency component was necessary is also a full description of the time series. The spectrum is a plot of the squared amplitude of each component against the frequency of that component. It is continuous and always greater than zero as long as there are no deterministic elements (that is, no exactly repeating components, or components which can be predicted exactly on the basis of the past). This is a very general way to describe a stochastic process...... The spectrum is a decomposition of the variance into the components contributed by each frequency.

The periodogram for the DM/$ exchange rate after removal of mean and trend is given in Figure 1. The procedure used to calculate the periodogram is provided in the Technical Appendix.

The first part of Engle's definition alludes to the Fourier representation of a discrete time series X_t. The Fourier representation states that X_t having N observations can be defined as:

$$X_t = a_0 + \sum_{p=1}^{N/2-1} \left(a_p \cos(2\pi pt/N) + b_p \sin(2\pi pt/N)\right) + a_{N/2} \cos \pi t \qquad t = (1, \ldots, N)$$

where:

---

[6] An introduction to Spectral Analysis is provided by Chatfield Chapter 7. For a more rigorous version see Koopmans Chapter 8. The notation of the Fourier representation used here is consistent with that of Chatfield.

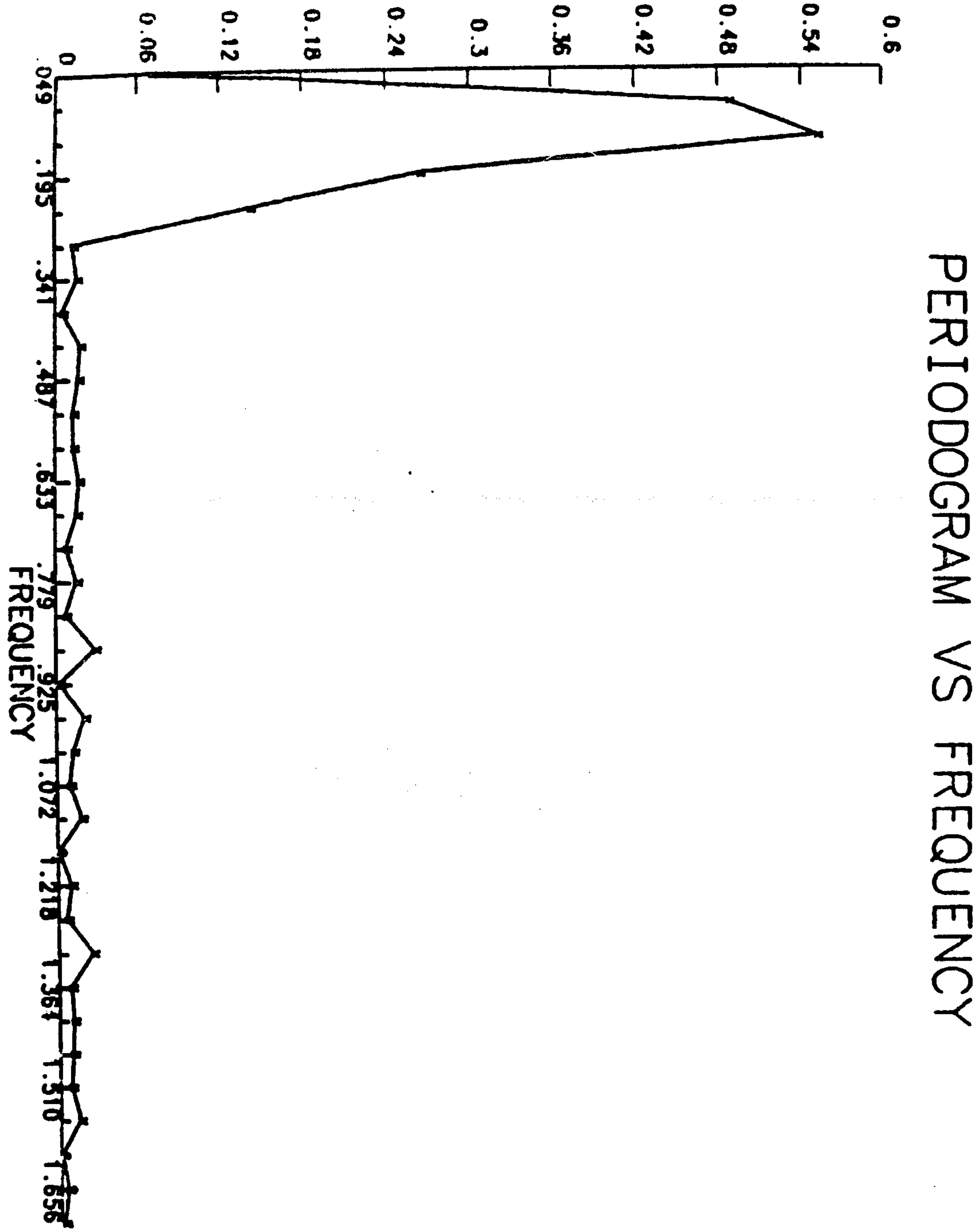
PERIODOGRAM VS FREQUENCY
FREQUENCY
0
0.06
0.12
0.18
0.24
0.3
0.36
0.42
0.48
0.54
0.6
.049
.195
.341
.487
.633
.779
.925
1.072
1.218
1.364
1.510
1.656

Figure 1

a_0 = sample mean of X

$a_{N/2} = \sum -1^t X_t / N$

$a_p = 2(\sum X_t \cos 2\pi pt/N)/N \qquad p = 1, \ldots, N/2 - 1$

$b_p = 2(\sum X_t \sin 2\pi pt/N)/N \qquad p = 1, \ldots, N/2 - 1$

Note that this formulation involves N equations and N parameters, therefore appropriately weighted sine and cosine waves can exactly duplicate any observation of X_t. Additionally, each frequency is associated with waves (or cycles) that can be thought of as completing in N/p periods. For example consider a time series having 100 months of data. Observation i of this time series can be decomposed into cycles completing in 100 months, 50 months, 33.3 months, etc. right through to approximately 2 months. Recasting Figure 1 in terms of length of cycles in lieu of frequency on the X axis results in Figure 2. Thus most of the variance of DM/$ can be explained in terms of cycles that complete in a little more than two years.[7]

The decomposition of X_t into its low frequency or long run component is accomplished as follows. First a key cycle length (and its associated frequency) is chosen. Next, the coefficients a_p and b_p from the above Fourier representation are set equal to zero for all cycles (frequencies) less than the chosen cycle. Finally, the Fourier representation equation is executed in reverse to define a new time series which is denoted the low frequency component. Alternatively, zeroing out coefficients for cycles equal to and greater than the chosen cycle results in the high frequency component.

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[7] Strictly speaking, the periodogram is an inconsistent estimator of the true spectrum. See the Technical Appendix for discussion of this point.

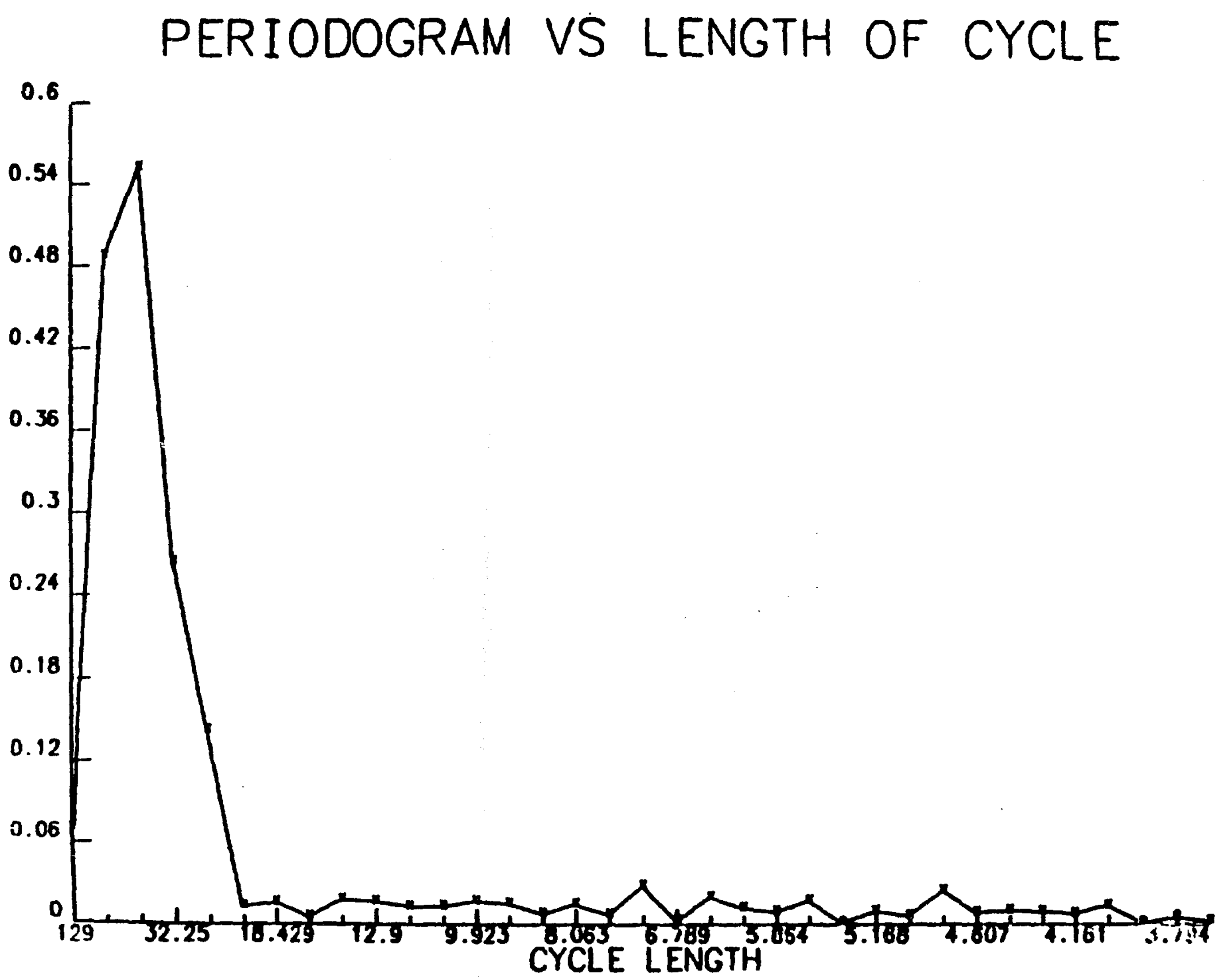
PERIODOGRAM VS LENGTH OF CYCLE
0.6
0.54
0.48
0.42
0.36
0.3
0.24
0.18
0.12
0.06
0
129
32.25
18.429
12.9
9.923
8.063
6.789
5.864
5.188
4.607
4.161
CYCLE LENGTH

Figure 2

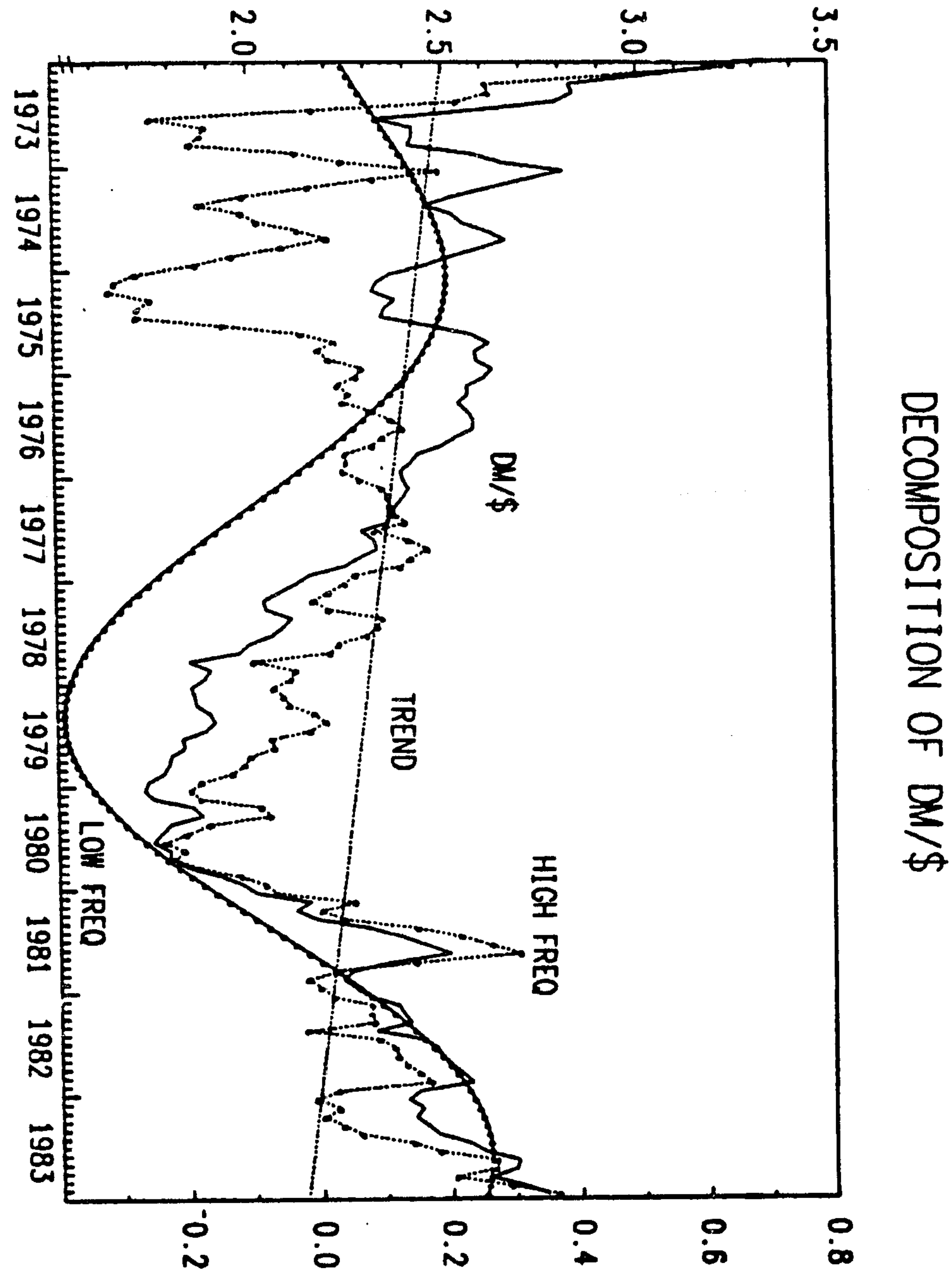
DECOMPOSITION OF DM/$
DM/$
TREND
HIGH FREQ
LOW FREQ
3.5
3.0
2.5
2.0
0.8
0.6
0.4
0.2
0.0
-0.2
1973
1974
1975
1976
1977
1978
1979
1980
1981
1982
1983

Figure 3

The decomposition of the DM/$ exchange rate after detrending is provided in Figure 3. One hundred and thirty-two data points - January, 1973 through December, 1983 - were used in the calculation. This roughly covers the modern period of floating, market-determined exchange rates. The key cycle length chosen was forty-three months. This figure roughly estimates the course of the business cycle and is consistent with the work of Geweke (1983) and Summers (1983).

The underlying DM/$ exchange rate after high frequency filtering is calculated to be the arithmetic sum of the low frequency component and the trend component. This time series is plotted against the true DM/$ rate in Figure 4. It is interesting to note that under the above definition, the observed exchange rate has been generally above the true underlying filtered exchange rate since early 1981. This is supportive of the view, held by most forecasters, that the dollar has been overvalued vis a vis the Deutsche Mark since 1981.[8]

Before proceeding on, I would like to address the relationship between the frequency decomposition methodology presented in this paper and the theory behind the seasonal adjustment of economic time series. In seasonal adjustment, recurring spikes in the periodogram at seasonal frequencies are eliminated via appropriate action on the corresponding Fourier coefficients. In this paper though, the zeroing of the Fourier coefficients corresponded not to seasonal spikes but instead to cycle lengths.

---

[8] Levich, p. 142.

