A Reassessment of Long-Run Elasticities of Japanese Import Demand

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Unlike the findings of Mah (1994) [Mah, J.S. (1994) Japanese Import Demand Behaviour: The Cointegration Approach. Journal of Policy Modeling 16:291–298] who, based on the Engle–Granger test of cointegration, fails to find evidence of a long-run relationship among variables associated with an import demand function for Japan, in this analysis the Johansen's MLE multivariate cointegration procedure reveals that such variables seem to be cointegrated, and thus share a long-run equilibrium relationship. Furthermore, the recently prescribed Stock and Watson (1993) Dynamic OLS (DOLS) procedure, which, apart from being superior to a number of alternative estimators, is robust to small sample and simultaneity bias as well as being able to accommodate higher orders of integration, is employed to derive long-run import price and income elasticity estimates. Results reveal that both price and income variables do affect import demand significantly, and more interestingly, contrary to previous findings, play an important role in explaining Japanese import demand, at least over the long run. This finding is quite intuitive in that, although nonmarket forces did play a role in destabilizing Japanese import demand, this was most likely a short-run phenomena. Over the long term, however, such theoretically postulated economic influences outweighed short-run disturbances in achieving an equilibrium relationship. Finally, the innovative analytical techniques used in this study have a far-reaching potential for use in future applied research in a variety of fields. © 2000 Society for Policy Modeling. Published by Elsevier Science Inc.

Key Words: Import; Elasticities; Long-run; Dynamic.
1. INTRODUCTION

Import demand behaviour has been an area of topical concern in the international and macroeconomic literature for several years [see, *inter alia*, Arize and Affi, 1987; Kohli, 1991; Wilkinson, 1992; Clarida, 1994; Marquez, 1994; to cite recent contributions]. Its importance stems from the fundamental factor of how sensitive import demand is to price and income changes, or otherwise price and income elasticities of import demand. In a recent article on the behavior of Japanese import demand, Mah (1994) adopts a cointegration approach to model Japanese import demand behavior. To account for a structural break in related variables, Mah (1994) employs a Perron-type detrending method on checking the univariate properties of variables, which are then shown to satisfy nonstationarity in levels but stationary in first differences. As these variables fulfil the prerequisite for cointegration (as least for the Engle–Granger testing procedure), the detrended variables were then tested for cointegration by the common Engle–Granger two-step residual-based approach, and were shown to be noncointegrated. Upon this finding Mah (1994) concludes that standard economic variables such as relative prices and income do not seem to play any significantly important role in determining Japanese import demand behavior. Consequently, previous (historical) findings of import demand based on standard economic theory, at least for Japan, are invalidated.

The purpose of this article is to draw upon some latest advances in econometric time-series modeling and use these techniques as a tool to re-assess estimates of the Japanese import demand function. In particular, rather than the residual-based approach of Engle and Granger (1987) as used by Mah (1994), we adopt a more robust test for multivariate cointegration provided by Johansen (1988, 1991) (hereafter referred to as ‘JJ’). As well as being able to directly test for multiple cointegrating relationships among a set of variables, the JJ procedure is also robust to both $I(0)$ and $J(1)$ variables, including trended data. This method has been shown to be far superior to the Engle–Granger approach in several ways (see Gonzalo, 1994), in terms of capturing long-run relationships previously unfounded by the Engle–Granger procedure.¹

¹Although applications of the JJ procedure have been quite popular in a multivariate context, results arrived from JJ statistics in bivariate studies have also been shown to be more robust than those arrived adopting the Engle–Granger approach (see, for example, Masih and Masih, 1994, 1995b).
Assuming a simple linear relationship, to estimate elasticities of a simple long-run import demand model, we then employ a procedure just recently prescribed by Stock and Watson (1993) known as Dynamic OLS (DOLS). Specifically, the DOLS procedure allows for cointegrated variables that are integrated of mixed $I(0)$ and $I(1)$ orders (in this sense, a higher order of integration), as well as tackling the problem of simultaneity among the regressors. Furthermore, based on Monte Carlo evidence, Stock and Watson show that DOLS is more favorable, particularly in small samples, compared to a number of alternative estimators of long-run parameters, including those proposed by Engle and Granger (1987), Johansen (1988), and Phillips and Hansen (1990).

