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The Demand for Australian Oil Reserves: Issues in Long-Term Forecasting

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I Introduction

The impending depletion of Australia's oil reserves will have important consequences for the real value of the dollar and its flow-through to the domestic economy.[1] Predictions of the rate of depletion depend, in part, upon econometric models of oil demand and/or estimates of long-run price and income elasticities.

There are no well-known econometric models for aggregate oil demand in Australia and inter-fuel substitution models tend to be too industry and region specific to draw general conclusions. The data requirements and specification problems of building a complete industrial/regional system of energy equations for Australia are immense. Indeed, the effects of the 1970's oil price shocks make even a single equation analysis difficult. Folie and Ulph (1979), faced with data only up to 1977, chose to impose rather than estimate regression coefficients.

This paper is concerned with modeling aggregate oil demand. The single-equation model allows for asymmetric price responses and contains a lagged dependent variable. Recently Bewley and Fiebig (1990) demonstrated that the long-run implications from *all* such dynamic models are quite complex. Long-run parameter estimators have distributions that are not symmetric and have fat tails. Given the limited Monte Carlo evidence available on the magnitude of this problem, this paper also provides additional insight into the general

[1] Recent studies by Naughten, Hogan and Jones (1989) and Hogan and Naughten (1989) have analyzed the implications of Australia's rapidly declining oil reserves. They have argued that Australia's level of self sufficiency in oil is likely to decline from around 96% currently to perhaps as low as 28% by the year 2000. This decline is predicted to have a base case of a 3% decline in the real exchange rate.

econometric issue by bootstrapping the estimates to obtain their approximate small sample distributions.

Given the trending nature of the data, estimation of the oil demand equation could also be put in Engle and Granger's (1987) cointegration framework. This amounts to estimating the preferred model without the lagged dependent variable. The properties of the two approaches are compared.

The model is developed in Section II and the long-run equation is estimated using the transformation suggested in Bewley (1979). This method also provides asymptotic standard errors and these are compared to the small sample bootstrapped distributions in Section III. The cointegrating relationships are developed in Section IV. Conclusions are drawn in Section V.

II The Model

Owing to the high cost of converting from one energy source to another, a large oil price increase would typically be needed to induce switching from oil while minor price increases may encourage a greater degree of conservation. Furthermore, price falls may have a differential effect from price rises of the same magnitude. Because oil is only an intermediate good, a small price fall would not induce new fuel-efficient technology to be retired but small price rises might induce an even greater degree of conservation through improved work practices and accelerated replacement investment.

The basic model used in this analysis is derived from Wolffram's (1971) asymmetric price decomposition model. Wolffram argued symmetric price responses, which assume reversibility, can lead to serious problems in estimating demand and supply functions in general but applications of his transformation are typically associated with models of habit persistence.[2]

Since there have only been two major price shocks, in 1973 and 1979, large price changes can adequately be modeled with dummy variables. Interestingly, the second shock effect was insignificant and so is omitted from the exposition for clarity. The model, in a partial stock adjustment (PAM) framework, is given by

$$Q_t = \alpha_0 + \alpha_1 PR1_t + \alpha_2 PR2_t + \alpha_3 PF1_t + \alpha_4 PF2_t + \alpha_5 Y_t \\ \ldots + \alpha_6 D_t + \alpha_7 Q_{t-1} + u_t \tag{1}$$

where Q is the log per capita quantity, Y is log per capita GDP, P is the log oil price relative to the GDP deflator, D is a dummy variable such that D = 1 after 1973 and D = 0 otherwise, u is a white noise disturbance term,

$$PR_t = \sum_{i=1}^{t} \delta_i (P_i - P_{i-1})$$

$$\delta_i = 1, \text{ if } P_i > P_{i-1}$$
$$0, \text{ otherwise}$$

and

$$PF_t = P_t - PR_t$$

$PR1_t = PR_t(1-D_t)$; $PR2_t = PR_tD_t$; $PF1_t = PF_t(1-D_t)$; and $PF2_t = PF_tD_t$. Thus, PR is the cumulative sum of price rises and PF is the cumulative sum of price

[2] See Young (1982, 1983) for applications to discontinuous habit persistence models of coffee and cigarette demand.

falls. The price data are plotted in Figure 1.