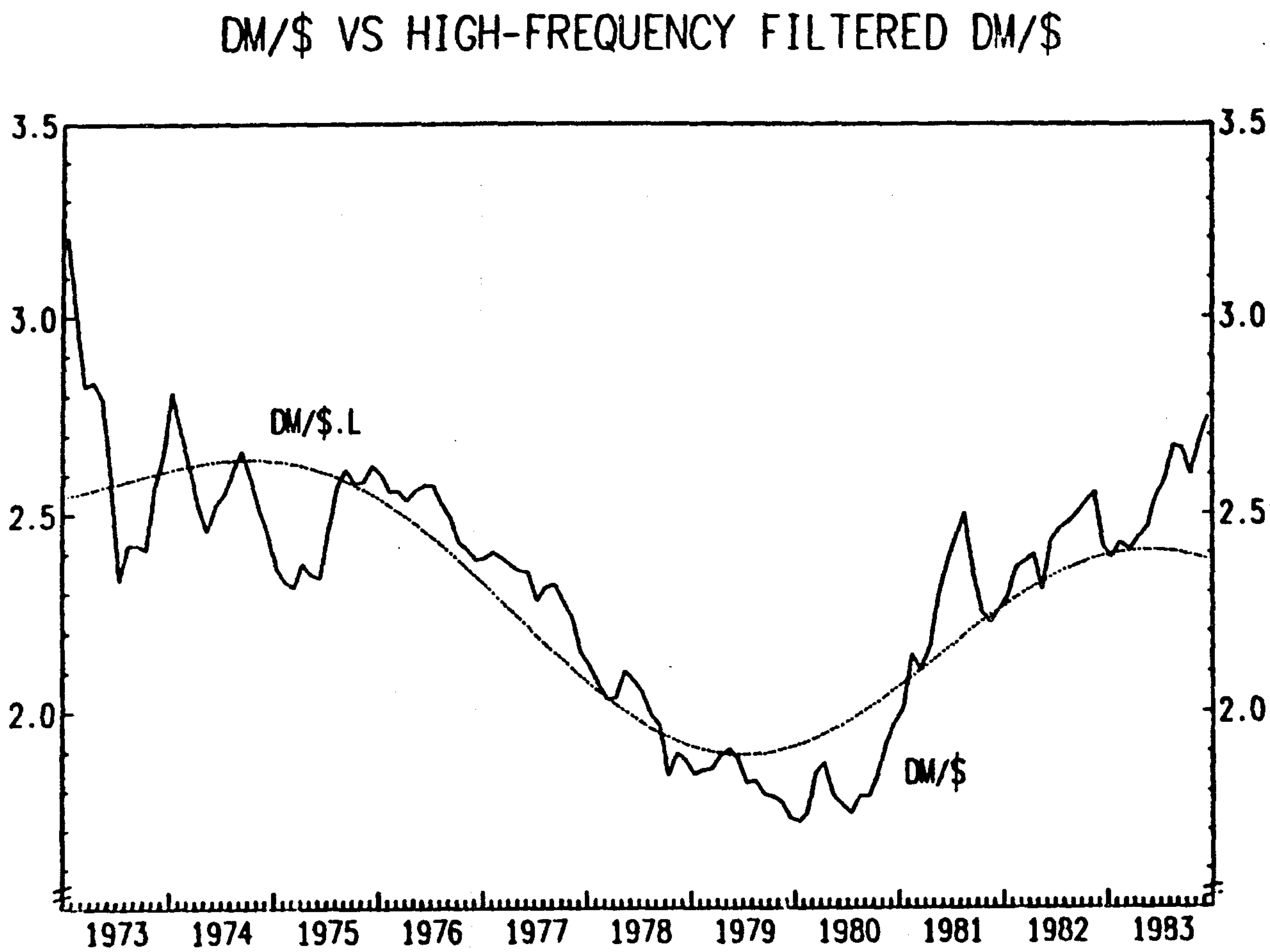

Figure 4

Frequency Decomposition of DM/$

3.0 Empirical Failures of Theories of Exchange Rate Determination

Models developed to explain exchange rate movements have been plentiful.[9] The traditional models however, utilizing purchasing power parity (in the form of relative price levels) as their underlying theory, have fallen out of favor amongst economists as predictors of exchange rate movements in the seventies. Frenkel (1981) has demonstrated that the traditional PPP approach which worked well during a period of floating in the twenties fails to do likewise in the floating period of mid 1973 to early 1979. The failure of traditional PPP models have given rise to much research and modification of classical theory in the late seventies. Much of this work is surveyed by Bergstrand (1983) and Shafer and Loopesko (1983).[10] The common denominator amongst most of the aforementioned research has been a recasting of the PPP doctrine in terms of the monetary approach. This approach is summarized by the following equations:

Let the demand for real cash balances in Germany be expressed as:

$$M_G/P_G = Y_G^b e^{-aI_G}$$

where Y is income and I is the interest rate. Likewise for the U.S.,[11]

$$M_{US}/P_{US} = Y_{US}^b e^{-aI_{US}}$$

---

9 See Isard (1978) for a survey article.

10 Additionally, Shafer and Loopesko provide a very detailed chronological history of just what occured in exchange rate markets in the past ten years experience of floating.

11 A possible shortcoming of the monetary approach is the assumption that the functional form of the demand for real balances is bilaterally identical, i.e. a and b are identical across countries. This is addressed by Haynes and Stone (1981).

then,

$$M_G P_{US} / P_G M_{US} = (Y_G / Y_{US})^b e^{a(I_{US} - I_G)}$$

rearranging,

$$P_{US} / P_G = (M_{US} / M_G)(Y_G / Y_{US})^b e^{a(I_{US} - I_G)}$$

inverting,

$$P_G / P_{US} = (M_G / M_{US})(Y_{US} / Y_G)^b e^{a(I_G - I_{US})}$$

PPP in its absolute form[12] states:

$$P_G / P_{US} = \text{DM}/\$$$

thus by substitution,

$$\text{DM}/\$ = (M_G / M_{US})(Y_{US} / Y_G)^b e^{a(I_G - I_{US})}$$

taking logs,

$$\ln \text{DM}/\$ = \ln M_G / M_{US} - b \ln Y_G / Y_{US} + a(I_G - I_{US}) \qquad [1.0]$$

The empirical representation of the above will be:

$$\ln \text{DM}/\$ = a_0 + a_1 \ln M_G / M_{US} + a_2 \ln Y_G / Y_{US} + a_3 (I_G - I_{US}) + \varepsilon$$

where:

---

12 Absolute PPP says the exchange rate is equal to the ratio of relative price levels. Relative PPP equates changes in the exchange rate to changes in relative price levels.

ε is a well behaved error term
$a_0 = 0$
$a_1 = 1$
$a_2 < 0$
$a_3 > 0$

The above specification assumes that prices react immediately to monetary shocks and therefore is termed the flexible price model. This model is dubbed the Frenkel-Bilson[13] model by Meese and Rogoff (1983) based on the work of Frenkel (1976) and Bilson (1979). This is the first of their representative models to be used in tests of out-of-sample forecasting accuracy. The second model based on Frankel (1979) and Dornbusch (1976) assumes that prices are "sticky" in the short run. Because prices are sticky monetary shocks result in a change in interest rates and a change in "expected" future inflation. Therefore, it is hypothesized that the current exchange rate will differ from its PPP equilibrium by an amount proportional to differentials in bilateral real interest rates. Mathematically,

$$\ln DM/\$ - \ln (DM/\$)^e = -1/\phi[(I_G - \pi_G) - (I_{US} - \pi_{US})] \qquad [1.1]$$

where $(DM/\$)^e$ is the equilibrium exchange rate and π is the expected future rate of inflation.

Note that in equilibrium,

$I_G - I_{US} = \pi_G - \pi_{US}$.

Assuming that $(DM/\$)^e = P_G/P_{US}$ we can substitute equation [1.0] and obtain:

---

13 The nomenclature employed by Meese and Rogoff "identifies particular models with authors who contributed significantly to their development..... But it is not comprehensive in that some of these authors have worked with more than one of the three models, and there are other researchers who have studied these models or closely-related ones."

$$\ln (DM/\$)^e = \ln M_G/M_{US} - b\ln Y_G/Y_{US} + a(I_G - I_{US})$$

at equilibrium,

$$\ln (DM/\$)^e = \ln M_G/M_{US} - b\ln Y_G/Y_{US} + a(\pi_G - \pi_{US})$$

substituting back into equation [1.1]:

$$\begin{aligned}\ln DM/\$ &= -1/\phi[(I_G - \pi_G) - (I_{US} - \pi_{US})] \\ &\quad + \ln M_G/M_{US} - b\ln Y_G/Y_{US} + a(\pi_G - \pi_{US})\end{aligned}$$

rearranging yields:

$$\begin{aligned}\ln DM/\$ &= \ln M_G/M_{US} - b\ln Y_G/Y_{US} - 1/\phi(I_G - I_{US}) \\ &\quad + (a + 1/\phi)(\pi_G - \pi_{US}).\end{aligned}$$

As with PPP, the above will be represented empirically as:

$$\begin{aligned}\ln DM/\$ &= a_0 + a_1\ln M_G/M_{US} + a_2\ln Y_G/Y_{US} \\ &\quad + a_3(I_G - I_{US}) + a_4(\pi_G - \pi_{US}) + \varepsilon\end{aligned} \qquad [2.0]$$

where it is now expected that:

$a_3 < 0$
$a_4 > 0$

The final structural model[14] tested by Meese and Rogoff extends the Frankel-Dornbusch model to include the effects of the current account proxied by the cumulative trade balances of Germany and the U.S. This model is based on Hooper and Morton (1982). Empirically this is:

$$\ln \mathrm{DM}/\$ = a_0 + a_1 \ln M_G/M_{US} + a_2 \ln Y_G/Y_{US} + a_3(I_G - I_{US}) + a_4(\pi_G - \pi_{US}) + a_5 TB_{US} + a_6 TB_G + \varepsilon$$

where the new coefficients are assumed to be:

$a_5 > 0$
$a_6 < 0$

The inclusion of the current account is rationalized by the assumption that changes in the long run real exchange rate are correlated with unanticipated shocks to the current account.[15]

The time period under which Meese and Rogoff operated consisted of March, 1973 through June, 1981. Their methodology consisted of estimation initially through October, 1976 with forecasts generated for one, three, six and twelve month horizons.[16] Next, estimation was extended to November, 1976 and forecasts were again generated over the same periods. These iterations continued until data was exhausted. Thus, a whole family of twelve month ahead forecasts, eleven month ahead forecasts, etc. were compiled. The forecasts were made using actual realized values on the right hand side. This, if anything, should result in biasing the forecasts to be better than they might otherwise have been. The results however, compared to a random walk specifi-

[14] Meese and Rogoff also tested a univariate autoregression and a vector autoregression utilizing all the variables in the Hooper-Morton model.

[15] Other rationales for inclusion of the current account will be discussed in Chapter 4.

[16] See Meese and Rogoff (1983) p. 21-22 for a description of the data used.

Table 1

Root Mean Square Forecast Errors

$/mark

Model	Horizon 1 month	6 months	12 months
Random Walk	3.72	8.71	12.98
Univariate Autoregression	3.51	12.40	22.53
Vector Autoregression	5.40	11.83	15.06
Frenkel-Bilson	3.17	9.64	16.12
Dornbusch-Frankel	3.65	12.03	18.87
Hooper-Morton	3.50	9.95	15.69

Notes:

1. Table derived from Meese and Rogoff (1983) p. 13.
2. RMSEs are approximately in percentage terms.
3. The structural models were estimated using Fair's instrumental variable technique to correct for first-order serial correlation.

cation are not at all encouraging. Focusing on root mean square errors, Table 1 of this paper reproduces part of Meese and Rogoff's Table 1. As can be seen, other than for a one month horizon, the random walk (or no change model) outperformed all of the candidate models.[17]

Reasons given for the forecasting failures of modern day exchange rate models are addressed by Meese and Rogoff (1983,1982), Shafer and Loopesko (1983), Haynes and Stone (1981) and Driskill and Sheffrin (1981) though no concensus emerges as to how to overcome them. The next chapter will test to see if the interaction of econometric modelling and frequency decomposition can be used to improve forecasting accuracy.

[17] That exchange rates follow a random walk was stated emphatically by Mussa (1979). Evidence to support this observation can also be found in Shafer and Loopesko (1983) and Adler and Lehmann (1983).

4.0 Empirical Tests and Results

This Chapter will test the proposition that the low frequency components of the DM/$ exchange rate can be better forecast with "structural" models than can the original series and further that by considering separate models for the underlying high frequency filtered DM/$ exchange rate (denoted DM/$.L) and the high frequency component (DM/$.H), introduced in Chapter 2, forecasting accuracy for the DM/$ can be improved. The plan to be followed in this Chapter is as follows. First, a structural econometric model will be developed and applied to DM/$.L. The same specifications will likewise be applied to the DM/$. The DM/$.L equation will then be combined with alternative time series models for DM/$.H such that forecasts can be generated for their sum. These forecasts will then be compared with the forecasts generated from the structural equation for DM/$. Root mean square errors will be examined for a short term forecasting period, the 24 months from January, 1981 through December, 1983 and a longer term horizon, the 48 months starting January, 1979 and ending December, 1983. Note that the algorithm used to generate forecasts is such that the models are reestimated at each forecast horizon to reflect only the data that was available at the time.

The first set of structural models to be employed will be the three monetary models introduced in the previous chapter. Recall all three models have in common the money supply, income and interest rate variables. In these estimations, money supply is taken to be the M1 definition. Additionally, 2 variables are used as representative of income. The first is real GNP, available quarterly and interpolated monthly such that the mid month of the quarter contains the quarterly

Table 2

Estimation of the Frenkel-Bilson Model Using DM/$.L

Period of Fit: January, 1973 - December, 1983

Model: $\ln DM/\$.L = a_0 + a_1 \ln M_G/M_{US} + a_2 \ln Y_G/Y_{US} + a_3(I_G - I_{US}) + \varepsilon$

Case 1. Y's are monthly interpolations of quarterly real GNP.

	a_0	a_1	a_2	a_3	Rho	SEE	R2	DW
OLS	.141 (1.6)	-1.158 (9.3)	.020 (0.4)	.007 (2.5)		.069	.63	0.05
GLS	.819 (6.9)	-.116 (2.5)	-.001 (0.4)	.000 (0.3)	.999	.006	.32	0.10

Case 2. Y's are monthly indices of Industrial Production.

	a_0	a_1	a_2	a_3	Rho	SEE	R2	DW
OLS	.116 (1.8)	-1.162 (11.4)	1.170 (7.6)	-.004 (1.3)		.058	.74	0.17
GLS	.819 (6.9)	-.115 (2.5)	.018 (0.6)	.000 (0.2)	.999	.006	.33	0.10

Notes:
1. Absolute T values in parentheses.
2. GLS uses a Cochrane/Orcutt correction for first order serial correlation.
3. SEE is standard error of estimate.
4. R2 is R squared adjusted for degrees of freedom.
5. DW is the Durbin/Watson statistic.

Table 3

Estimation of the Frankel-Dornbusch Model using DM/$.L

Period of Fit: January, 1973 - December, 1983

Model: $\ln DM/\$.L = a_0 + a_1 \ln M_G/M_{US} + a_2 \ln Y_G/Y_{US} + a_3(I_G - I_{US}) + a_4(\pi_G - \pi_{US}) + \epsilon$

Case 1. Y's are monthly interpolations of quarterly real GNP.

	a_0	a_1	a_2	a_3	a_4	Rho	SEE	R2	DW
OLS	.365 (5.8)	-.825 (8.6)	1.125 (8.7)	-.004 (1.6)	.014 (7.5)		.048	.82	0.21
GLS	.824 (7.2)	-.107 (2.3)	.024 (0.9)	.000 (0.2)	.002 (2.2)	.999	.005	.36	0.16

Case 2. Y's are monthly indices of Industrial Production.

	a_0	a_1	a_2	a_3	a_4	Rho	SEE	R2	DW
OLS	.405 (4.7)	-.802 (6.5)	0.022 (0.5)	.007 (2.7)	.015 (6.3)		.061	.71	0.06
GLS	.822 (7.2)	-.109 (2.3)	-.001 (0.1)	.000 (0.3)	.002 (2.1)	.999	.005	.36	0.15

Notes:
1. T values in parentheses.
2. GLS uses a Cochrane/Orcutt correction for first order serial correlation.
3. SEE is standard error of estimate.
4. R2 is R squared adjusted for degrees of freedom.
5. DW is the Durbin/Watson statistic.
6. π (expected inflation) is taken to be the most recent 12 month change in consumer prices.

Table 4

Estimation of the Hooper-Morton Model using DM/$.L

Period of Fit: January, 1973 - December, 1983

Model: $\ln DM/\$.L = a_0 + a_1 \ln M_G/M_{US} + a_2 \ln Y_G/Y_{US} + a_3(I_G - I_{US}) + a_4(\pi_G - \pi_{US}) + a_5 TB_{US} + a_6 TB_G + \varepsilon$

Case 1. Y's are monthly interpolations of quarterly real GNP.

	a_0	a_1	a_2	a_3	a_4	a_5	a_6	Rho	SEE	R2	DW
OLS	.816	-1.555	1.669	-.010	.014	.294	.057		.034	.91	0.39
	(4.1)	(13.9)	(6.1)	(5.1)	(9.5)	(7.6)	(4.7)				
GLS	.997	-.108	.169	.000	.002	.026	-.022	.999	.005	.35	0.15
	(6.6)	(2.3)	(1.1)	(0.0)	(1.9)	(0.5)	(1.3)				

Case 2. Y's are monthly indices of Industrial Production.

	a_0	a_1	a_2	a_3	a_4	a_5	a_6	Rho	SEE	R2	DW
OLS	-.199	-1.613	.592	-.010	.011	.309	.058		.035	.91	0.44
	(2.3)	(14.4)	(5.5)	(5.0)	(8.1)	(8.1)	(4.7)				
GLS	.905	-.103	.022	.000	.002	.029	-.023	.999	.005	.35	0.15
	(7.1)	(2.2)	(0.8)	(0.1)	(1.9)	(0.6)	(1.3)				

Notes:
1. T values in parentheses.
2. GLS uses a Cochrane/Orcutt correction for first order serial correlation.
3. SEE is standard error of estimate.
4. R2 is R squared adjusted for degrees of freedom.
5. DW is the Durbin/Watson statistic.
6. π (expected inflation) is taken to be the most recent 12 month change in consumer prices.
7. TB is the Trade Balance divided by interpolated nominal GNP and cumulated.

average. The other income variable is the monthly index of industrial production. Finally, interest rates are taken to be market determined short term rates.[18] Unfortunately, all three models fail as candidates to explain DM/$.L. The backbone of the money approach is the expected coefficient of positive 1.0 on the relative money supply variables. As shown in Tables 2 through 4, this coefficient is always a highly significant negative 1.0. This finding, by the way, is consistent with recent empirical work on the DM/$ by Frankel (1982) who offers the explanation that the apparent flip in sign is due to the exclusion of wealth in the money demand equation. I am more inclined to view the flip in sign as indicative of the failure of absolute purchasing power parity as the rationale behind exchange rate movements.