The paper is organized in the following manner: Section 2 contains the basic theoretically postulated import demand function analyzed and a brief and intuitive account of the statistical methodology employed; the application of these methods and a discussion of the results appear in Section 3. Some policy and methodological implications for future research, as well as conclusions of the study, are made in Section 4.

2. MODEL AND ECONOMETRIC METHODOLOGY

2A. Theoretical Model and Data

The model used in this analysis is dictated by the typical formulation postulated by economic theory for the “elasticity approach” in aggregate import demand functions, which, expressed in its double-log form is given in Eq. (1) by:

$$\log M_t = \alpha + \beta (\log P_t) + \delta (\log Y_t) + \nu_t$$ (1)

where $M_t$ is quantity (tons) of imports, $P_t$ is the relative price of imports defined as the ratio of the import price index to the domestic wholesale price index, and $Y_t$ represents real income or a representative for an economic activity variable (gross national product), $\nu_t$ is an error term assumed to be white noise and normally and identically distributed. This formulation is typical of several studies of import demand in the literature (see Thursby and Thursby, 1984), Arize and Afifi, 1987). Estimation of Equation 1 with appropriate data will provide approximate long-run ($\beta$) and income ($\delta$) elasticities. Augmenting lagged terms will add structure to the dynamics.

All data described above is the same as used in Mah (1994), and was obtained from various issues of the International Financial
Statistics, published by the IMF. The sample period (1974:1 to 1989:2) and frequency (half-yearly or bi-annual) was also dictated by the data-set employed in Mah’s (1994) empirical analysis.

2B. Econometric Methodology

Like all other models that utilize time series data, it is important to recognize that unless the analytical tools used account for the dynamics of the relationship within a temporal framework, the complexity of the interrelationships involved may not be fully captured. Hence, there is a requirement for employing the latest advances in dynamic time-series modeling within a temporal “causal” framework that allows for the coexistence of both short- and long-run forces that drive the often ignored deviating and cyclical influences so inherently interactive with these aggregate variables over such a time horizon.2 The following sequential procedures will be adopted as part of our methodology:

Tests for univariate integration: to verify to what degree these series share univariate integration properties, we perform both unit root tests and mean stationary tests. Although this is a necessary condition prior to tests for cointegration, it should be acknowledged that the JJ procedure also allows series that are integrated of mixed orders up to \( I(1) \), i.e., both data that are stationary in levels \([I(0)]\) and stationary in its first differences \([I(1)]\) can be accommodated for tests of cointegration in the JJ procedure.

The DF type tests and the nonparametric Phillips–Perron (PP) type tests developed by Phillips (1987), Phillips and Perron (1988), and Perron (1988) are convenient testing procedures, both based on the null hypothesis that a unit root exists in the autoregressive representation of the time series. DF tests attempt to account for temporally dependent and heterogeneously distributed errors by including lagged sequences of first differences of the variable in its set of regressors. The PP tests try to account for dependent and IID processes through adopting a nonparametric adjustment,

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2 For an application of cointegration techniques in testing Granger causal hypotheses in a bivariate framework, see Masih and Masih (1996a). Also, see Masih and Masih (1995a) and Masih and Masih (1996b) for an investigation of the dynamics of economic activity within a multivariate cointegrated system.
hence eliminating any nuisance parameters. Recently, these tests have been shown (see Campbell and Perron, 1991 and DeJong et al., 1992) to suffer from lack of power, as they often tend to accept the null of a unit root too frequently against a stationary alternative. Moreover, the Phillips–Perron statistics have been shown to perform poorly over small samples.