Estimates of α_i ($i = 0,\ldots,6$) produce short-run elasticities while

$$\beta_i = \alpha_i/(1-\alpha_7), \qquad i = 0,\ldots,6 \tag{2}$$

are long-run responses and

$$\phi = \alpha_7/(1-\alpha_7) \tag{3}$$

is the mean lag. Consistent estimates of (2) and (3) can be derived from the OLS estimates of equation (1) or directly, using the transformation suggested in Bewley (1979), hereafter the BT estimator, by two stage least squares (2SLS) applied to[3]

$$\begin{aligned} Q_t = \beta_0 + \beta_1 PR1_t + \beta_2 PR2_t + \beta_3 PF1_t + \beta_4 PF2_t + \beta_5 Y_t \\ \ldots + \beta_6 D_t + \beta_7 \Delta Q_t + v_t \end{aligned} \tag{4}$$

where $\phi = -\beta_7$.

Although the relationship between derived long-run elasticities and those from equation (4) is exact, the use of 2SLS on the exactly identified equation (4) highlights a general problem of analyzing long-run responses. Bewley and Fiebig (1990) used Monte Carlo methods to show that the distribution of $\hat{\beta}_i$ can be heavily skewed and the non-existence of moments can yield outliers with a much higher frequency than from normal or t-distributions.

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[3] See Hylleberg and Mizon (1989) for a comparison of the BT with other estimators.

Table 1: Symmetric Price Models

Variable	Short-Run Equations (1)	(2)	(3)	Long-Run Equations (4)	(5)	(6)
Constant		0.183 (0.41)	0.745 (0.99)		1.965 (0.37)	6.336 (0.97)
P	-0.050	-0.041 (3.94)	-0.133 (1.30)	-0.330	-0.443 (2.10)	-1.134 (1.48)
P.D			0.083 (0.80)			0.70[illegible] (0.88)
Y	0.150	0.070 (0.95)	0.046 (0.58)	1.000	0.752 (1.35)	0.394 (0.65)
D			-0.118 (0.64)			-1.005 (0.69)
Q(t-1) or ΔQ	0.850	0.907 (20.01)	0.882 (16.69)	-5.667	-9.732 (1.86)	-7.503 (1.96)
DW		2.166	2.364			

Note: Absolute asymptotic t-ratios are given in parentheses.

Since distributional assumptions are crucial in testing hypotheses about the asymmetry of the price response and, indeed, for providing confidence intervals for the long-run responses, the empirical distributions are bootstrapped in the next section.[4] In order to shed further light on the extent of these distributional problems in estimating long-run coefficients, the conventional method is followed in this section to provide a basis for comparison.

[4] Note, however, unlike Marquez and McNeilly (1988) who bootstrap the long-run coefficients using the derived method, we do not only compute means and standard errors of these distributions since the underlying parameters do not exist in finite samples and do not reveal the degree of skewness and kurtosis present.

The imposed estimates of Folie and Ulph (1979) are presented in column (1) of Table 1 and an estimated version of it, using the full data set, is given in column (2). This model is augmented with an intercept and slope dummy on the price variable in column (3) to allow for the first oil shock.

While Folie and Ulph's imposed parameter values are reasonably close to the OLS estimates in column (2), the size and significance of the lagged dependent variable coefficient causes some concern. On the basis of a Dickey-Fuller (1979) test, a value of unity cannot be rejected.[5] This implies that the *growth* in demand is explained by the *level* of price and GDP. Under such circumstances, there is no equilibrium solution relating demand and price. Furthermore, an equation relating changes to levels assumes permanent growth in the oil demand for constant levels of price and GDP.