All of the following empirical work in this chapter will focus upon four variables which are considered fundamental to exchange rate determination. Of the four, two have already appeared in the money models namely the current account balance and relative interest rates. The current account balance, it will be recalled, was used by Hooper and Morton under the assumption that changes in the long run real exchange rate are correlated with unanticipated shocks to the current account. However, the current account balance also appears in the portfolio-balance approach (Frankel (1982), Dornbusch and Fischer (1982)) which Frankel explains as follows.

> In the portfolio-balance approach, domestic and foreign bonds are assumed to be imperfect substitutes. Due to exchange risk or other factors, investors wish to diversify their bond holdings across currencies. Thus the exchange rate becomes not just the relative price of foreign and domestic money, but the relative price of foreign and domestic assets. If we make the further assumption that foreign residents have a greater propensity to hold foreign assets relative to domestic residents, then we get the result that a domestic current account deficit, which redistributes wealth from domestic to foreign residents, will raise the net world demand for foreign assets and thus raise the price of the foreign exchange.

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[18] Sources of all data are provided in the Data Appendix.

Following the lead of Hooper and Morton, the current account as used here, denoted CCABY, will be Germany's current account balance divided by interpolated nominal GNP and cumulated over time.

The second and third fundamentals to be addressed, the relative rates of interest (RI) and the relative rates of real interest (RRI),[19] also have underpinnings in the portfolio-balance approach. Here it is assumed that investors move funds across borders in search of optimal rates of return (or real return) such that an increase in relative interest rates between the U.S. and Germany causes an excess demand for U.S. dollars and a decrease in demand for marks culminating in a depreciation of the DM/$.

The final fundamental I will employ is the relative rate of inflation (denoted PPP) and defined as the twelve month percent change in U.S. consumer prices less the same for Germany.[20] This is a version of relative purchasing power parity and the argument for it basically says that in the world of traded goods, for a country to maintain its competitiveness, its exchange rate must adjust so as to offset domestic inflation differentials. Given the way variables have been defined in this paper, the following relationships are expected to hold:

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[19] Here the real rate is defined as the nominal domestic rate of interest minus the percent change over 12 months in domestic consumer prices.

[20] The choice of the proper price series to use is an ongoing argument in PPP literature. Officer (1976) addresses this point. Consumer prices are used here because there is more definitional uniformity.

Exchange rate and

CCABY	negative
RI	positive
RRI	positive
PPP	positive

To get a flavor for how the exchange rates and the fundamentals have interacted and also to see why present day forecasting has been so difficult consider Tables 5 and 6 which detail simple correlation coefficients between contemporaneous values of the fundamentals and the DM/$ and DM/$.L exchange rates respectively. Additionally, Figures 5 through 12 give a pictorial representation of the same observances. The thrust of this paper would imply that the correlations should be stronger between the fundamentals and DM/$.L rather than between DM/$, as DM/$ is subject to non-fundamental shocks and while this is, in general, marginally true both the filtered and unfiltered exchange rates still suffer from a total fall off of their fundamental relationships in the post 1981 period. Only RI which at least moves in the right direction is immune from this fall off though it is nonetheless a totally uncorrelated relationship. Part of this fall off may be due to the argument recently expressed in several periodicals that since 1981 the U.S. has been envisioned as a "safe haven" among the world's turmoil and therefore is "the" place to have funds invested which, again, create upward demand pressure appreciating the $ and therefore causing other major currencies, such as the DM, to depreciate. The "safe haven" argument in the context of this paper should show up then in the DM/$.H, however, the rapid fall off in the relationships between the fundamentals and DM/$.L does not bode well for this occurence.

Before examing the "fundamentals" model for DM/$.L and DM/$, I would like to say a few words about the models developed for DM/$.H. Initially, it is assumed that the DM/$.H is gen-

Table 5

Simple Correlation Coefficients
Between DM/$ and

	CCABY	RI	RRI	PPP
1973 - 1983	-.735	-.491	.317	.842
1974 - 1983	-.737	-.446	.395	.825
1975 - 1983	-.706	-.311	.661	.903
1976 - 1983	-.692	-.306	.721	.926
1977 - 1983	-.697	-.226	.730	.922
1978 - 1983	-.732	-.159	.765	.922
1979 - 1983	-.728	-.089	.801	.930
1980 - 1983	-.623	.067	.816	.915
1981 - 1983	.340	.043	.601	.707
1982 - 1983	.528	.005	.232	.413

Table 6

Simple Correlation Coefficients
Between DM/$.L and

	CCABY	RI	RRI	PPP
1973 - 1983	-.784	-.625	.047	.680
1974 - 1983	-.810	-.576	.146	.639
1975 - 1983	-.755	-.429	.457	.767
1976 - 1983	-.735	-.376	.675	.924
1977 - 1983	-.776	-.288	.706	.935
1978 - 1983	-.802	-.236	.739	.940
1979 - 1983	-.774	-.148	.805	.968
1980 - 1983	-.573	.039	.866	.991
1981 - 1983	.444	.026	.806	.973
1982 - 1983	.747	.007	.476	.855