These studies have also implied that it would be worthwhile to conduct tests of the null hypothesis of mean stationarity to determine whether variables are stationary or integrated. Mean stationarity tests are performed with a test recently proposed by Kwiatkowski et al. (1992). This test (abbreviated as KPSS) is based on the statistic:

$$
\eta(u) = \left(\frac{1}{T^2}\right) \sum_{i=1}^{T} S_i / \sigma_i^2,
$$

where $S_i = \sum_{t=1}^{i} v_t$, $t = 1, \ldots, T$, with $v_t$ being the residual term from a regression of $y_t$ on a intercept, and $\sigma_i^2$ is a consistent long-run variance estimate of $y_t$ and $T$ represents the sample size. Kwiatkowski et al. (1992) show that the statistic $\eta(u)$ has a nonstandard distribution, and critical values have been provided therein. If the calculated value of $\eta(u)$ is large, then the null of stationarity for the KPSS test is rejected. Because we entertain both the Phillips–Perron tests and the KPSS test in this exercise, we consider a variable to contain a unit root or be unit root nonstationary if the null hypothesis of nonstationarity is not rejected by the PP tests but the null hypothesis that the variable is mean stationary is rejected by the KPSS test.4

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1A treatment of the sequential steps involved in applying the PP tests appear in Taylor (1993). Basically, Perron (1988) shows that if a time series is trend stationary and if no account is made of this in implementing the test procedure, this may lead to high probabilities of making a type II error. While the precise form of the assumptions (with regard to distributional properties of error terms, etc.) is contained in Perron (1988), the following sequence is suggested with a detailed list of test equations available upon request from authors: (i) apply $Z(ta^*)$, $Z(F_2)$ and $Z(F_3)$, respectively, and if the unit root hypothesis is rejected, we should halt the procedure here; (ii) if the unit root hypothesis cannot be rejected, then the greatest power may be obtained by estimating equations associated with the Phillips-Perron transformations of the relevant $t$- and $F$-statistics, $Z(ta^*)$ and $Z(F_1)$. Due to the fact that these two tests are not invariant to the constant term, this is only valid if the drift term ($\mu^*$) used in test equations applied in (i) was zero. In this respect, these two tests should only be used if $Z(F_2)$ cannot be rejected.

4This guideline in considering the stochastic properties of univariate time series is also used in an empirical analysis containing error-correction modeling by Mehra (1994).
Tests for multivariate cointegration: the cointegration technique pioneered by Engle and Granger (1987), Hendry (1986), and Granger (1986) made a significant contribution towards modeling stationary relationships while preserving the long-run relationship lost through differencing. Two or more variables are said to be cointegrated, i.e., they exhibit long-run equilibrium relationship(s), if they share common trend(s). According to this technique, if two variables are cointegrated, the finding of no causality in either direction is also ruled out. As long as the two variables have a common trend, causality (in the Granger sense, not in the structural sense), must exist in at least one direction either unidirectional or bidirectional (Granger, 1986, 1988). Evidence of cointegration among variables also rules out the possibility of the estimated relationship being “spurious.” Cointegration among variables has also been used in analyses involving model stability (see Masih, 1996).

In this analysis we employ the Johansen’s (JJ) procedure of testing for the presence of multiple cointegrating vectors. Unlike its predecessor, the JJ procedure poses several advantages over the popular residual-based Engle–Granger two-step approach in testing for cointegration. Specifically, they may be summarized as follows: (1) the JJ procedure does not, a priori, assume the existence of at most a single cointegrating vector; rather, it explicitly tests for the number of cointegrating relationships; (2) unlike the Engle–Granger procedure, which is sensitive to the choice of the dependent variable in the cointegrating regression, the JJ procedure assumes all variables to be endogenous; (3) related to (2), when it comes to extracting the residual from the cointegrating vector, the JJ procedure avoids the arbitrary choice of the dependent variable as in the Engle–Granger approach, and is insensitive to the variable being normalized; (4) the JJ procedure is established on a unified framework for estimating and testing cointegrating relations within the VECM formulation; (5) JJ provide the appropriate statistics and the point distributions to test hypothesis for the number of cointegrating vectors and tests of restrictions upon the coefficients of the vectors.