The inclusion of a structural break in price at 1973 does not rectify the situation. Indeed, the results given in column (3) demonstrate that the only significant variable is the lagged dependent variable. However, when the coefficients on price are allowed to have an asymmetric effect, as in column (1) of Table 2, several coefficients are significantly different from zero using the asymptotic t-ratios and, importantly, the coefficient on the lagged dependent variable falls from around 0.9 to 0.5. A Dickey-Fuller test implies that a value of unity on the lagged dependent variable coefficient can easily be rejected which in turn implies that an equilibrium relationship between the levels of demand, price, and GDP exists.

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[5] Dickey-Fuller tests specifically allow for the distributional problems discussed earlier.

Table 2: Asymmetric Price Models

Variable	Short-Run Equations (1)	(2)	(3)	Long-Run Equations (4)	(5)	(6)
PR1	-0.167 (1.44)	-0.140 (4.16)	-0.148 (4.41)	-0.321 (1.33)	-0.308 (4.56)	-0.390 (9.85)
PR2	-0.155 (4.25)	-0.140 (4.16)	-0.148 (4.41)	-0.298 (4.79)	-0.308 (4.56)	-0.390 (9.85)
PF1	-0.335 (1.34)	-0.402 (1.81)	-0.148 (4.41)	-0.644 (1.56)	-0.883 (2.41)	-0.390 (9.85)
PF2	0.043 (1.17)			0.082 (1.26)		
Y	0.565 (2.28)	0.367 (2.22)	0.500 (4.16)	1.086 (2.25)	0.806 (2.04)	1.320 (11.44)
D	0.353 (2.57)	0.347 (2.89)		0.678 (4.29)	0.764 (5.74)	0.611 (6.40)
Constant	-1.315 (0.61)	-0.006 (0.01)	-1.727 (2.92)	-2.526 (0.59)	-0.014 (0.01)	-4.559 (4.28)
Q(t-1) or ΔQ	0.480 (3.86)	0.545 (5.29)	0.621 (7.79)	-0.922 (2.01)	-1.196 (2.41)	-1.639 (2.95)
DW	2.231	2.166	2.058			

Note: Absolute asymptotic t-ratios are given in parentheses.

Given the number of observations in each regime, and the number of price changes in a given direction within each regime, the use of four price coefficients might be deemed somewhat excessive. If the price rise effect is assumed to have been unaffected by the price shock, but that the post-shock price fall effect is zero owing to a new awareness of conservation and the recent introduction of relatively newer fuel-efficient technology, $\alpha_1 = \alpha_2$, and $\alpha_4 = 0$. A test of this hypothesis produced an observed value of the approximate F-test equal to 0.8 which can be compared to a 5% critical value of $F(2,19) = 3.52$.[6] The restricted estimates are presented in column (2) of

[6] Because of the distributional problems, a Monte Carlo test procedure was

Table 2, hereafter, the preferred model. The BT estimates of equation (4) and the restricted version are also presented in Table 2.

The short-run estimates suggest that the price rise coefficient is well-determined but that the price-fall coefficient is only just significant at the 5% level with a one sided test. Indeed, an asymptotic t-test failed to reject equality of these two elasticities with a value of 1.15. Columns (3) and (6) of Table 2 show the estimates for this restricted model.[7]

The three sets of long-run coefficients presented in columns (4), (5), and (6) display a wide range of elasticities for key variables. In particular, the GDP elasticity varies from 0.81 to 1.32 and that on PFI from -0.39 to -0.88. While these coefficients are in broad agreement with Folie and Ulph's long-run elasticities, the estimates of the speed of adjustment conflict. The mean lag coefficients ($-\hat{\beta}_7$) vary between 0.9 years and 1.6 years and substantially differ from Folie and Ulph's imposed value of 5.7 years. It is also worth noting that the asymptotic t-ratios rise dramatically when $\alpha_1 = \alpha_3$ is also imposed but it is shown in the next section that this model fails an important diagnostic test.