DM/$ VS CUMULATED CURR ACCT BALANCE TO GNP RATIO

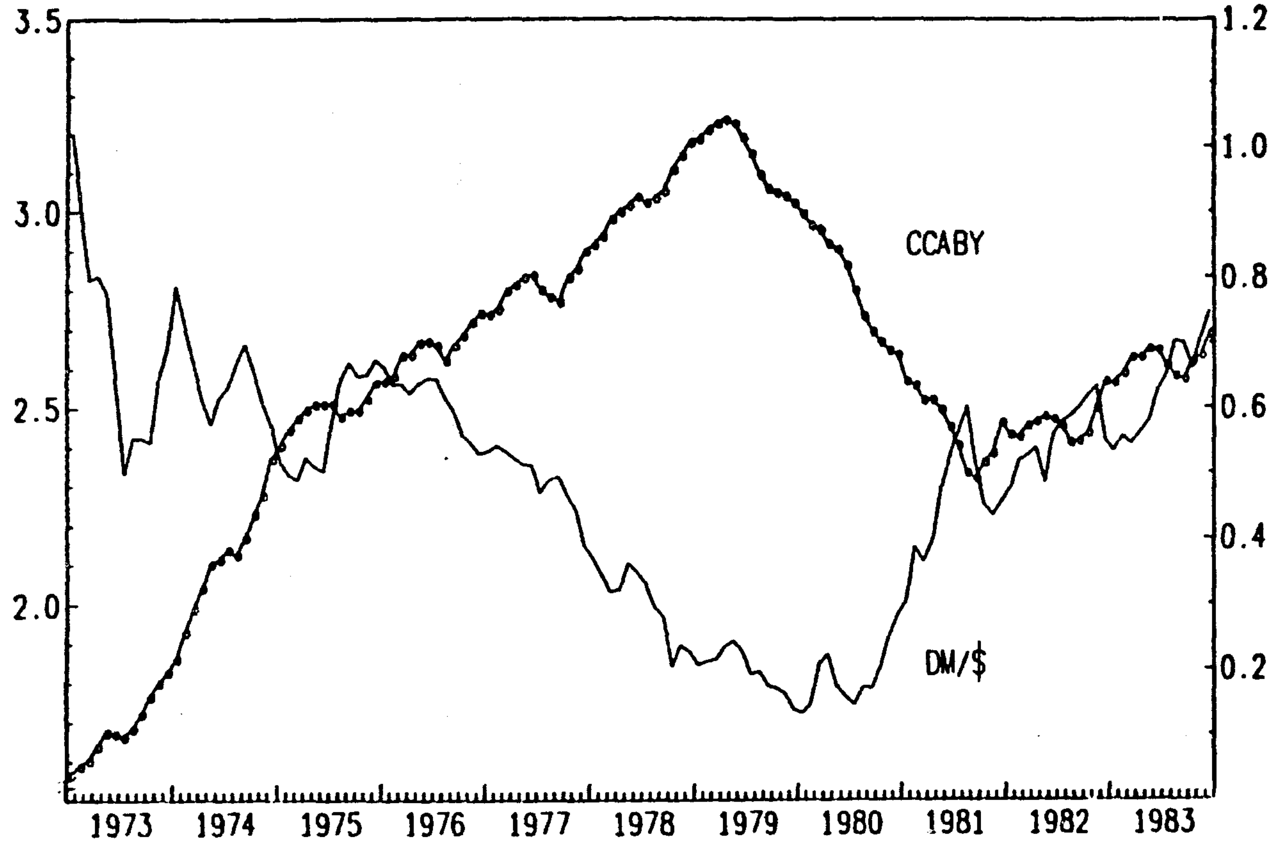


Figure 5

DM/$ VS RELATIVE NOMINAL INTEREST RATES

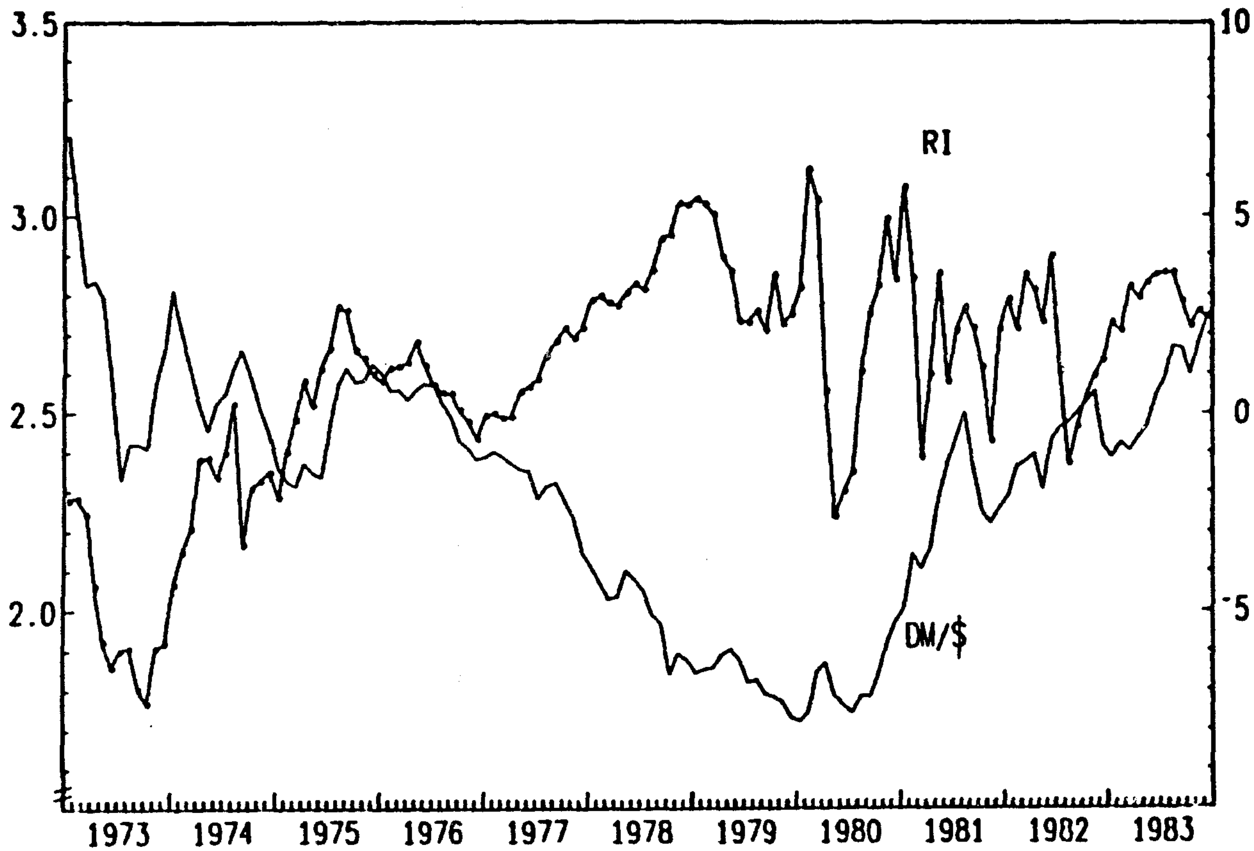


Figure 6

DM/$ VS RELATIVE REAL INTEREST RATES

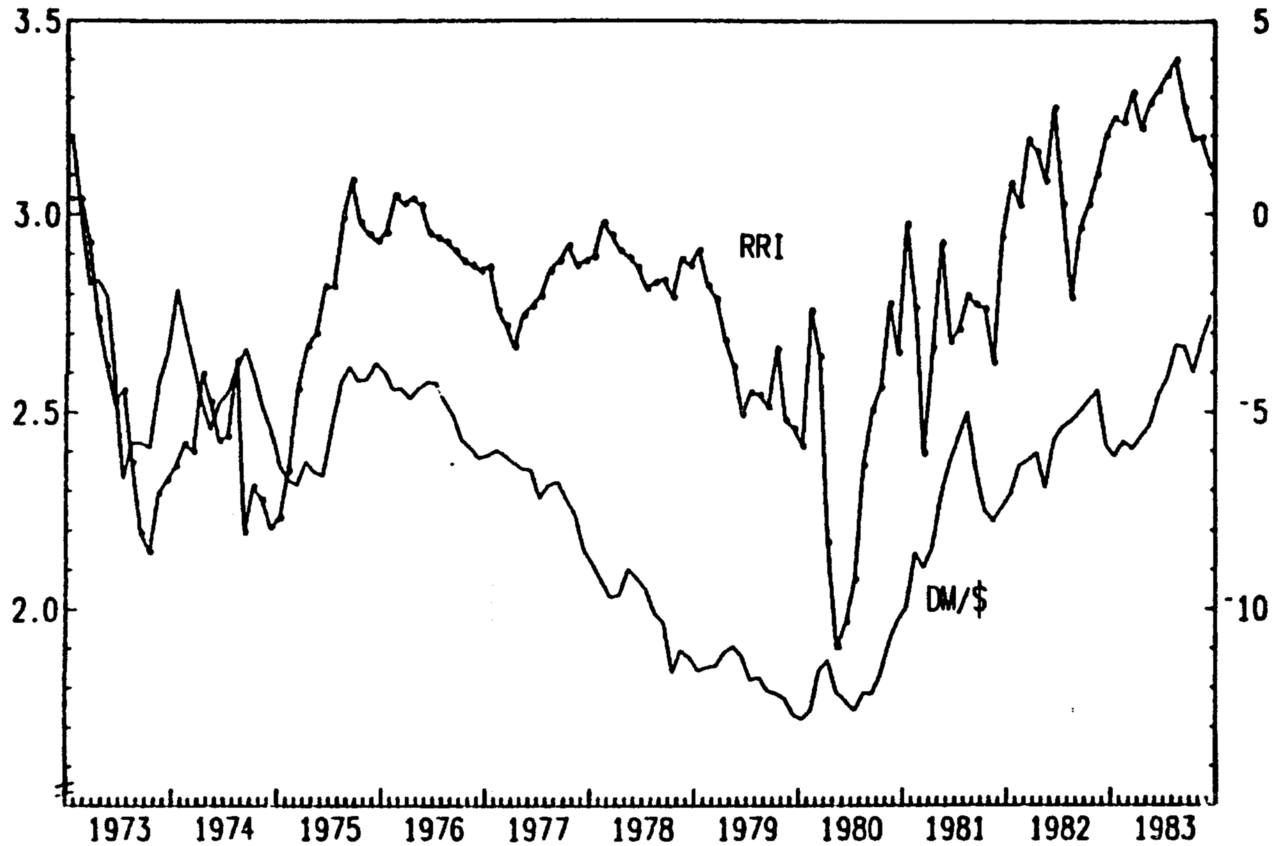


Figure 7

DM/$ VS RELATIVE RATES OF INFLATION

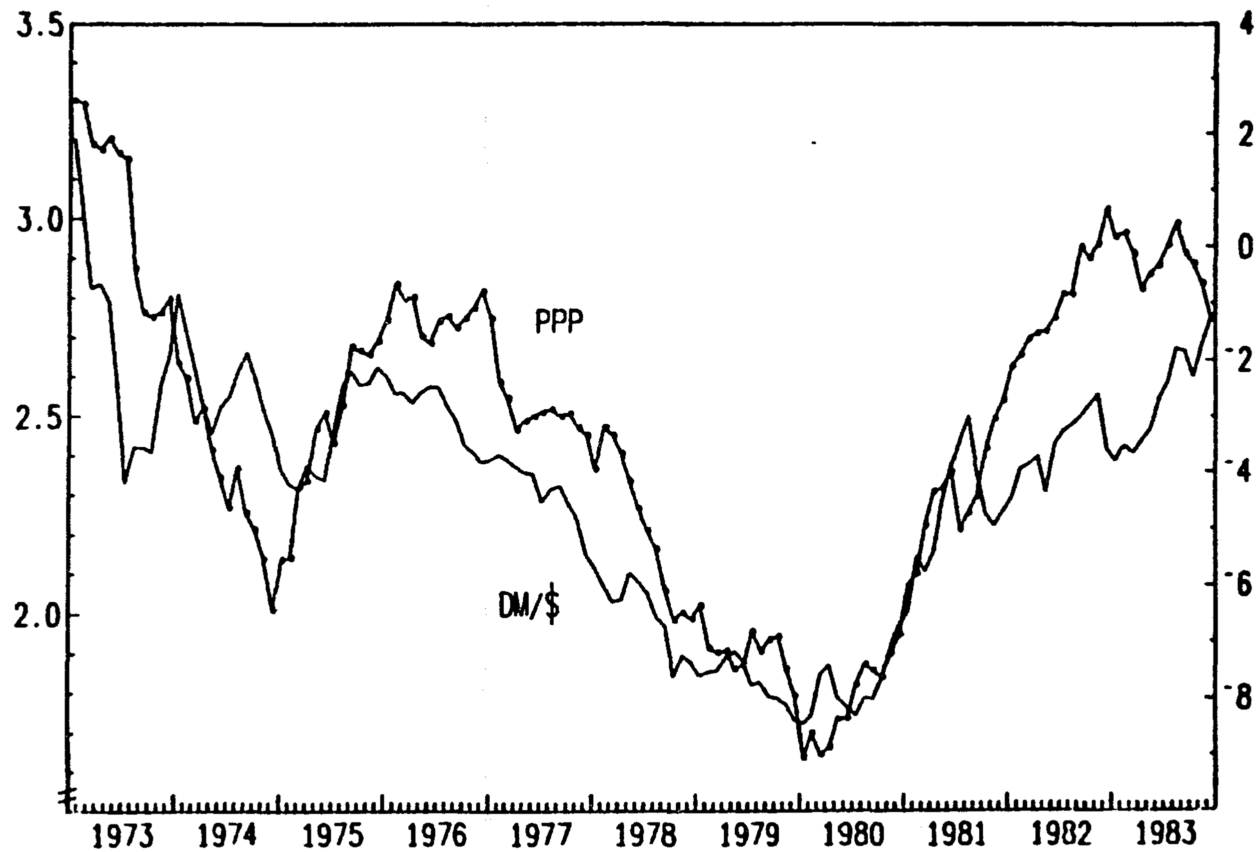
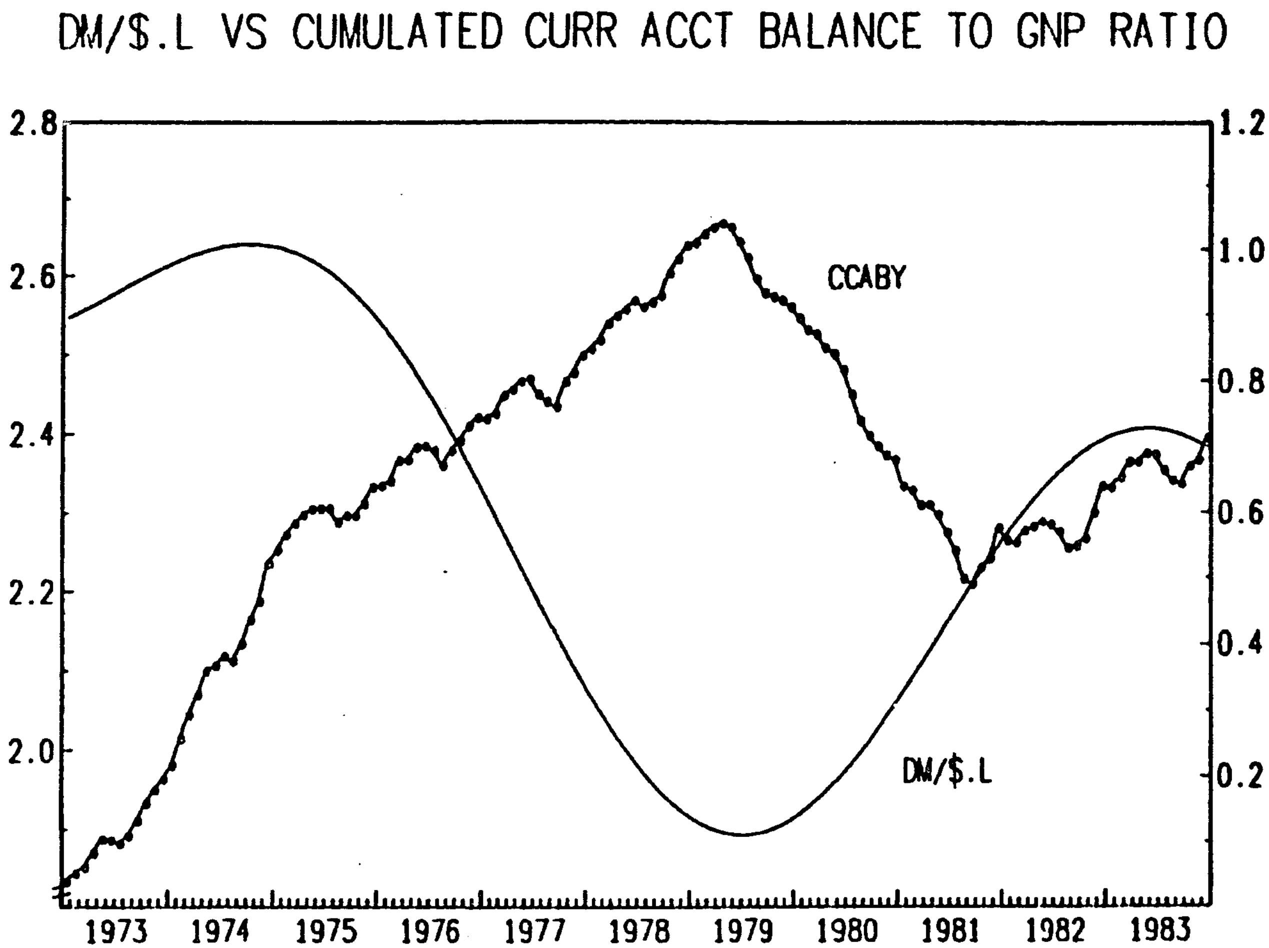


Figure 8



DM/$.L VS CUMULATED CURR ACCT BALANCE TO GNP RATIO
2.8
2.6
2.4
2.2
2.0
1.2
1.0
0.8
0.6
0.4
0.2
CCABY
DM/$.L
1973
1974
1975
1976
1977
1978
1979
1980
1981
1982
1983

Figure 9

DM/$.L VS RELATIVE NOMINAL INTEREST RATES

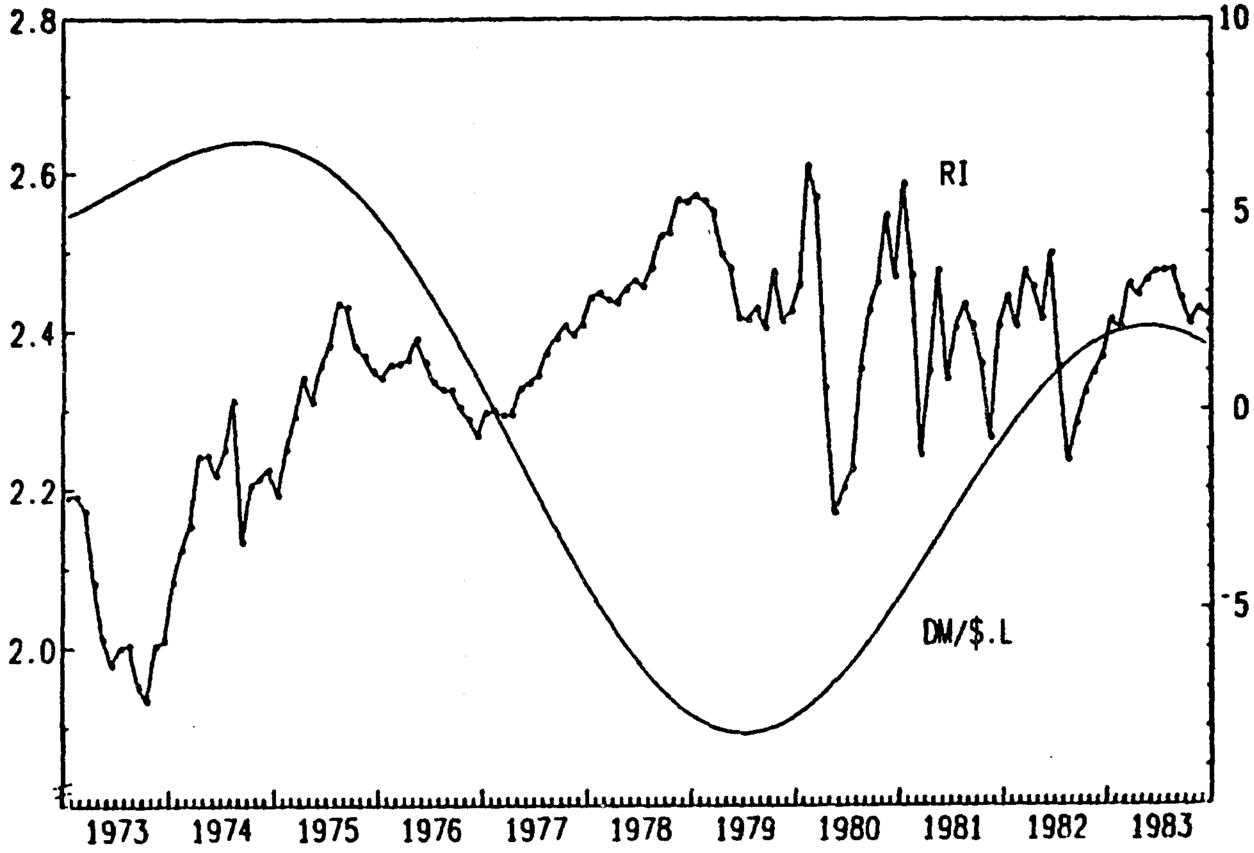


Figure 10

DM/$.L VS RELATIVE REAL INTEREST RATES

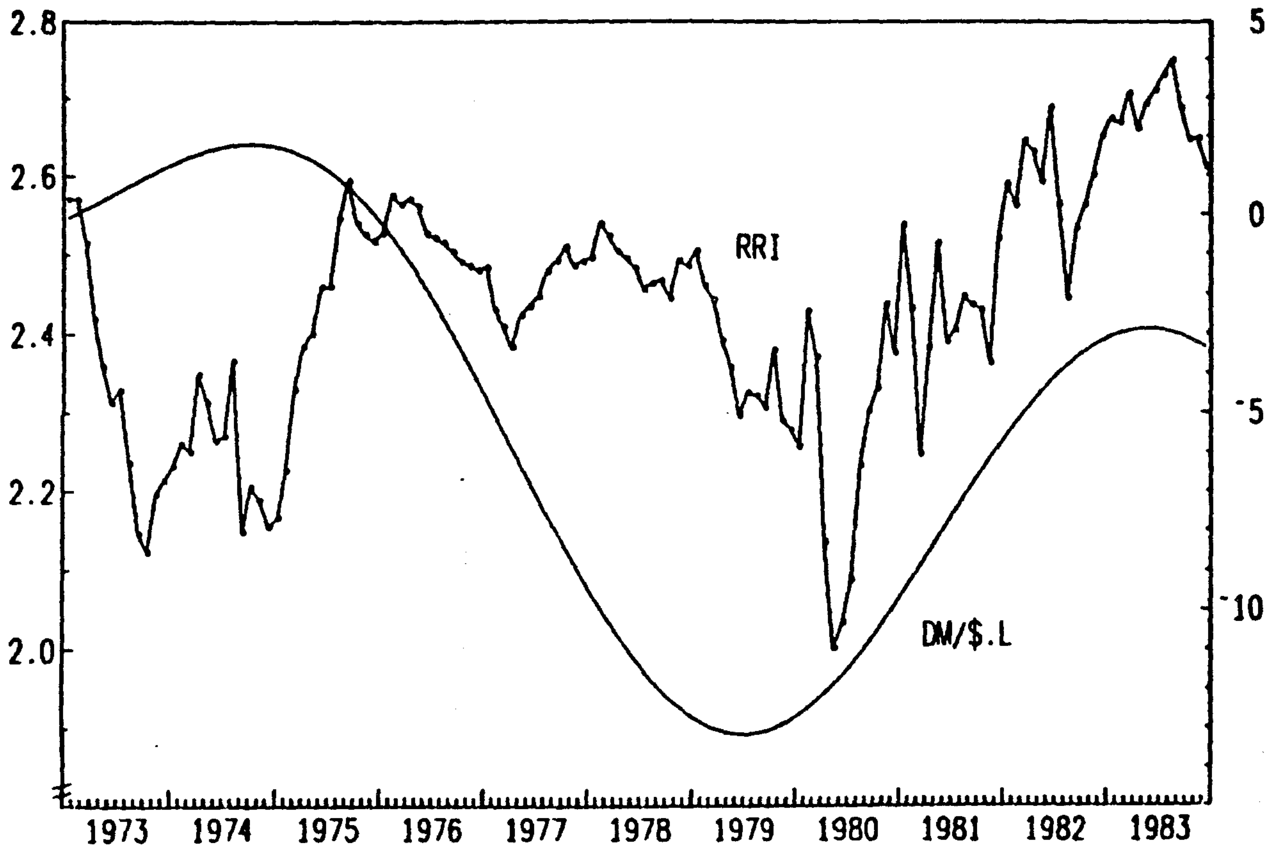


Figure 11

DM/$.L VS RELATIVE RATES OF INFLATION

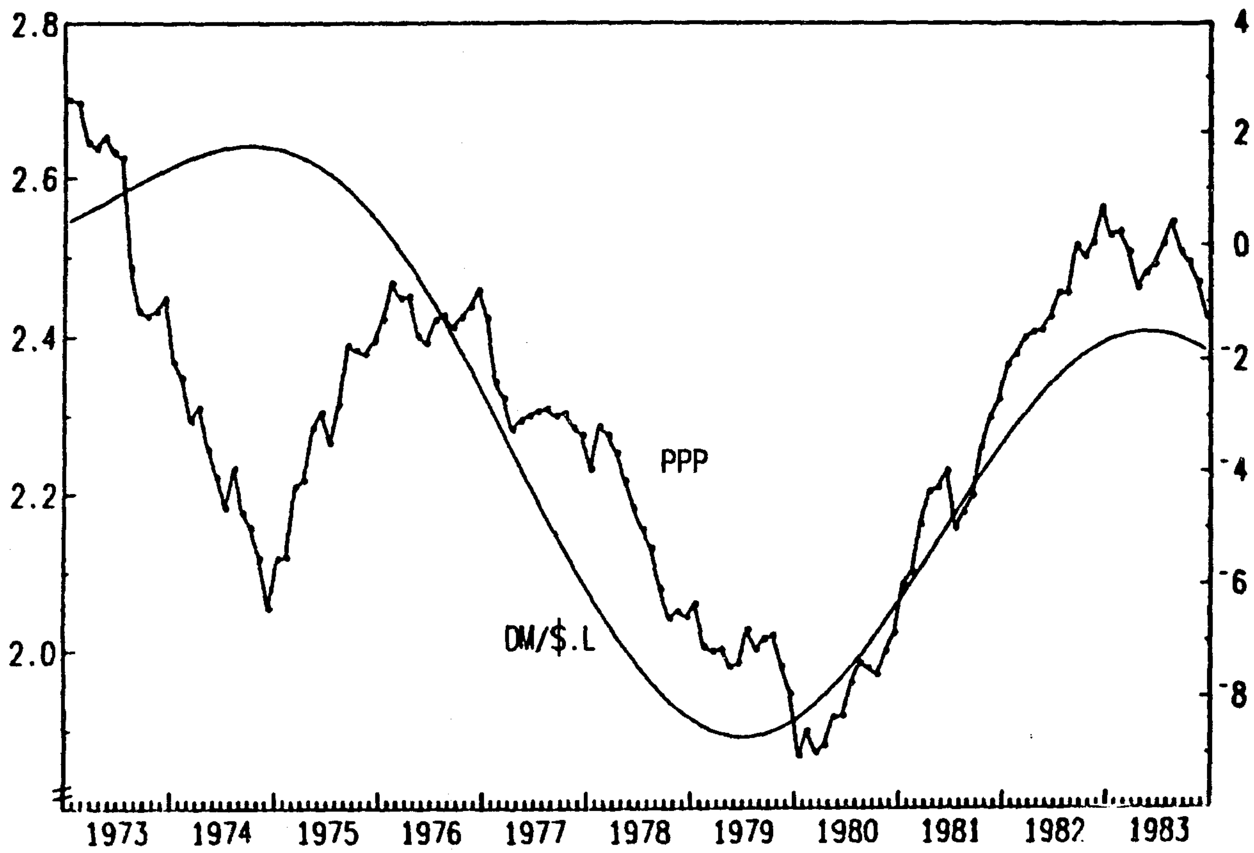


Figure 12

erated via an ARIMA process. This is justifiable if one reasons that the high frequency components are produced by random shocks that tend to be pervasive and wear away slowly. For example, a government-union confrontation in Poland is likely to have an immediate effect on Germany's exchange rate and even after this confrontation is no longer news there is bound to remain some nervousness which in some way or another is going to affect the mark. After performing the standard Box-Jenkins analysis, inspection of estimated autocorrelation and partial autocorrelation functions reveal that DM/\$.H is stationary in its level and appears to follow an AR(2) process. The interested reader will find the correlogram and partial correlogram in Figures 13 and 14. The residuals from this estimation give no signal that testing of a different order is called for. In addition to the AR(2), it is also hypothesized that DM/\$.H can be generated via a random walk (or no change) model. The result of this random walk specification may be very interesting. As the footnote at the conclusion of Chapter 3 suggests, several authors have claimed the exchange rate follows a random walk. It may turn out to be the case however, only in that the exchange rate contains a random walk component.