It is demonstrated in Johansen (1991a) that the procedure involves the identification of rank of the $m$ by $m$ matrix $\Pi$ in the specification given in Eq. (2):

$$\Delta X_t = \delta + \sum_{j=1}^{k-1} \Gamma_j \Delta X_{t-j} + \Pi X_{t-k} + \epsilon_t,$$  \hspace{1cm} (2)

where, $X_t$ is a column vector of the $m$ variables, $\Gamma$ and $\Pi$ represent
coefficient matrices, \( \Delta \) is a difference operator, \( k \) denotes the lag length, and \( \delta \) is a constant. If \( \Pi \) has zero rank, no stationary linear combination can be identified. In other words, the variables in \( X_t \) are noncointegrated. If the rank \( r \) of \( \Pi \) is greater than zero, however, there will exist \( r \) possible stationary linear combinations, and \( \Pi \) may be decomposed into two matrices \( \alpha \) and \( \beta \), (each \( m \times r \)) such that \( \Pi = \alpha \beta' \). In this representation \( \beta \) contains the coefficients of the \( r \) distinct cointegrating vectors that render \( \beta'X_t \) stationary, even though \( X_t \) is itself nonstationary, and \( \alpha \) contains the speed-of-adjustment coefficients for the equation.

There are two tests to determine the number of cointegrating relationships. First, in the trace test, the null hypothesis \( (H_0) \) is that there is at most \( r \) cointegrating relationships, i.e., \( r = 0, 1, 3 \) is tested against a general alternative. An alternative test, the maximum eigenvalue test \( (L) \), is based on the comparison on \( H_1(r-1) \) against the alternative \( H_1(r) \) and is given by:

\[
-2 \ln Q[H_1(r - 1)|H_1(r)] = -N \ln(1 - \lambda_{r+1}).
\]

In this case, the null hypothesis \( (H_0; r = 0) \) is tested against an alternative \( (H_1; r = 1) \) followed by \( (H_0; r = 1) \) against \( (H_1; r = 2) \), and so on. The JJ procedure is implemented using a range of lags with the final lag selection was based on minimising the Akaike’s Final Prediction Error criteria (FPE).

*Estimation of long-run equilibria: Stock–Watson dynamic OLS:* one method of purely extracting the long-run coefficients is by JJ procedure, which is based on an MLE approach. Another more recent and more robust method, (particularly in small samples) proposed by Stock and Watson (1993), which also corrects for possible simultaneity bias among the regressors, involves estimation of long-run equilibria via dynamic OLS (DOLS). Stock and Watson (1993) suggest a parametric approach for estimating long-run equilibria in systems that may involve variables integrated of different orders but still cointegrated. The potential of simultaneity bias and small-sample bias among the regressors is dealt with by the inclusion of lagged and led values of the change in the regressors. The procedure advocated is similar to recent estimators proposed by Phillips and Loretan (1991), Phillips and Hansen.

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5 Detailed discussion of the Johansen–Juselius MLE procedure can be found in Catherton, Hall, and Taylor (1992), and a wide-ranging surveys by and Muscatelli and Hurn (1992).
(1990), Saikkonen (1991), and Park (1992), but much more practically convenient to implement and estimate. Although these are all single-equation methods for estimating cointegrating vectors, they share a common bond through the asymptotic distribution as FIML estimates. In this regard, asymptotically, they are optimal estimators. Their approach differs in the particular manner by which these estimators account for serial correlation among the residuals and whether parametric or nonparametric techniques are used to correct for endogeneity among the regressors. The DOLS procedure is preferred here due to its favourable performance, as well, in small samples.