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adopted on the F-ratio using the method discussed in Bewley and Theil (1987). A prob-value of 0.574 was found, confirming the conclusions of the approximate F-test.

[7] Since this sequence of hypotheses was not specified in advance of the testing procedure, the model in column (2) of Table 2 is retained as the preferred model to avoid further pre-testing bias. See also Section IV.

III Bootstrapped Distributions

ll of the tests of significance, with the exception of the Monte-Carlo -test, have only asymptotic justification. The presence of the lagged ependent variable in the preferred model

$$Q_t = \alpha_0 + \alpha_1 PR_t + \alpha_3 PFI_t + \alpha_5 Y_t + \alpha_6 D_t + \alpha_7 Q_{t-1} + u_t \qquad (5)$$

roduces biased but consistent OLS estimates that are not t-distributed; the stimates are, however, asymptotically normal.

the case of the long-run estimates derived from the BT,

$$Q_t = \beta_0 + \beta_1 PR_t + \beta_3 PFI_t + \beta_5 Y_t + \beta_6 D_t + \beta_7 \Delta Q_t + v_t \qquad (6)$$

e coefficients are consistent and asymptotically normal but the small sample roperties are such that the population mean and variance of the distributions o not exist. The Monte Carlo evidence in Bewley and Fiebig (1990) only onsidered samples of size 40 but concluded that incidence of outliers in both quilibrium and mean responses increases with autocorrelation in the egressors and that bias increases with the size of the lagged dependent ariable coefficient.

iven the particular importance of providing reliable estimates of price and come elasticities for long-run forecasting of demand, and because of limited vidence on the general econometric nature of the problem, bootstrapped istributions are generated.

Table 3: Bootstrapped Distributions

	Coefficients					
	β_0	β_1	β_3	β_5	β_6	β_7
Bewley Transformation						
2SLS estimate	-0.014	-0.308	-0.883	0.806	0.764	-1.196
2SLS s.e.	3.506	0.068	0.366	0.394	0.133	0.497
Fixed Regressors						
Mean bias	0.026	0.082	-0.056	-0.030	0.077	0.404
s.e.(stand.)	0.905	0.922	0.890	0.903	0.874	0.785
Skewness	-0.190	-0.244	0.186	0.195	-0.197	-1.107
Kurtosis	3.241	3.161	3.294	3.247	3.359	5.820
Jarque-Bera	84.8	110.1	93.7	89.1	118.3	5355.5
Lower 2.5% size	1.81	1.80	1.21	1.10	1.46	0.99
Upper 2.5% size	1.13	1.35	1.68	1.78	1.24	0.20
I(1) GDP						
Mean bias	0.164	0.285	-0.143	-0.165	0.062	0.542
s.e.(stand.)	0.875	1.250	0.588	0.870	0.664	0.876
Skewness	-0.608	-0.723	0.776	0.623	-0.234	-1.400
Kurtosis	5.710	6.207	7.291	5.721	4.365	7.443
Jarque-Bera	3675.6	5156.6	8673.5	3731.1	867.2	11490.8
Lower 2.5% size	1.67	4.30	0.12	1.31	0.38	1.70
Upper 2.5% size	1.33	7.29	0.48	1.65	0.33	1.63
Cointegrating Equation						
OLS estimate	3.252	-0.240	-1.266	0.431	0.921	
OLS s.e.	2.197	0.042	0.224	0.246	0.079	
Fixed Regressors						
Mean	-0.824	-0.566	0.818	0.825	-0.814	
s.e.	0.994	1.105	0.967	0.993	1.032	
Skewness	-0.053	-0.111	0.018	0.053	0.057	
Kurtosis	2.895	2.854	2.874	2.893	2.900	
Jarque-Bera	9.3	29.4	7.1	9.4	9.6	
Lower 2.5% size	13.09	10.77	0.16	0.19	13.26	
Upper 2.5% size	0.19	0.75	11.87	13.12	0.39	
I(1) GDP						
Mean	-0.061	0.772	0.556	0.071	-1.532	
s.e.	1.002	1.402	0.713	0.994	1.065	
Skewness	-0.141	0.071	-0.061	0.145	-0.062	
Kurtosis	3.733	3.153	3.989	3.740	3.289	
Jarque-Bera	257.0	18.2	414.0	263.1	40.2	
Lower 2.5% size	3.16	2.33	0.15	2.06	33.48	
Upper 2.5% size	2.21	19.47	2.34	3.13	0.11	