The first attempt at a model for DM/\$.L using the aforementioned fundamentals takes the form of a vector autoregression (VAR) such as that introduced in Sims (1964). The choice of a VAR specification is intuitively appealing for two major reasons. First, it endogenizes[21] all variables and therefore eliminates the forecasting bias that was seen in Meese and Rogoff. Moreover, the VAR incorporates lagged dependent variables as explanatory variables which is consistent with the expectational approach of many authors, such as Argy and Semudram (1981). The significance of the lag structure in the VAR was found to be maximized with a second order (i.e. lags 1 and 2 of all variables appear on the right hand side of all equations) specification using CCABY,

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21 It endogenizes all variables in the sense that the forecaster need not supply his own exogenous inputs for the fundamentals.

Correlogram of DM/$.H

"/" Represents +/- Two Standard Deviations

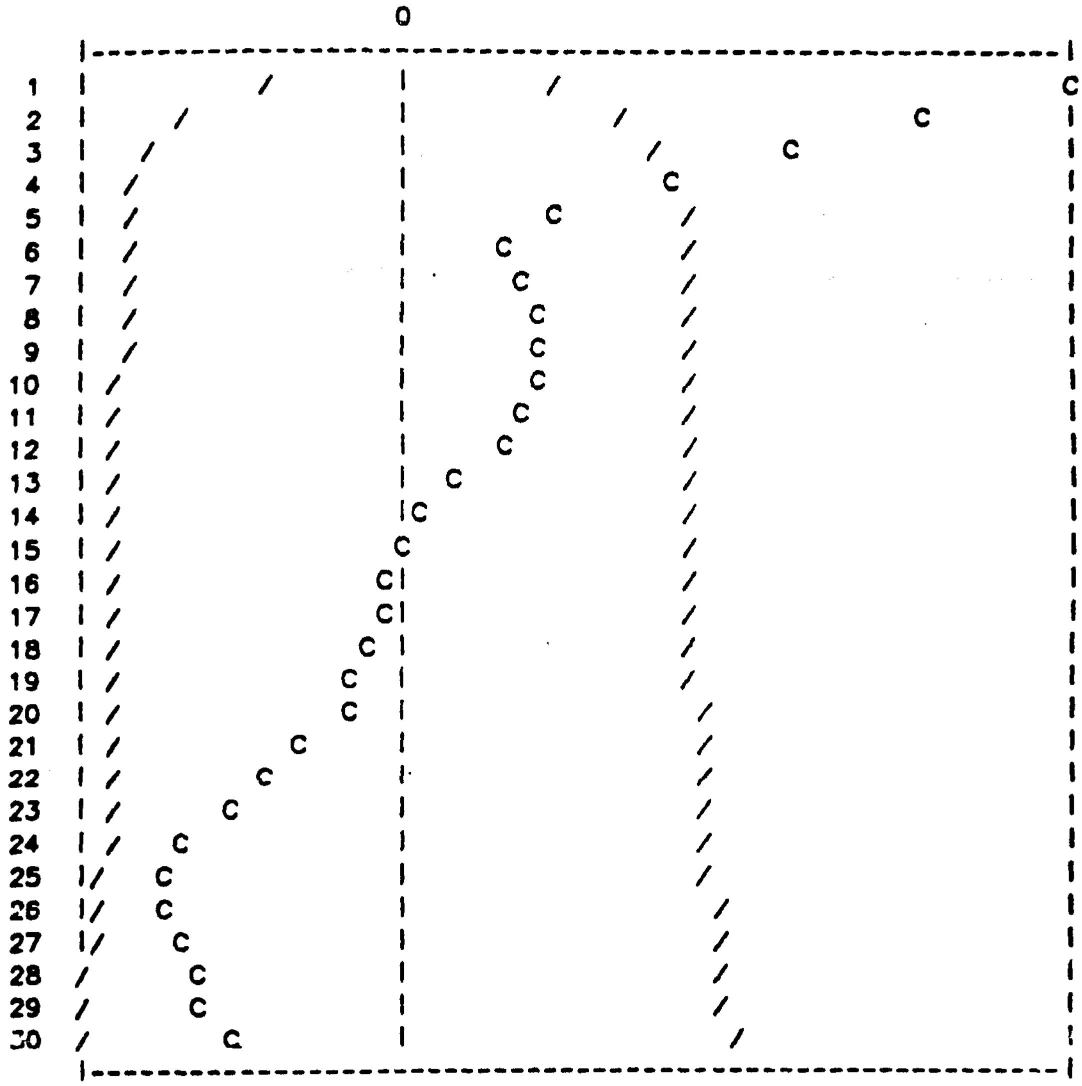

Figure 13

Partial Correlogram of DM/$.H

"/" Represents +/- Two Standard Deviations

```
              0
    |-----------------------------------------------------------|
 1  /         |           /                                     P
 2  / P       |           /                                     |
 3  /         |P          /                                     |
 4  / P       |           /                                     |
 5  /      P  |           /                                     |
 6  /         |      P    /                                     |
 7  /         |           /P                                    |
 8  /       P |           /                                     |
 9  /         P           /                                     |
10  /         P           /                                     |
11  /    P    |           /                                     |
12  /         |    P      /                                     |
13  /    P    |           /                                     |
14  /         P           /                                     |
15  /         P           /                                     |
16  /         |P          /                                     |
17  /        P|           /                                     |
18  /      P  |           /                                     |
19  /      P  |           /                                     |
20  /         P           /                                     |
21  /   P     |           /                                     |
22  /       P |           /                                     |
23  /      P  |           /                                     |
24  /    P    |           /                                     |
25  /        P|           /                                     |
26  /         | P         /                                     |
27  /         P           /                                     |
28  /     P   |           /                                     |
29  /      P  |           /                                     |
30  /         |P          /                                     |
    |-----------------------------------------------------------|
```

Figure 14

RI and PPP. The result regarding RI instead of RRI in light of the correlations indicated in Table 6 is somewhat surprising.

The results of the RMSE analysis under the above VAR specification for both DM/$.L and DM/$ are reported in Table 7 for the short term horizon results and in Table 8 for the longer term horizons. On the surface, these results are very encouraging. Both the DM/$ based VAR and the DM/$.L based VAR combined with the DM/$.H time series models out-perform a random walk unlike the results of Meese and Rogoff.[22] The decomposition based models are superior to the un-decomposed model for all horizons in the longer term and for the 24 month horizon in the shorter term. In this instance, it also appears that DM/$.H is better forecast with ARIMA than it is when assumed to be a random walk. Another observation that can be made from Tables 7 and 8 is that the majority of the error in the frequency decomposition based model is coming from the DM/$.H portion and that the fundamentals appear to be doing a good job of predicting DM/$.L. This however, upon further inspection, is shown to be untrue and subsequently leads to the dismissal of the above specified VAR as a candidate model.

Tables 9 through 12 provide the statistics behind the estimation of the VAR. Focussing on Table 9, one can observe the problems with this model. First, the RI and PPP variables must be dismissed as having the wrong theoretical sign, further the overall effect of the CCABY on DM/$.L is very marginal. All of the significance seen in the low RMSEs of Tables 7 and 8 are being produced via the momentum of the lagged dependent variables. This is a problem for forecasting, as the lags will keep moving DM/$.L in one direction and the other variables do not have

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22 Table 7 also reports the results of an ARIMA model used as a control model for DM/$. This is found to take the form of a MA(1), but its results are so poor that is will be disregarded in subsequent discussion.

Table 7

Root Mean Square Forecast Errors 1/81 - 12/83

Vector Autoregression Incorporates CCABY, RI and PPP

Model	Horizon 12 months	24 months
1. Vector Autogression Forecasting DM/$.L Combined with ARIMA (AR(2)) Forecasting DM/$.H		
DM/$.L	.00990	.04942
DM/$	.12519	.13802
2. Vector Autoregression Forecasting DM/$		
DM/$	.12268	.25540
3. ARIMA (MA(1)) Forecasting DM/$		
DM/$	.59747	.
4. Random Walk Specification		
DM/$	.18377	.32485
5. Vector Autoregression Forecasting DM/$.L Combined with a Random Walk Specification for DM/$.H		
DM/$	.12423	.14800

Table 8

Root Mean Square Forecast Errors 1/79 - 12/83

Vector Autoregression Incorporates CCABY, RI and PPP

Model	Horizon 12 mnths	24 mnths	36 mnths	48 mnths
1. Vector Autogression Forecasting DM/$.L Combined with ARIMA (AR(2)) Forecasting DM/$.H				
DM/$.L	.01193	.04567	.06889	.03676
DM/$	.14452	.12847	.12019	.17006
2. Vector Autoregression Forecasting DM/$				
DM/$	.15936	.23772	.28957	.36282
3. Random Walk Specification				
DM/$	.27056	.47047	.66813	.72481
4. Vector Autoregression Forecasting DM/$.L Combined with a Random Walk Specification for DM/$.H				
DM/$	.17846	.20596	.24475	.27228

Table 9

Estimation of VAR Incorporating DM/$.L, CCABY, RI and PPP

Dependent Variable: DM/$.L
Period of Fit: January, 1974 - December, 1983

		Coeffficent	T-value
Constant		.0079	17.5
DM/$.L:	LAG 1	1.9737	934.0
	LAG 2	-.9770	-480.5
CCABY:	LAG 1	.0016	1.3
	LAG 2	-.0032	-2.7
RI:	LAG 1	-.0000	-0.1
	LAG 2	-.0000	-1.2
PPP:	LAG 1	-.0001	-4.2
	LAG 2	-.0000	-0.2

Standard Error of Estimate: .00014

RBAR Squared: 1.00

Durbin/Watson: 0.26

Table 10

Estimation of VAR Incorporating DM/$.L, CCABY, RI and PPP

Dependent Variable: CCABY
Period of Fit: January, 1974 - December, 1983

		Coefficent	T-value
Constant		.0544	1.7
DM/$.L:	LAG 1	-.5064	-3.4
	LAG 2	.4972	3.5
CCABY:	LAG 1	1.3683	15.8
	LAG 2	-.4123	-4.9
RI:	LAG 1	-.0009	-1.1
	LAG 2	.0009	1.1
PPP:	LAG 1	-.0010	-0.5
	LAG 2	.0013	0.6

Standard Error of Estimate: .0100

RBAR Squared: 0.997

Durbin/Watson: 2.51

Table 11

Estimation of VAR Incorporating DM/$.L, CCABY, RI and PPP

Dependent Variable: RI
Period of Fit: January, 1974 - December, 1983

		Coeffficent	T-value
Constant		-1.1784	-0.3
DM/$.L:	LAG 1	26.5031	1.6
	LAG 2	-26.7072	-1.6
CCABY:	LAG 1	6.4110	0.6
	LAG 2	-2.3778	-0.2
RI:	LAG 1	.7663	8.2
	LAG 2	-.1915	-2.1
PPP:	LAG 1	.1013	0.4
	LAG 2	.0128	0.1

Standard Error of Estimate: 1.1492

RBAR Squared: 0.71

Durbin/Watson: 2.00

Table 12

Estimation of VAR Incorporating DM/$.L, CCABY, RI and PPP

Dependent Variable: PPP
Period of Fit: January, 1974 - December, 1983

		Coefficent	T-value
Constant		-2.8942	-2.0
DM/$.L:	LAG 1	12.7524	1.9
	LAG 2	-11.7528	-1.8
CCABY:	LAG 1	-.8768	-0.2
	LAG 2	1.5604	0.4
RI:	LAG 1	-.0361	-1.0
	LAG 2	.0744	2.0
PPP:	LAG 1	1.0485	10.9
	LAG 2	-.0824	-0.8

Standard Error of Estimate:	0.4670
RBAR Squared:	0.969
Durbin/Watson:	1.97

enough power (large enough coefficents) to produce turning points. Part of the excellent ex-post performance of this DM/$.L VAR stems from the fact that in the forecast period DM/$.L was essentially moving on a unidirectional path (refer back to Figure 3). Another problem observed in Table 9 and one that will reappear throughout is the very low Durbin/Watson statistic. However, in this case this is not serious as Figure 15 reveals that the actual and estimated values come out right on top of each other.

The VAR specification dismissed above for DM/$.L is actually not that bad when applied to DM/$, as Tables 13 through 16 reveal. The fundamentals are overall marginally significant with generally correct signs though again most forecasts are being generated directly from the lagged dependent variable. A plot of the fit for DM/$ under this specification is provided in Figure 16.

Further empirical research concludes that the optimal VAR specification of the fundamentals is a first degree VAR consisting surprisingly of only CCABY and, again, RI. Under these circumstances, the RMSE analysis presented in Tables 17 and 18 are disappointing and not at all supportive of the proposition set out at the beginning of the chapter. For both the short term and long term horizons, again both the DM/$.L VAR combined with the DM/$.H ARIMA as well as the DM/$ based VAR outperform the random walk. However, this time the DM/$ based VAR is clearly superior to the decomposition based models, especially in the longer term forecasts. Replacing the DM/$.H ARIMA with a random walk specification yields no improvement. The estimation statistics, Tables 19 through 21 for DM/$.L and Tables 22 through 24 for DM/$ do not present any of the problems that were observed in the prior VAR specification. Again, the lagged dependent variable is the prime determinant though the fundamentals are all statistically significant with the correct economic sign. The DM/$.L equation again suffers from first order serial

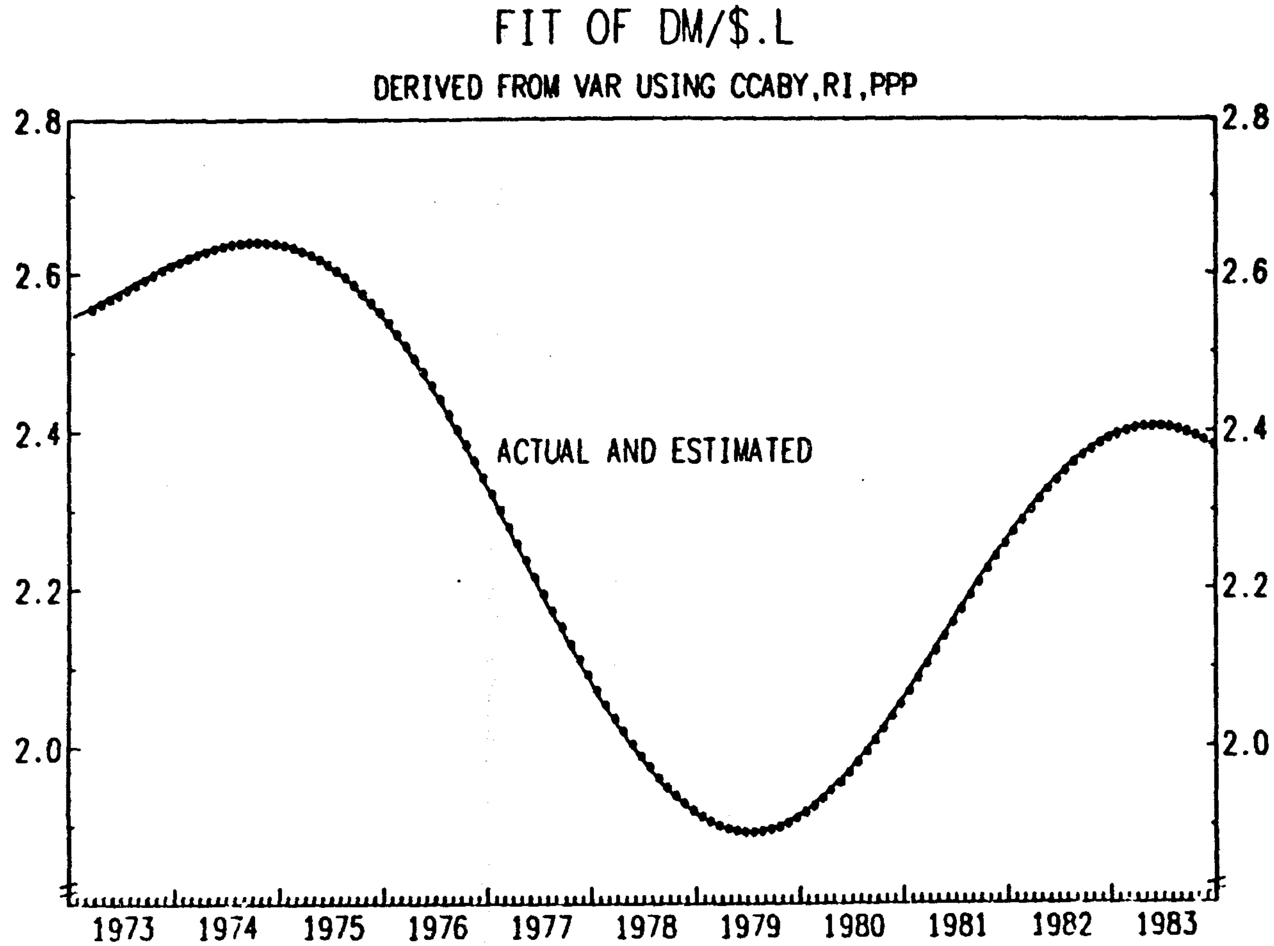
FIT OF DM/$.L
DERIVED FROM VAR USING CCABY,RI,PPP
ACTUAL AND ESTIMATED
2.8
2.6
2.4
2.2
2.0
1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983