Model Equation: 1

Stock–Watson (1993) Dynamic OLS (DOLS): \( B = [c, \alpha, \beta]' \), \( X = [1, P, Y] \)

\[ M_t = B'X_t + \sum_{j=-K}^{K} \eta_j \Delta P_{t-j} + \sum_{j=-L}^{L} \lambda_j \Delta Y_{t-j} + \epsilon_t \]

In estimating the long-run parameters of the demand function, we adopt the DOLS procedure, which basically involves regressing any \( I(1) \) variables on other \( I(1) \) variables, any \( I(0) \) variables and leads and lags of the first differences of any \( I(1) \) variables. These estimates will facilitate inferences made for the long-run. Robust standard errors are derived via the procedure recommended by Newey and West (1987).

3. APPLICATION AND DISCUSSION OF RESULTS

3A. Univariate Integration: Tests of the Unit Root Hypothesis

A necessary but not sufficient condition for cointegration is that each of the variables should be integrated of the same order (more than zero) or that both series should contain a deterministic trend (see Granger, 1986). Prior to testing for cointegration, we investigated the integrational properties of each of the variables by applying a battery of unit root testing procedures. Based on augmented Phillips–Perron tests, which are present in Table 1 (Perron, 1988; Phillips and Perron, 1988), we could not find any significant evidence that \( [M, P, Y] \) were not integrated of order one or \( I(1) \). \(^6\)

\(^6\)Using the appropriate notation, a series \( x_t \) is said to be integrated of order \( d \), if it has an invertible ARMA representation after being differenced \( d \) times. For example, a stationary series is indicated by \( I(0) \), whereas a nonstationary series in levels, but stationary in first differences is indicated by \( I(1) \).
Table 1: Kwiatkowski–Phillips–Schmidt–Shin (KPSS) Tests for Mean Stationarity and Phillips-Perron (PP) Tests for Unit Roots

<table>
<thead>
<tr>
<th>Variable</th>
<th>KPSS $\eta(\mu)$</th>
<th>Phillips-Perron</th>
<th>Z($t_a$)</th>
<th>Z($t_a^*$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M_t$</td>
<td>0.814*</td>
<td></td>
<td>-1.490</td>
<td>-1.884 (-5.864)</td>
</tr>
<tr>
<td>$P_t$</td>
<td>0.775*</td>
<td></td>
<td>-1.680</td>
<td>-1.533 (-4.499)</td>
</tr>
<tr>
<td>$Y_t$</td>
<td>0.802*</td>
<td></td>
<td>-0.801</td>
<td>-1.945 (-5.638)</td>
</tr>
</tbody>
</table>

Notes: The KPSS test statistic is associated with a null hypothesis that the variable in question is mean stationary [the 5% critical value for $\eta(\mu)$ is provided in Kwiatkowski et al. (1992, p. 166, Table 1)]. Figures presented in parentheses for PP tests refer to the adjacent test carried out on the variable in first-differenced ($\Delta$) form $Z(t_a)$ is the Phillips-Perron (PP) test allowing for a drift term, whereas $Z(t_a^*)$ is the PP test allowing for a drift and a deterministic trend. The null hypothesis is that the variable under consideration contains a unit root in its autoregressive representation. The 5 percent critical values for a sample size of 25 pertaining to $Z(t_a)$ and $Z(t_a^*)$ are -3.45 and -2.89, respectively.

* Represents significance (rejection of null) at the 5 percent level.

This is indicated by tests of all individual series for each country in level and first difference form. These results are not surprising, given Nelson and Plosser’s (1982) findings that most macroeconomic aggregates are difference stationary processes.