Note: The distributions are standardized by the 2SLS estimates in the upper half of the table and the OLS estimates in the lower. That is, the mean and s.e.(stand.) are with respect to the relevant standardized distributions.

The dynamic version of the model, given by equation (5) was estimated and the OLS estimates of the parameters and residuals were used as the basis for the experiment. The bootstrapping was performed by sampling with replacement from the $\hat{u}$ vector using a uniform random number generator and creating synthetic dependent variables as in a dynamic stochastic simulation with PR, PF1, Y, and D assumed to fixed in repeated trials. Equation (6) was estimated on each of 10,000 replications and each coefficient estimate from each replication was standardized with the BT coefficient estimate and asymptotic standard error.

Because Bewley and Fiebig emphasized the role of autocorrelated regressors, a second set of 10,000 replications was conducted with Y also being bootstrapped from a random walk model with drift. Owing to the large change in price and the OPEC agreement, it was decided to hold PR and PF1 fixed over replications as no simple time series model could reasonably be expected to adequately model the data. Thus, Y, which is I(1) in Granger's (1981) terminology because of the differencing operator implied in a random walk, is the only generated regressor in the second experiment.[8]

Since none of the distributions have moments, the computation and interpretation of sample moments should be treated with caution. Nevertheless, certain characteristics of the coefficient distributions are presented in Table 3.

The mean bias under the fixed regressor assumption is less than 0.1 asymptotic standard errors, except for that associated with the lagged dependent variable coefficient which is still fairly small. From Bewley and Fiebig, this result

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8 Of course, the lagged dependent variable is generated in both experiments. Furthermore, from Stock (1987), the inclusion of an I(1) regressor gives rise to even asymptotic non-normality.

is not unexpected as the coefficient on the lagged dependent variable is only around 0.5 and highly significantly different from unity. The bias in the I(1) regressor experiment is a little larger.

From the row marked s.e.(stand.) it can be noted that the sample standard error is of the order of 90% of the asymptotic value but there is far more disparity in the I(1) regressor experiment. The Jarque-Bera (1987) test for normality, which should be compared to a critical value of 5.99 at the 5% level, and the value of kurtosis, which is 3.00 for a normal distribution, highlight the nature of the problem. If it can be assumed that the regressors are truly fixed in repeated trials, the empirical distributions are somewhat distorted but not sufficiently to cause too much of a problem to applied workers. The size statistics suggest a reasonable degree of symmetry and a slight over-reporting of the widths of confidence intervals. On the other hand, integrated data cause skewness of an indeterminate sign and a low probability of particularly large coefficient estimates. The possibility of producing extreme values raises the question of whether or not the base values given in Table 2 are representative or not. It should be emphasized that this problem is not caused by the estimation procedure; an identical result would have been found if the long-run estimates had been derived from the dynamic equation (5) estimated by OLS.

The presence of integrated data implies that the recently introduced cointegration framework of Engle and Granger (1987) could be exploited in this context. In essence, if Y is I(1) and the other regressors are exogenous (deterministic time trends), Q must also be I(1), about a deterministic trend. The simplest variant of testing for cointegration is to perform the regression without the lagged dependent variable and test the residuals for stationarity, that is being I(0).[9] Engle and Granger recommend a Dickey-Fuller (DF) test with a critical value of 3.17. The cointegrating equivalents of columns (4), (5) and (6) in Table 2 are produced in Table 4.