Figure 15

Table 13

Estimation of VAR Incorporating DM/$, CCABY, RI and PPP

Dependent Variable: DM/$
Period of Fit: January, 1974 - December, 1983

		Coefficent	T-value
Constant		.4573	3.2
DM/$:	LAG 1	1.0935	11.6
	LAG 2	-.2350	-2.5
CCABY:	LAG 1	-.8021	-1.9
	LAG 2	.6644	1.5
RI:	LAG 1	.0081	1.9
	LAG 2	-.0058	-1.4
PPP:	LAG 1	.0214	2.0
	LAG 2	-.0104	-1.0

Standard Error of Estimate: .0510

RBAR Squared: 0.97

Durbin/Watson: 1.87

Table 14

Estimation of VAR Incorporating DM/$, CCABY, RI and PPP

Dependent Variable: CCABY
Period of Fit: January, 1974 - December, 1983

		Coefficent	T-value
Constant		-.0393	-1.4
DM/$:	LAG 1	-.0361	-1.9
	LAG 2	.0550	2.9
CCABY:	LAG 1	1.3998	16.5
	LAG 2	-.4000	-4.7
RI:	LAG 1	-.0005	-0.6
	LAG 2	.0000	0.1
PPP:	LAG 1	-.0029	-1.4
	LAG 2	.0029	1.4

Standard Error of Estimate:	.0102
RBAR Squared:	0.997
Durbin/Watson:	2.51

Table 15

Estimation of VAR Incorporating DM/$, CCABY, RI and PPP

Dependent Variable: RI
Period of Fit: January, 1974 - December, 1983

		Coefficent	T-value
Constant		8.0236	2.6
DM/$:	LAG 1	-5.2562	-2.5
	LAG 2	2.3511	1.1
CCABY:	LAG 1	-2.4758	-0.3
	LAG 2	2.5778	0.3
RI:	LAG 1	.7888	8.3
	LAG 2	-.1310	-1.5
PPP:	LAG 1	.0636	0.3
	LAG 2	.1785	0.8

Standard Error of Estimate: 1.1141

RBAR Squared: 0.72

Durbin/Watson: 1.98

Table 16

Estimation of VAR Incorporating DM/$, CCABY, RI and PPP

Dependent Variable: PPP
Period of Fit: January, 1974 - December, 1983

		Coefficent	T-value
Constant		-.3491	-0.3
DM/$:	LAG 1	.9725	1.1
	LAG 2	-.7559	-0.8
CCABY:	LAG 1	-1.0119	-0.3
	LAG 2	.4800	0.1
RI:	LAG 1	-.0371	-0.9
	LAG 2	.0840	2.2
PPP:	LAG 1	1.1088	11.3
	LAG 2	-.1581	-1.6

Standard Error of Estimate:	0.4752
RBAR Squared:	0.967
Durbin/Watson:	1.99

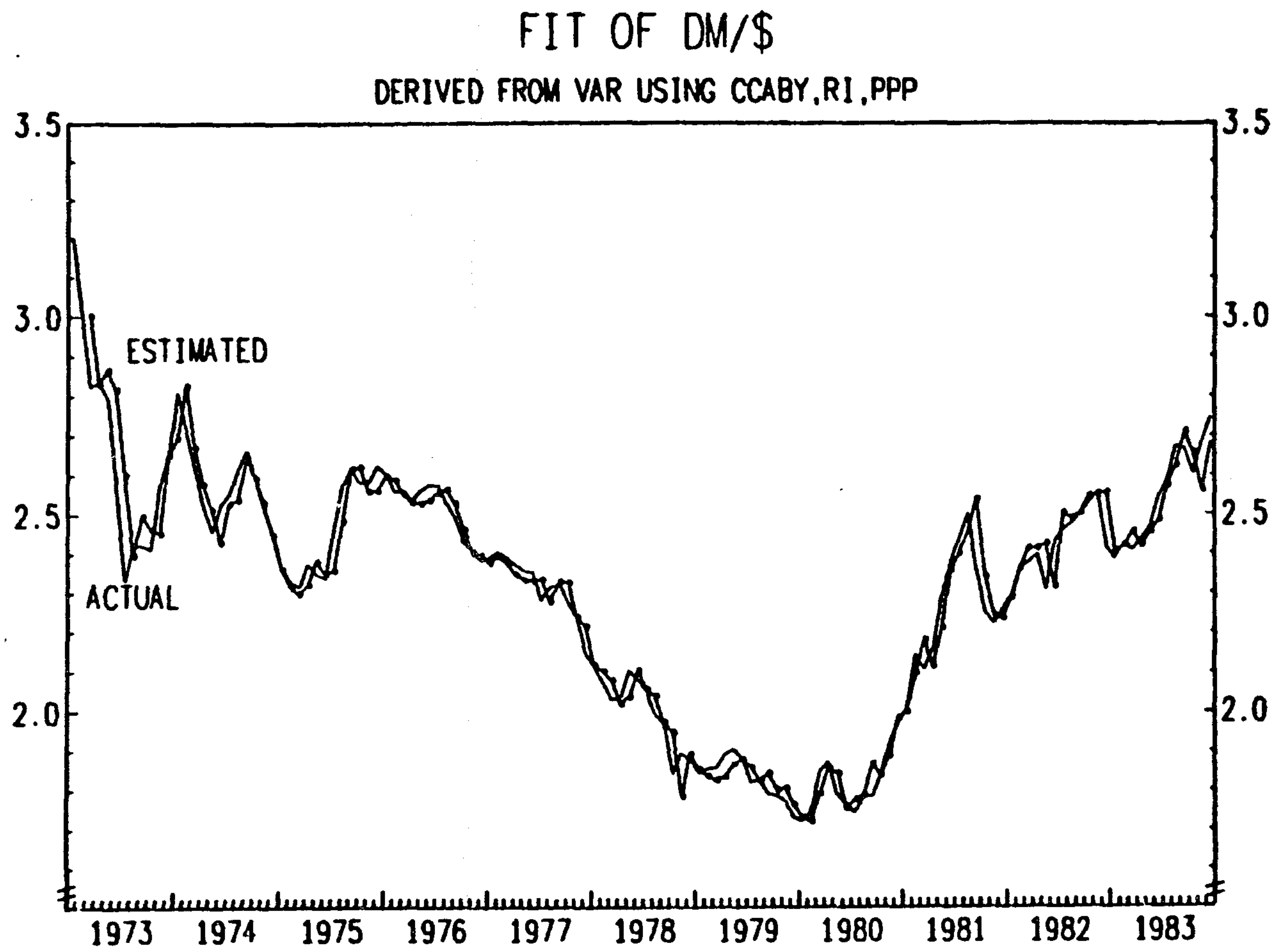
FIT OF DM/$
DERIVED FROM VAR USING CCABY,RI,PPP
ESTIMATED
ACTUAL
3.5
3.0
2.5
2.0
1973
1974
1975
1976
1977
1978
1979
1980
1981
1982
1983

Figure 16

Table 17

Root Mean Square Forecast Errors 1/81 - 12/83

Vector Autoregression Incorporates CCABY and RI

	Horizon	
Model	12 months	24 months
1. Vector Autogression Forecasting DM/$.L Combined with ARIMA (AR(2)) Forecasting DM/$.H		
DM/$.L	.04070	.06408
DM/$	.15991	.19954
2. Vector Autoregression Forecasting DM/$		
DM/$	.14911	.22721
3. Random Walk Specification		
DM/$	.18377	.32485
4. Vector Autoregression Forecasting DM/$.L Combined with a Random Walk Specification for DM/$.H		
DM/$	.14758	.18571

Table 18

Root Mean Square Forecast Errors 1/79 - 12/83

Vector Autoregression Incorporates CCABY and RI

Model	Horizon 12 mnths	24 mnths	36 mnths	48 mnths
1. Vector Autogression Forecasting DM/$.L Combined with ARIMA (AR(2)) Forecasting DM/$.H				
DM/$.L	.07143	.15381	.21837	.21326
DM/$	.17132	.24541	.31202	.34467
2. Vector Autoregression Forecasting DM/$				
DM/$	.16497	.22660	.29867	.38366
3. Random Walk Specification				
DM/$	.27056	.47047	.66813	.72481
4. Vector Autoregression Forecasting DM/$.L Combined with a Random Walk Specification for DM/$.H				
DM/$	.22305	.34372	.45767	.44714

Table 19

Estimation of VAR Incorporating DM/$.L, CCABY and RI

Dependent Variable: DM/$.L
Period of Fit: January, 1974 - December, 1983

		Coefficent	T-value
Constant		.2001	13.9
DM/$.L:	LAG 1	.9404	199.8
CCABY:	LAG 1	-.0991	-14.6
RI:	LAG 1	.0014	3.6

Standard Error of Estimate:	.0075
RBAR Squared:	0.999
Durbin/Watson:	0.07

Table 20

Estimation of VAR Incorporating DM/$.L, CCABY and RI

Dependent Variable: CCABY
Period of Fit: January, 1974 - December, 1983

		Coefficent	T-value
Constant		-.1080	-4.5
DM/$.L:	LAG 1	.0430	5.5
CCABY:	LAG 1	1.0238	91.2
RI:	LAG 1	-.0013	-1.9

Standard Error of Estimate:	.0124
RBAR Squared:	0.995
Durbin/Watson:	0.95

Table 21

Estimation of VAR Incorporating DM/$.L, CCABY and RI

Dependent Variable: RI
Period of Fit: January, 1974 - December, 1983

		Coefficent	T-value
Constant		.8782	0.4
DM/$.L:	LAG 1	-.5150	-0.7
CCABY:	LAG 1	1.1915	1.1
RI:	LAG 1	.6958	11.1

Standard Error of Estimate: 1.1638

RBAR Squared: 0.70

Durbin/Watson: 1.78

Table 22

Estimation of VAR Incorporating DM/$, CCABY and RI

Dependent Variable: DM/$
Period of Fit: January, 1974 - December, 1983

		Coeffícent	T-value
Constant		.2464	3.0
DM/$:	LAG 1	.9382	36.3
CCABY:	LAG 1	-.1730	-3.7
RI:	LAG 1	.0100	3.4

Standard Error of Estimate:	.0554
RBAR Squared:	0.96
Durbin/Watson:	1.51

Table 23

Estimation of VAR Incorporating DM/$, CCABY and RI

Dependent Variable: CCABY
Period of Fit: January, 1974 - December, 1983

		Coefficent	T-value
Constant		-.0823	-4.5
DM/$:	LAG 1	.0333	5.8
CCABY:	LAG 1	1.0194	98.3
RI:	LAG 1	-.0018	-2.8

Standard Error of Estimate:	.0123
RBAR Squared:	0.995
Durbin/Watson:	1.00

Table 24

Estimation of VAR Incorporating DM/$, CCABY and RI

Dependent Variable: RI
Period of Fit: January, 1974 - December, 1983

		Coefficent	T-value
Constant		1.4466	0.8
DM/$:	LAG 1	-.6813	-1.3
CCABY:	LAG 1	.9099	0.9
RI:	LAG 1	.7031	11.3

Standard Error of Estimate:	1.1584
RBAR Squared:	0.70
Durbin/Watson:	1.78

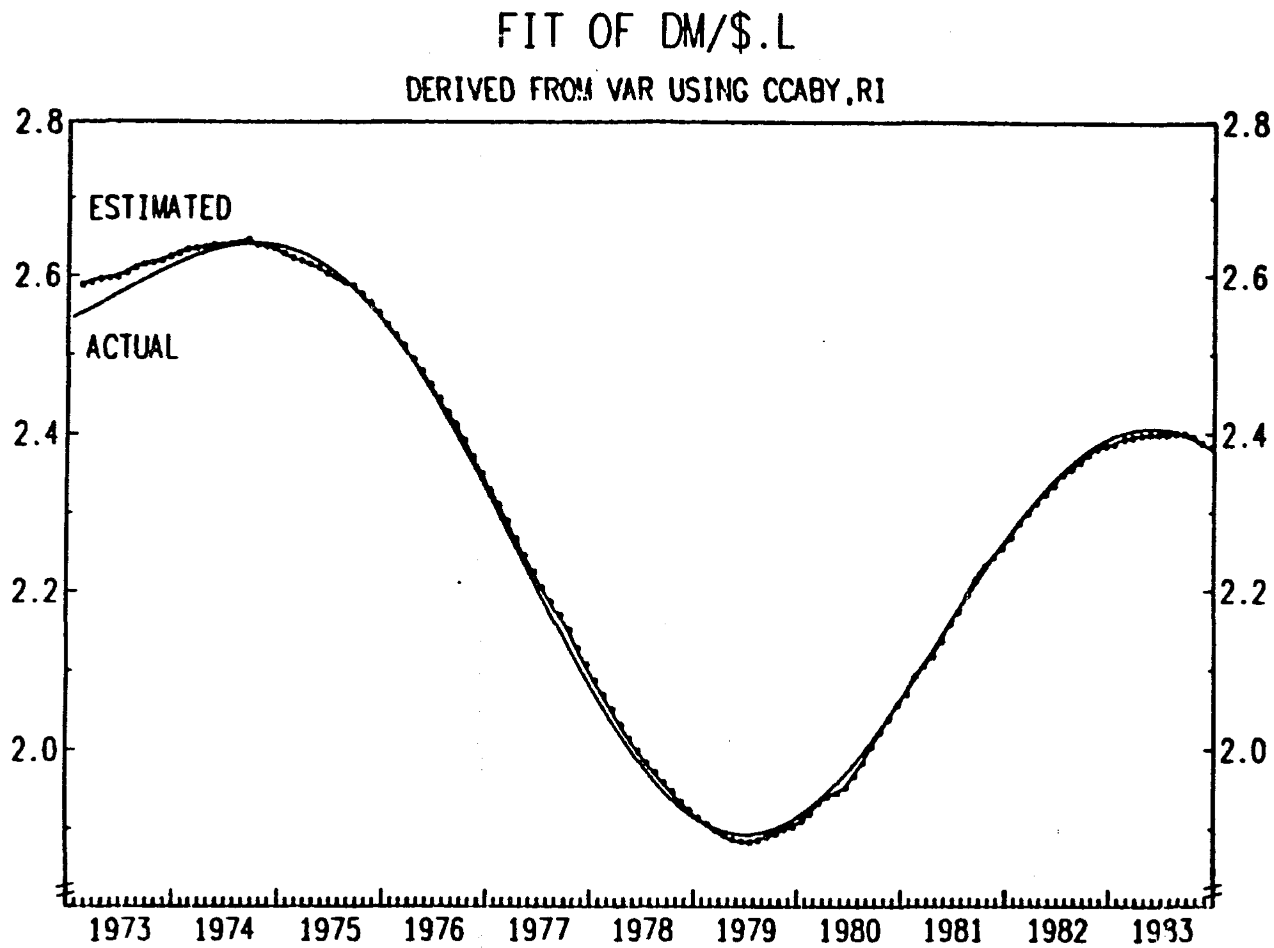
FIT OF DM/$.L
DERIVED FROM VAR USING CCABY,RI
ESTIMATED
ACTUAL
2.8
2.6
2.4
2.2
2.0
1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983

Figure 17

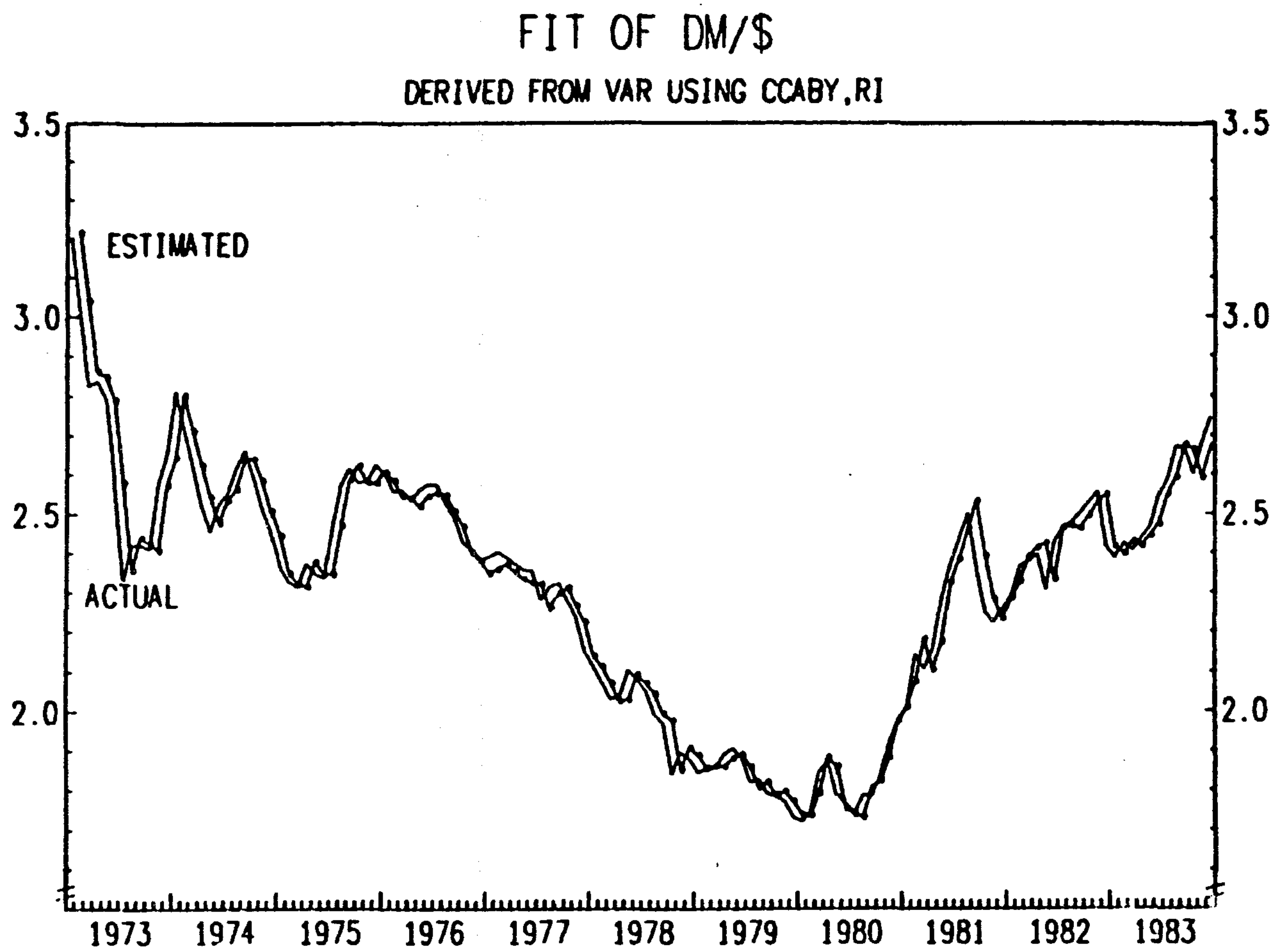
FIT OF DM/$
DERIVED FROM VAR USING CCABY,RI
ESTIMATED
ACTUAL
3.5
3.0
2.5
2.0
1973
1974
1975
1976
1977
1978
1979
1980
1981
1982
1983

Figure 18

correlation though again this does not appear serious as Figure 17 shows. For comparison, Figure 18 provides the fit for the DM/$ equation coming out of the VAR specification.