On the other hand, the KPSS test statistic $\eta(\mu)$ that tests the null hypothesis that a particular variable is mean stationary is large for all variables, and further confirm our earlier conclusion that these variables associated with a demand model have a unit root and are clearly nonstationary in levels. However, once we take the first difference of these variables and apply the PP tests, all test values exceed the critical value (in its absolute value). Tests for higher orders of integration were also applied using the procedure outlined by Dickey and Pantula (1987); however, as with several other tests that were applied, these procedures confirmed the finding that $[M_t, P_t, Y_t]$ were difference (as opposed to trend) stationary time series processes. This leads us to the conclusion that all series concerned are stationary in their first differences, while nonstationary in their level form. In other words, we could not find any significant evidence that $[M_t, P_t, Y_t]$ were not integrated of order one or $I(1)$.

3B. Multivariate Cointegration Analysis

Given the common integrational properties of these variables, we then proceeded to test for the presence of cointegration in the
vector \([M_t, P_t, Y_t]\) by using Johansen’s multivariate MLE procedure. Results of JJ LR and trace tests are presented in Table 2. Results for indicate that there exists at most one cointegrating relationship because both the null hypotheses of \(r = 0\) is clearly rejected in favour of \(r = 1\); but \(r \leq 1\) cannot be rejected by the 95 percent critical values. Given that there exists \((n - r)\) common trends within the system, by Stock and Watson (1988), we can conclude that there exists two separate common trends within the trivariate import demand system.

The finding of cointegration is not merely a statistical coincidence. It hold several implications that we can correspond with economic theory. Moreover, the novelty of this technique is that, given an adequate sample period under investigation, economically inferred relationships can be put under test. Although the finding of cointegration should not be taken for granted, the rejection of cointegration should also be thoroughly justified in the light of certain destabilizing forces, structural breaks, and omission of relevant theoretically inferred variables. Cointegration also holds implications of dynamic specification of models in that, regardless of the frequency of the data, a valuable source of information may be ignored through inadequate dynamic modeling (for such an approach involving fractional cointegration, see Masih and Masih, 1995c).

### 3C. Long-Run Elasticities: Stock–Watson DOLS

Stock–Watson DOLS parameter estimates of the long-run parameters with all variables appearing in levels, along with their

<table>
<thead>
<tr>
<th>Vector ([M_t, P_t, Y_t])</th>
<th>Hypotheses</th>
<th>Test statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>(r = 0) (r &gt; 0)</td>
<td>23.790(^a)</td>
<td>33.670(^a)</td>
</tr>
<tr>
<td>(r \leq 1) (r &gt; 1)</td>
<td>9.768</td>
<td>9.879</td>
</tr>
<tr>
<td>(r \leq 2) (r = 3)</td>
<td>0.111</td>
<td>0.111</td>
</tr>
</tbody>
</table>

Notes: \(r\) indicates the number of cointegrating relationships. The optimal lag structure for the VAR was selected by minimizing the Akaike’s FPE criteria. Critical values are sourced from Osterwald–Lenum (1992).

\(^a\) Indicates rejection at the 95 percent critical values.
Table 3: Stock-Watson Dynamic OLS Long-Run Parameter Estimates of Japanese Import Demand

Stock–Watson Dynamic OLS (DOLS): $B = [c, \alpha, \beta]', X = [1, P, Y]$

$$M_t = B'X_t + \sum_{j=1}^{\infty} \eta_j \Delta P_{t-j} + \sum_{j=1}^{\infty} \lambda_j \Delta Y_{t-j} + \zeta_t$$

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimated value (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>4.3918 (1.4090)</td>
</tr>
<tr>
<td>$P_t$</td>
<td>$-1.8917^* (0.65809)$</td>
</tr>
<tr>
<td>$Y_t$</td>
<td>1.2770* (0.12207)</td>
</tr>
<tr>
<td>$\Delta P_t$</td>
<td>$-0.4741^* (1.3909)$</td>
</tr>
<tr>
<td>$\Delta P_{t+1}$</td>
<td>3.5006† (1.5095)</td>
</tr>
<tr>
<td>$\Delta Y_{t-1}$</td>
<td>0.8609* (0.4034)</td>
</tr>
<tr>
<td>$\Delta Y_{t+1}$</td>
<td>0.6996‡ (0.4069)</td>
</tr>
</tbody>
</table>

Summary statistics

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum of squared residuals</td>
<td>0.1458</td>
</tr>
<tr>
<td>$R^2$-Adjusted</td>
<td>0.8382</td>
</tr>
</tbody>
</table>

Notes: Standard errors are derived using procedure prescribed by Newey and West (1987).