Table 4: Cointegrating Equations

Variable	(1)	(2)	(3)
PR1	-0.135	-0.240	-0.381
	(0.89)	(5.75)	(13.44)
PR2	-0.242	-0.240	-0.381
	(6.42)	(5.75)	(13.44)
PF1	-0.891	-1.266	-0.381
	(3.34)	(5.67)	(13.44)
PF2	0.096		
	(2.18)		
Y	0.799	0.431	1.375
	(2.55)	(1.75)	(16.80)
D	0.792	0.921	0.685
	(7.93)	(11.67)	(10.32)
Constant	-0.017	3.252	-5.146
	(0.01)	(1.48)	(6.84)
DW	1.490	1.525	0.754
DF	3.959	4.229	2.091

Note: Absolute asymptotic t-ratios are given in parentheses.

[9] Multivariate versions can be found in Johansen (1988) and Bewley, Fisher and Parry (1988). The presence of complex deterministic time trends, such as those present, cause additional problems and are not pursued here. Banerjee, Dolado, Hendry, and Smith (1986) consider a dynamic version of a cointegrating equation which is implicitly equivalent to that presented in the BT with the ΔQ variable excluded *after estimation*. See also Bewley and Elliott (1988) for a discussion of this variant.

It is of some importance to note that the DF test for the most restricted model fails to reject the presence of a unit root in the residuals. This implies that an equilibrium solution *does not exist* and the PAM version should not be pursued. To some extent, the higher value of the lagged dependent variable coefficient compensates for the lack of stationarity in the residuals.

In the following section, the conventional method of specification is compared to that of cointegration for the purpose of assessing the implicit bias induced by omitting ΔQ from the BT.[10] Since an I(1) regressor would generate an I(1) regressand, ΔQ is necessarily I(0). Given that an I(0) is likely to minimally correlated with any I(1) variable in a reasonably sized sample, the bias in the cointegrating equation from omitted (orthogonal) regressors is also relatively small. In Stock's terminology, the estimates in the CE are 'super-consistent' as the estimate rapidly approaches its probability limit.[11]

IV Cointegrating Equations

If the coefficients in the cointegrating equation (CE)

$$Q_t = \beta_0 + \beta_1 PR_t + \beta_3 PF1_t + \beta_5 Y_t + \beta_6 D_t + w_t \tag{7}$$

were to be bootstrapped assuming that both the model specification was correct and the regressors were fixed, the distributions should be symmetric and

[10] This assumes that the PAM is the correct specification. Cointegrating equations have the advantage that any number of I(0) variables can be omitted.

[11] Stock also discusses the an error correction method of estimating the cointegrating vector.

possibly approximately t-distributed. Howevei on-normality in $\hat{w}_t$ and/or autocorrelation due to omitted variables coul cause significant departures from the typical OLS situation.

For the purpose of the following experiments, it is assumed that equation (5) is still the true model and the specification (8) is known to be an approximation. For the purpose of long-run forecasting, where ΔQ becomes relatively unimportant in equilibrium, it is reasonable to question whether there are any gains in estimating the dynamic model. Furthermore, the distributional problems of the BT discussed above suggests that the simplicity of the static equation has positive features.

The bootstrapping experiments were repeated for equation (7) and the results are presented in the lower half of Table 3. Note that the distributions are standardized by the estimate and standard error from the cointegrating equation in column (2) of Table 4.

In each case, the asymptotic standard error reported in the base regression is approximately 62% lower for the cointegrating equation. There is no consistent pattern for the difference in the two sets of coefficients. For the purposes of policy, however, it matters whether the long-run GDP elasticity is 0.431, as in the CE, or 0.806, as in the BT. Even the difference between -0.240 and -0.308 for the coefficients on PR causes a little concern.