The final model to be explored makes two changes in tactic. Firstly, the VAR specification is replaced by Ordinary Least Squares. This change brings back the forecasting bias first observed in Chapter 3 however, it allows one to focus on the model itself as the source of forecasting error. Secondly, an econometric model is derived for DM/$.H. Of the fundamentals addressed in this chapter, CCABY and PPP can be thought of as being more related to long run movements in the exchange rate while relative interest rates are more indicative of short run determination. DM/$.L, basically a long run concept as expressed in the introduction, will be forecast using the contemporaneous values of CCABY and PPP as is shown in Table 25. In this instance, the low Durbin/Watson cannot merely be dismissed by appealing to the fit expressed by Figure 19.[23] Part of the reason for the positive serial correlation is undoubtedly due to the inherent smoothing of DM/$.L. Additionally, the poor fit between 1973 and 1976 may be indicative of a slow adjustment process following the freeing up of exchange rates.

The model for DM/$.H is now assumed to include the current period's RRI as well as the lagged dependent variable. This specification holds up well as can be seen in both Table 26 and Figure 20. Finally, the control equation for DM/$ utilizes all three of the above fundamentals though RRI enters very marginally with its correct sign as indicated in Table 27. A low

---

[23] Note that estimation using generalized least squares makes no improvement in reducing serial correlation.

Table 25

Estimation of OLS Model for DM/$.L

Period of Fit: January, 1973 - December, 1983

	Coefficient	T-value
Constant	2.7954	74.6
CCABY	-.6341	-9.5
PPP	.0282	5.0

Standard Error of Estimate:	.1464
RBAR Squared:	.67
Durbin/Watson:	0.02

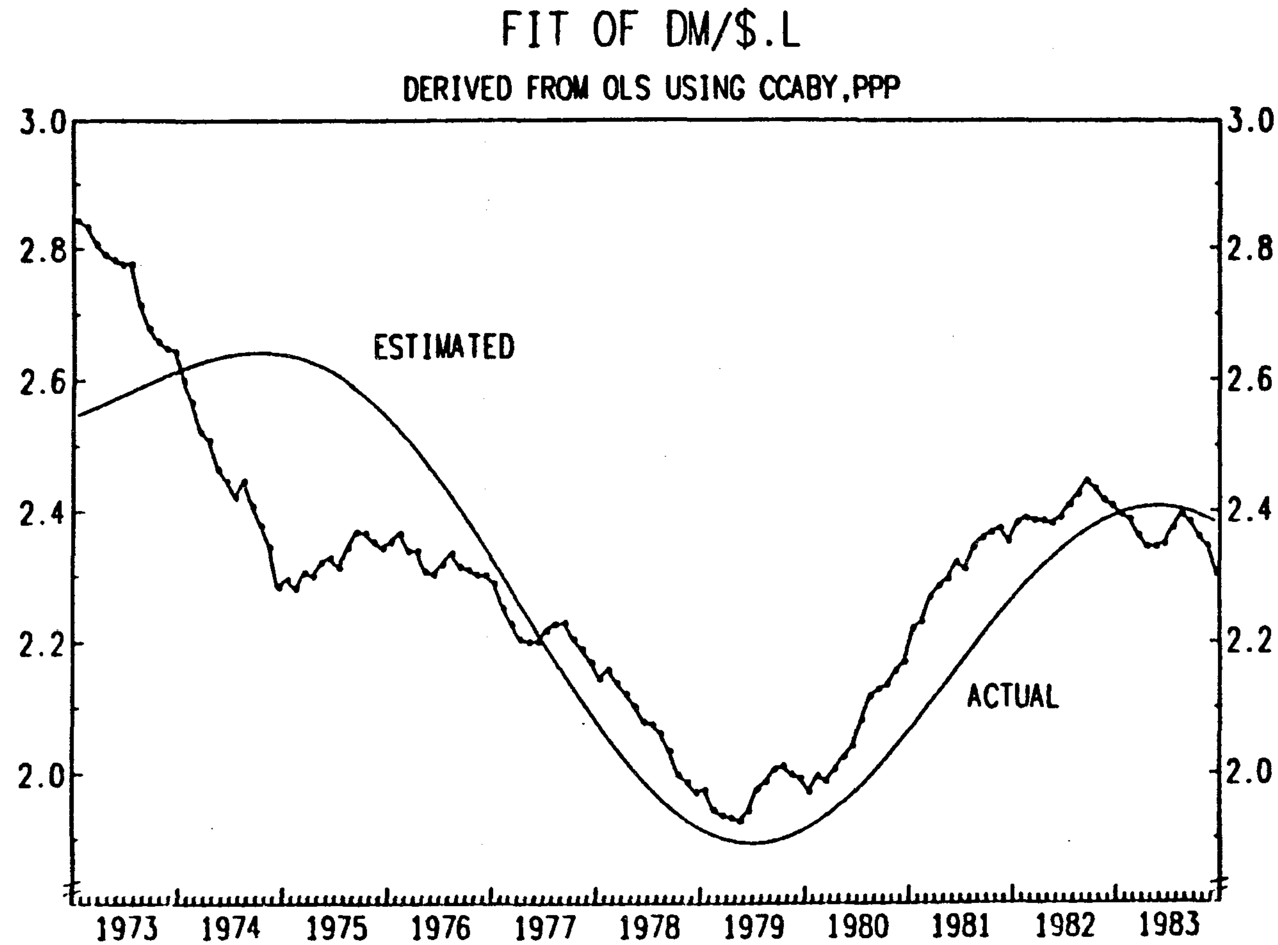
FIT OF DM/$.L
DERIVED FROM OLS USING CCABY,PPP
3.0
2.8
2.6
2.4
2.2
2.0
ESTIMATED
ACTUAL
1973
1974
1975
1976
1977
1978
1979
1980
1981
1982
1983

Figure 19

Table 26

Estimation of OLS Model for DM/$.H

Period of Fit: January, 1973 - December, 1983

	Coefficient	T-value
Constant	-.0215	3.1
RRI	.0088	4.6
DM/$.H Lagged 1	.7676	19.5

Standard Error of Estimate:	.0606
RBAR Squared:	.83
Durbin/Watson:	1.33

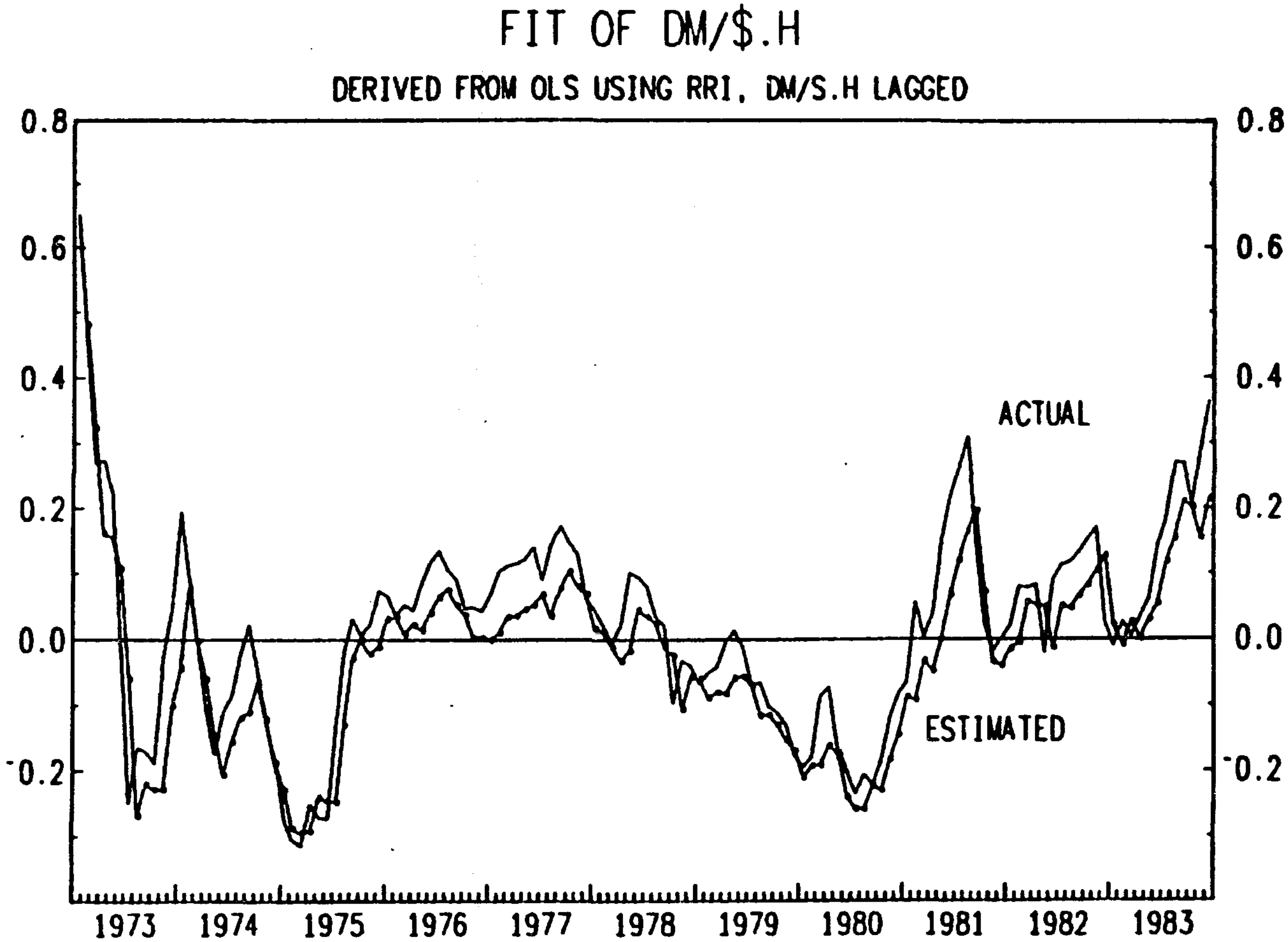
FIT OF DM/$.H
DERIVED FROM OLS USING RRI, DM/S.H LAGGED
0.8
0.6
0.4
0.2
0.0
-0.2
ACTUAL
ESTIMATED
1973
1974
1975
1976
1977
1978
1979
1980
1981
1982
1983

Figure 20

Table 27

Estimation of OLS Model for DM/$

Period of Fit: January, 1973 - December, 1983

	Coefficient	T-value
Constant	2.8700	55.5
CCABY	-.5344	-5.5
PPP	.0606	6.2
RRI	.0072	1.0

Standard Error of Estimate:	.1452
RBAR Squared:	.78
Durbin/Watson:	0.29

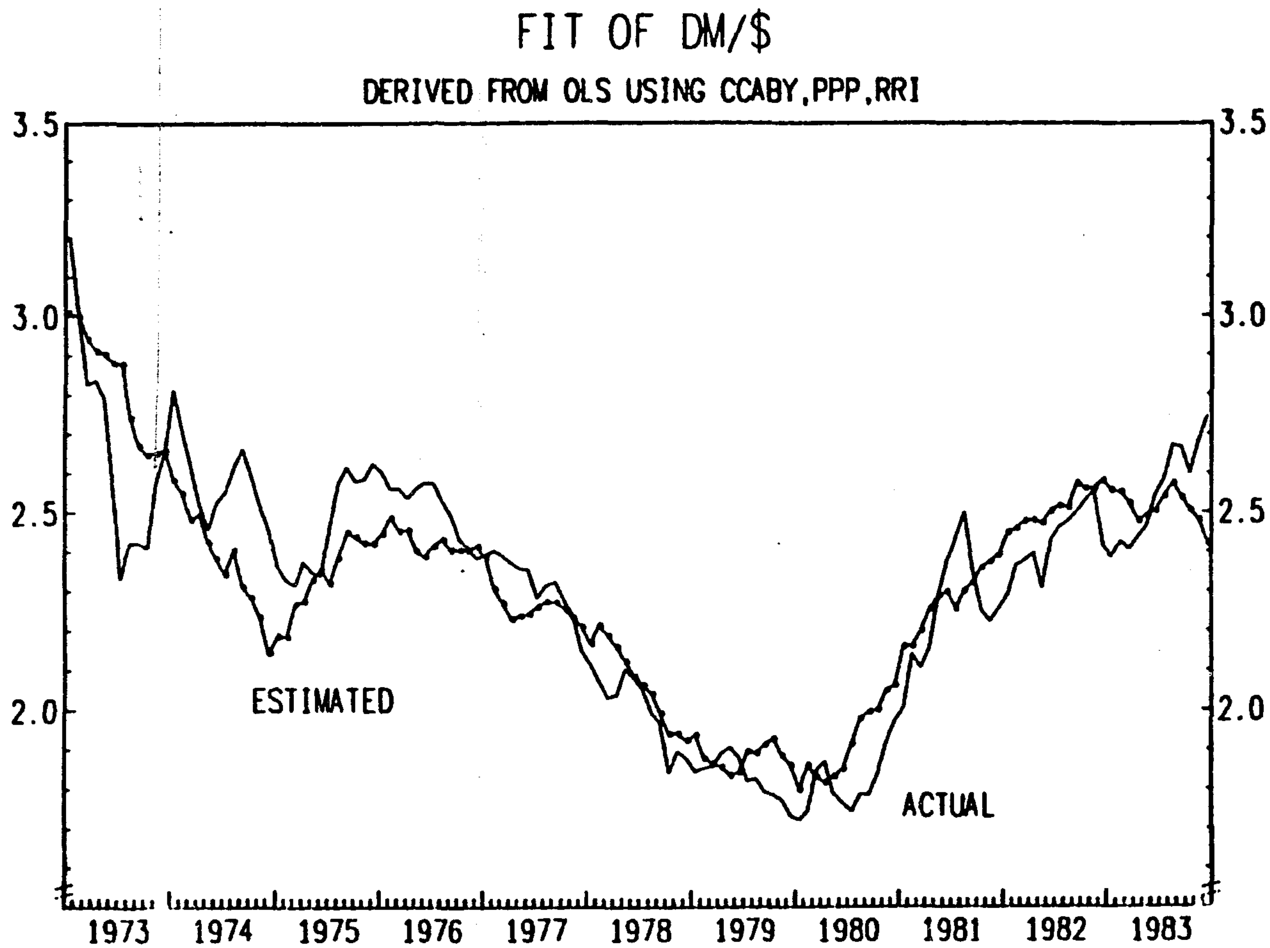
FIT OF DM/$
DERIVED FROM OLS USING CCABY,PPP,RRI
3.5
3.0
2.5
2.0
ESTIMATED
ACTUAL
1973
1974
1975
1976
1977
1978
1979
1980
1981
1982
1983

Figure 21

Durbin/Watson is again observed though Figure 21 tends to negate its significance.[24] The RMSEs generated under these equations are presented in Tables 28 and 29.

At last, the proposition stated at the outset is supported. The separate models for DM/$.L and DM/$.H out-forecast the single fundamental based model for DM/$ for every forecast horizon detailed in Tables 28 and 29. Furthermore, focussing now on the longer term forecasts of Table 29, the decomposition based models make about a 10 percent better forecast at the end of 12 months but extend this to a better than 25 percent improvement at the end of four years. Additionally, it is interesting to note that the RMSE for DM/$.L actually declines as the forecast span increases. This finding can be interpretted as meaning that long run deviations in the actual exchange rate from its "fundamentals" equilibrium is due to random and other short term forces.