*, †, and ‡ indicate significance at the 1, 5, and 10 percent levels.

The results indicate fairly clearly that, even allowing for simultaneity bias, both relative prices and real income significantly influence Japanese import demand. Interestingly, both price and income elasticities as well as being strongly significant and of the a priori expected signs, exceed unity in absolute value. This is more apparent in the case of relative prices than income long-run elasticities. These results tend to further illustrate the elastic response of import demand to changes in prices in particular, and
income. Moreover, quite contrary to the findings of Mah (1994), the model also seems to be associated with a reasonably satisfactory tracking performance.

Acknowledging some of arguments proposed by Mah (1994) as to supporting the findings of noncointegration between these same variables, such as the imposition of an unofficial private barrier that is not quantified by any liberalization measure for Japan, it is important to realize that such a finding (of noncointegration) is difficult to justify in light of a “long-run analysis” undertaken over such a long time horizon. In other words, while such nonmarket forces may lead to disequilibrium, this will only be a short-term phenomena, with such traditional market-force variables determining the fundamental characteristic of import demand behavior over the long-run. Furthermore, our results would seem to be substantiated in the light of the correspondence between the technique adopted and the empirical proposition postulated by fundamental economic theory.

4. SUMMARY, IMPLICATIONS, AND CONCLUSIONS

The purpose of this paper was to reassess estimates of a single-equation import demand model for Japan using bi-annual data over the period 1974:1 to 1989:2. This analysis with the same data set was also undertaken by Mah (1994), using the Engle–Granger two-step approach in testing for whether such variables associated with an import demand shared a long-run equilibrium relationship. Given the time span and number of observations the data set provided, techniques offered by the most recent developments in time-series modeling were adopted in estimating price and income elasticities of import demand. In particular, in addition to testing univariate and multivariate properties of the data set via several unit root tests and Johansen’s MLE multivariate cointegration tests, a recent robust technique to simultaneity and small sample bias, proposed by Stock and Watson (1993), known as dynamic OLS, was applied with its superiority over other long-run model estimators. By using these recently developed techniques we are able to extract, what would seem to suggest at face value, more intuitive findings and a greater degree of robustness from the results generated.

Results obtained from these robust techniques tend to suggest, quite contrary to those found by Mah (1994), both price and income elasticities are of the expected sign and exceed unity in
absolute value. In particular, import demand in the long run seems to be quite responsive to relative prices, although it remains more or less constant to changes in aggregate income with an income elasticity of close to unity. Although not discounting the justifications forwarded by Mah (1994) as to his favorable findings of a long-run relationship between these variables, this analysis presents evidence that such nonmarket influences that contributed towards destabilizing Japanese import demand did not exert a strong enough influence to dampen the role of fundamental economic influences over the long run.

It is important to recognize, however, that our analysis was restricted to a single-equation method for modeling import demand. Such specifications have been questioned in the literature and put under scrutiny (Thursby and Thursby, 1984). On the other hand, refinements to a simple, parsimonious specification involving certain structural parameters have also been entertained recently for U.S. import demand (see Clarida, 1994). This analysis also holds potential for further empirical pursuit. With certain caveats in mind, both at a methodological and intuitive point of view, the value added from this analysis may not be fully realized until future research utilizes such methods on this and related areas to illustrate its potential in applications, especially for policy inference.

REFERENCES