The coefficients in the CE, fixed regressor case are much better approximated by a normal distribution with no evidence of fat-tails. However, the lateral shift in the distribution is sufficient to cause vary large size errors on one side of the distribution. The I(1) generated GDP results, however, again reveal important departures from non-normality but none of the kurtosis measures is greater than four, compared to nothing less than four for the BT. The empirical size estimates are mixed with some coefficients being well-approximated by the asymptotic normal distribution and in three of the five cases, the asymptotic standard error is very close to the bootstrapped standard error.

There would appear to be advantages to both the BT and CE estimators. In Figure 2, dynamic simulations of both models reveal that both estimators produced acceptable results from a long-run forecasting perspective. Some residual autocorrelation is apparent with the CE estimator but both cope well with the dramatic slowdown in the growth of oil consumption. On the other hand, distributional aspects, presented in Figure 3, reveal some interesting differences.

The normal distribution curves in Figure 3 represent the asymptotic normality of the BT estimator while BT and CE refer to the bootstrapped small sample distributions based on a stochastic GDP variable. In each case the bias in the CE is greater than, and in the same direction as, the bias in the BT. This suggests that a combined estimator, along the lines suggested in Sawa (1973) might correct for the bias in small samples.

The disparity of the estimates from the BT is quite apparent. In the 10,000 replications of the PR coefficient, one estimate had an asymptotic t-ratio of -13.6 and another was equal to -9.5 before the the distribution started to build from -6.8. The major problem from a bootstrapping perspective is whether the base estimate is, indeed, an outlier from the true distribution.

V Conclusions

The results presented here suggest that whenever equations are estimated with lagged dependent variables and trending data, serious consideration should be given to the distribution of the estimates before any policy conclusions or long-term forecasts are generated. This is true whether or not simple OLS is applied to the dynamic equation or direct estimators are employed.

The implication of the bootstrapping performed on the demand for oil equation suggests that the elasticity for a price rise is -0.31 with a 95% confidence interval of [-0.46, -0.14] and zero for a price fall. The GDP elasticity is 0.81 with a 95% interval of [0.13, 1.57]. If the cointegration bias could be reduced, however, there would appear to be some scope for reducing the width of the confidence interval. In particular, outliers are far less prevalent in the CE framework.

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Figure 1 : Log Relative Price

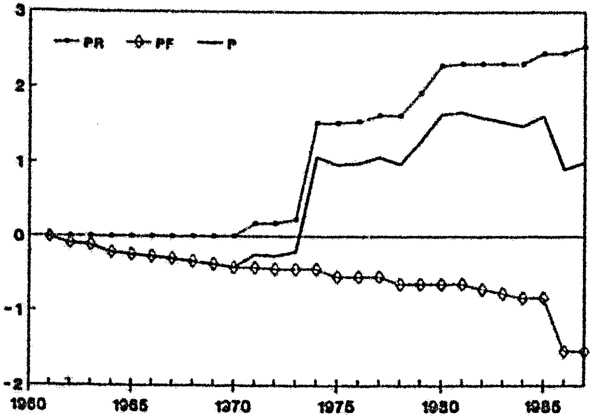

Figure 2 : Dynamic Simulations

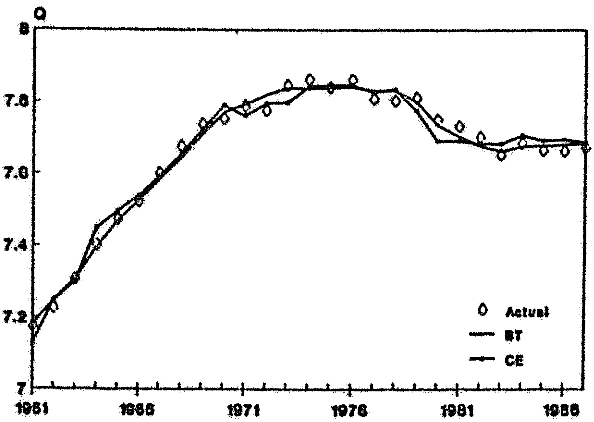

Figure 3 : Bootstrapped Distributions