The preceding analysis focussed on estimation diagnostics and the forecasting ability of both DM/$.L and DM/$ to narrow down the field of candidate models. In actuality however, there was a bias in the calculation of the RMSEs. To see this, consider the following. The calculation, in the frequency domain, of DM/$.L is a function of how much information is available on DM/$. In the ex-post simulations that have been reported up to now, DM/$.L was calculated over the entire span of January, 1973 through December, 1983 and was assumed to have been known throughout.[25] If the calculation of DM/$.L based on information about DM/$ through 1980 was roughly similar to that over the entire span then this bias is minimal. However, it is apparent from Figure 22, which compares the two time series, that DM/$.L definitely is changing as more information is known about the original exchange rate.

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[24] Again GLS yields no improvement.

[25] I am indebted to Professor Ronald Anderson for pointing this problem out to me.

Table 28

Root Mean Square Forecast Errors 1/81 - 12/83

OLS Models Incorporates CCABY, RRI and PPP

	Horizon	
Model	12 months	24 months
1. OLS Models Forecasting DM/$.L and DM/$.H		
DM/$.L	.05858	.03590
DM/$	.11187	.11961
2. OLS Model Forecasting DM/$		
DM/$	.13080	.15079

Table 29

Root Mean Square Forecast Errors 1/79 - 12/83

OLS Models Incorporates CCABY, RRI and PPP

Model	Horizon 12 mnths	24 mnths	36 mnths	48 mnths
1. OLS Models Forecasting DM/$.L and DM/$.H				
DM/$.L	.09668	.09988	.05858	.03590
DM/$	.11705	.11152	.11043	.11959
2. OLS model forecasting DM/$				
DM/$	.12730	.12830	.13080	.15079

COMPARISON OF DM/$.L TIME SERIES

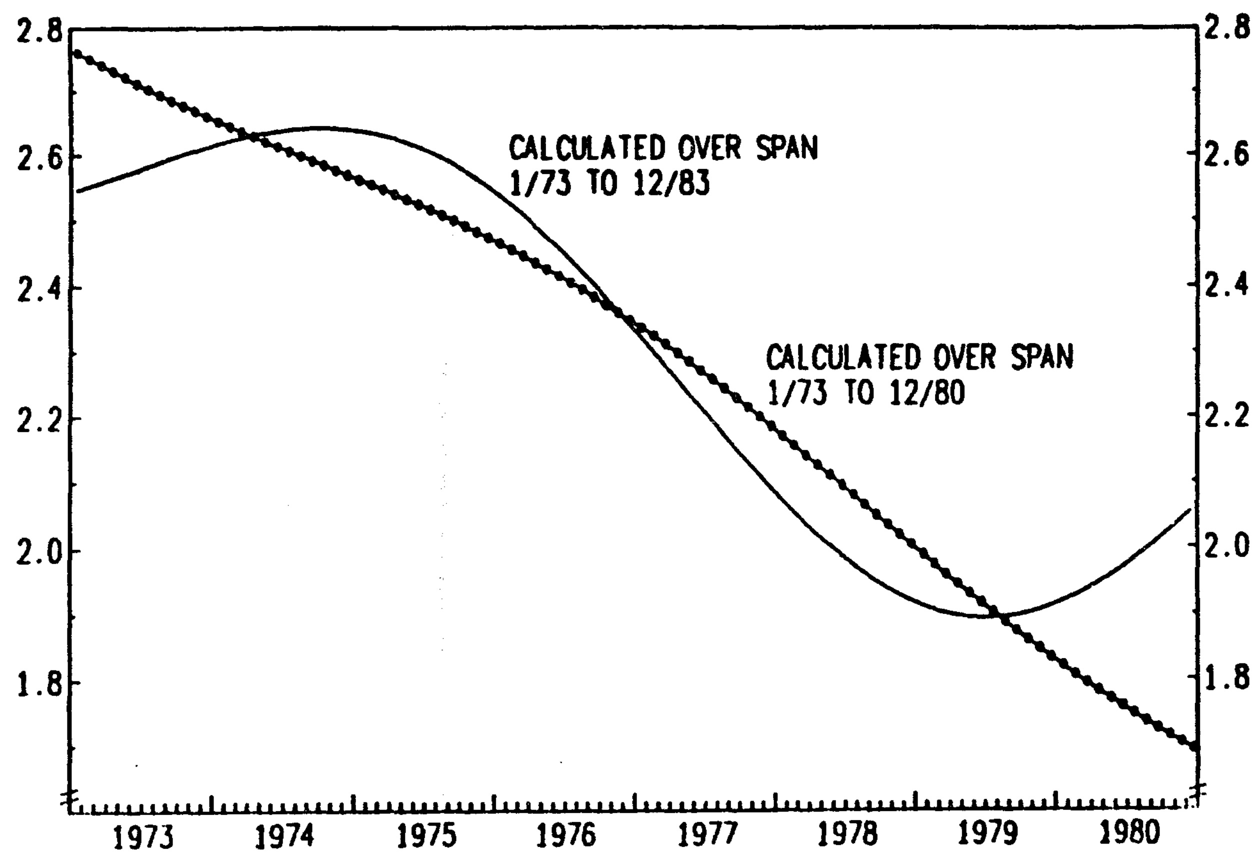

Figure 22

To be technically correct, DM/$.L must be calculated iteratively, in the same fashion as the RMSEs are generated. The iterative procedure used was as follows. First, DM/$.L was calculated through December, 1980 with the candidate models being estimated through the same point. They were then projected out in steps of up to 24 months (considering now the short term hori-At the second iteration, DM/$.L was calculated based on the availability of DM/$ from January, 1973 to January, 1981. The models were again reestimated and another series of up to 24 month ahead forecasts were generated. The iterations proceeded in a similar fashion until all data was exhausted. The series of up to 24 month ahead forecasts were then converted to RMSEs. Note in this procedure DM/$.L, and likewise DM/$.H, do not exist beyond the iterative date so RMSEs cannot be calculated for them but they can be calculated for their sum, namely DM/$.

Tables 30 and 31 present the results under the iterative procedure for the first degree VAR incorporating CCABY and RI. The results of the OLS models, which emerged as the best candidate under the biased data set, are given in Tables 32 and 33. The VAR, though rejected initially, is repeated here to gauge the effects of the correction. In general, the RMSEs of the VAR system are much greater than they were previously. In addition, whereas before the VAR models (for both decomposed and undecomposed data) proved superior to a random walk, this now is only the case for the DM/$ based VAR and only for selected forecast horizons.

The results for the OLS models, while not as clear cut as previously, are nevertheless somewhat encouraging. Using actual values of exogenous variables, both the DM/$ equation and the decomposition based model outperform a random walk. Additionally, the model based on the frequency decomposed time series, which far outperformed the DM/$ model under the biased data, is now superior at a span of 24 months under the short term forecasting horizon and at spans of 24 and 36 months under the longer term.

Table 30

Root Mean Square Forecast Errors 1/81 - 12/83

Vector Autoregression Incorporates CCABY and RI

	Horizon	
Model	12 months	24 months
1. Vector Autogression Forecasting DM/$.L Combined with ARIMA (AR(2)) Forecasting DM/$.H		
DM/$	.41294	.62968
2. Vector Autoregression Forecasting DM/$		
DM/$	.18671	.31712
3. Random Walk Specification		
DM/$	.18377	.32485
4. Vector Autoregression Forecasting DM/$.L Combined with a Random Walk Specification for DM/$.H		
DM/$	.19239	.32644

Table 31

Root Mean Square Forecast Errors 1/79 - 12/83

Vector Autoregression Incorporates CCABY and RI

Model	Horizon 12 mnths	24 mnths	36 mnths	48 mnths
1. Vector Autogression Forecasting DM/$.L Combined with ARIMA (AR(2)) Forecasting DM/$.H				
DM/$	.45349	.80209	1.19614	1.62656
2. Vector Autoregression Forecasting DM/$				
DM/$	.22774	.44206	.67141	.94421
3. Random Walk Specification				
DM/$	.27056	.47047	.66813	.72481
4. Vector Autoregression Forecasting DM/$.L Combined with a Random Walk Specification for DM/$.H				
DM/$	.34901	.73975	1.20506	1.71261

Table 32

Root Mean Square Forecast Errors 1/81 - 12/83

OLS Models Incorporates CCABY, RRI and PPP

	Horizon	
Model	12 months	24 months
1. OLS Models Forecasting DM/$.L and DM/$.H		
DM/$	.19831	.14412
2. OLS Model Forecasting DM/$		
DM/$	.15139	.15957

Table 33

Root Mean Square Forecast Errors 1/79 - 12/83

OLS Models Incorporates CCABY, RRI and PPP

Model	Horizon 12 mnths	24 mnths	36 mnths	48 mnths
1. OLS Models Forecasting DM/$.L and DM/$.H				
DM/$	.23249	.14995	.10934	.15245
2. OLS model forecasting DM/$				
DM/$	.18907	.18113	.16079	.13984

A final non-econometric forecasting technique inspired by Figure 22 will be the last attempt in this paper. To recall, Figure 22 compared two DM/$.L time series defined under alternative spans of dates. The frequency decomposition methodology used to calculate these components utilized the Fourier representation introduced in Chapter 2. The Fourier representation is essen-a function of time thus, one can use it to extrapolate into the future. The original DM/$ time series can be converted into a trend and non-trend component. The non-trend component can be extrapolated in complex space, converted back to real space, and be combined with extrapolations of trend to produce forecasts of DM/$. Doing these operations in an iterative fashion as before produced the RMSEs given in Table 34. Unfortunately, these errors are again large and much greater than those generated by a random walk leading us to disregard this methodology.

Table 34

Root Mean Square Forecast Errors

Extrapolation of Fourier Representation and Trend

	Horizon			
	12 mnths	24 mnths	36 mnths	48 mnths
Period 1/81 - 12/83	.72751	.98492		
Period 1/79 - 12/83	.60315	.83953	1.02565	1.10747

5.0 Concluding Remarks

The goal of this paper was to see if the forecasting accuracy of monthly exchange rates could be improved using the tools of frequency domain analysis. Indications are that such may be the case. Granted that only one exchange rate, that between the Deutsche mark and dollar, was examined. Likewise, the time periods over which forecasts were computed represent a relatively small sample, though this period was particularly difficult for forecasters. However, the observed results cannot be dismissed. When the fundamentals are known with absolute certainty, a system of structural models, based on decomposed data, performs at least as well as an economic structural model based on un-decomposed data.

The results of this study favor further research on two fronts. First, to improve the ability to predict high frequency components and secondly, to apply the methodology to other "market-oriented" exchange rates. In fact, there is no reason to limit the methodology to exchange rates. It seems that application of the frequency decomposition approach lends itself to forecasting any economic time series that is both subject to an underlying economic theory yet plagued by short term shocks.

Data Sources

THE DEUTSCHE MARK PER DOLLAR EXCHANGE RATE

Source: International Monetary Fund (IMF), International Financial Statistics Tape.

GERMAN CURRENT ACCOUNT BALANCE

Source: Organization for Economic Development (OECD), Monthly Economic Indicators Tape Series is seasonally adjusted by the author using the "X-11" method.

CONSUMER PRICES

Source: OECD

INTEREST RATES

Source: OECD

Germany: 3 month loans (Frankfort)

U.S.: 3 month Treasury Bills

NOMINAL AND REAL GNP

Source: IMF

MONEY SUPPLY (M1)

Source: IMF

INDEX OF INDUSTRIAL PRODUCTION

Source: OECD

Technical Appendix

The construction of the periodogram begins with the Finite Fourier Transform defined in complex space as:

$$\tilde{X}(2\pi j/T) = \sum_{t=0}^{T-1} X_t e^{-2\pi i j t/T} \qquad j = 0, \ldots, T-1$$

where $i = \sqrt{-1}$. T is chosen to be optimal according to the following two criteria:

1. For computer computational efficiency, its length is a product of small primes and is greater than the number of original data points.

2. T is evenly divisable by the periodicity of the original data. In this way, exact seasonal frequencies can be computed.

In this instance, T is taken to be 288. This number is a product of small primes ($3^2 2^5$) and is divisable by 12 (monthly data). Additionally, because the original DM/$ series has only 132 data points, a T of 288 provides ample padded zeroes which are appropriate when filtering is to be done.

Given the Fourier Transform, the periodogram is easily derived by complex multiplication (i.e. multiplying the transform by its conjugate) and then scaling each ordinate by $1/2\pi N$, where N is the number of original data points (N=132).

The periodogram as described above and as pictured in Figure 1 is an inconsistent estimator of the true spectrum (i.e. the variance does not go to zero as the number of data points increase). Techniques have been developed in frequency domain analysis which trade off some bias for a decrease in variance by "smoothing" the periodogram. The smoothing takes the form of "windows" which take moving averages of the entries of the periodogram about each ordinate. The smoothed entries are related to the original periodogram (I) by the following formula.

$$S(j) = \sum_{-(n-1)}^{n-1} w_k I(j-k)$$

where m is the window width, n=(m+1)/2 and w_k are window weights such that their sum is 1. A common weighing scheme used in spectral analysis, though not the only one[26] is where the w's = 1/m.

Smoothing the periodogram in Figure 1 according to three representative window widths (m=5, m=23, m=41) results in Figure 23. Figure 1 would imply that most of the spectrum's variance (area under the periodogram) is exhausted by the time cycles fall below approximately 32 months. This contrasts sharply with the smoothed periodogram where cycles below 32 months still account for approximately 50 percent of the variance where m=5 and account for much more than 50 percent of the variance for other values of m.

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26 See Chatfield for a discussion of more sophisticated smoothing techniques.

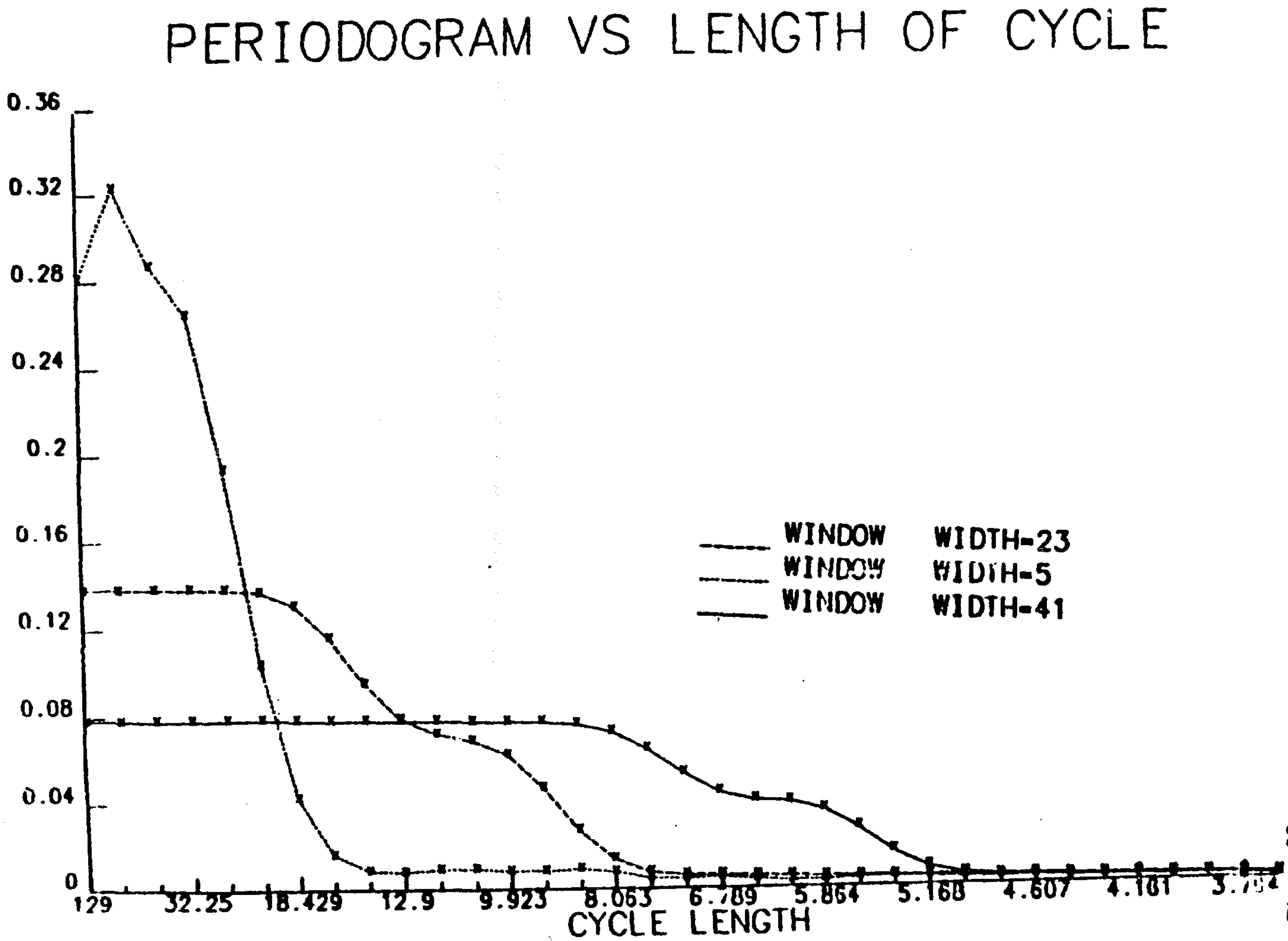
PERIODOGRAM VS LENGTH OF CYCLE
0.36
0.32
0.28
0.24
0.2
0.16
0.12
0.08
0.04
0
WINDOW WIDTH=23
WINDOW WIDTH=5
WINDOW WIDTH=41
129
32.25
18.429
12.9
9.923
8.063
6.789
5.864
5.168
4.607
4.161
CYCLE LENGTH

Figure 23

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