Beware of Econometricians Bearing Estimates: Policy Analysis in a "Unit Root" World

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Abstract

Current statistical approaches to modeling many economic relationships are grounded in traditional ideas of deterministic trends. Some of the failures of these approaches are due to inappropriate models using time series with "unit roots." After a shock, unit root processes do not revert to some time trend, but rather can drift up or down without bounds. A "random walk" is a well-known example of a unit root process. The purpose of this paper is to explain the importance of unit root processes to policy analysts who make or rely upon econometric models using time series data. In particular, the presence of unit root processes in GNP, energy and electricity consumption, exports, imports, and other variables suggests that modifications to the way economic relationships are estimated may be necessary. Once these modifications are made, many important parameters turn out to be much different, with substantive implications for both forecasting and policy.

INTRODUCTION

Policy makers sometimes evince an unhealthy overconfidence in forecasts, or the parameters embodied in statistical models. Then, when reality confronts prediction, deep frustration (not to mention embarrassment) all too often results. An example from recent history is illustrative. In the years immediately after the dollar's peak in 1985, when the dollar began to depreciate it was commonly asserted that the trade balance would improve over the medium run. Over the short-term, however, the "J-Curve" phenomenon would result in a significant *deterioration* of the trade deficit, as import prices rose immediately, while quantity responses were more long-term. Yet, over the next 3 years—a period much longer than the six months to a year originally anticipated—the trade deficit only widened.

The empirical origins of the J-Curve phenomenon are found in regressions of the level of imports or exports (or net exports) on distributed lags of the levels of the variables thought to determine net exports, such as the real

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exchange rate, and the level of domestic and foreign economic activity. However, more recent work [Rose and Yellen, 1989] indicates that when analogous regressions are run using the first differences of these variables, this J-Curve effect all but disappears. Indeed, it is difficult to find *any* statistically reliable relationship between the real exchange rate and U.S. net exports.[1] Despite these results, policy analysts still speak of the J-Curve as an established empirical regularity of an economically meaningful magnitude.[2] Moreover, J-Curve effects are evident in most of the large macroeconometric models.[3]

The J-Curve is an excellent example of a pitfall in statistical analysis that is only now becoming widely recognized outside of macroeconomics: the problem of "spurious correlations" that arises when two variables that independently drift upwards over time are regressed upon each other. Technically, both series possess "unit roots." One property of processes with unit roots is that there is no tendency to revert to a trend (see the Technical Appendix for details). While most of the application of a new methodology accounting for this issue has been in finance and macroeconomics, it is by no means clear that the relevance of this problem is restricted to those fields. Often an analyst will recognize that some variable of interest (suppose electricity consumption) is trending upwards. A common response would be to hope that one of the independent variables (perhaps population) will have a similar upward trend or to add to the regression equation a deterministic time trend to proxy for omitted time-related factors (e.g., technological progress). After doing so, there may be some residual serial correlation, to which the researcher will respond with some specification searches, either by adding in a serial correlation correction, or some sort of distributed lag of either endogenous or exogenous variables.[4]

While this approach is not necessarily incorrect, it may lead to grossly inaccurate inferences. First, the upward drift of the variable in question may not be deterministic, but rather random. Alternatively, it may or may not be drifting upwards along with one of the exogenous variables. Even if they are not drifting together, they will appear to be significantly associated, according to the *t*-statistics; in other words, they are "spuriously correlated" [Granger and Newbold, 1986, pp. 205–215].

A different approach takes a more skeptical view of what one knows about the world. First, one tests (by methods later described) to see whether the

[1] Supporting evidence—from a different perspective—for the inconstancy of the J-Curve is to be found in Meade's [1988] study, which found only very small J-Curve effects in the recent dollar depreciation. In some stochastic simulations, Marquez [1988] finds great uncertainty in the parameters underlying the J-Curve phenomenon. Moffett [1989] finds a "sinusoidal" J-Curve, although his results are questionable, since his pass-through equations appear to have a unit root in the residuals.

[2] "Depreciating the dollar may not, however, bring about an improvement in the current account for some time, and in fact may even temporarily worsen it, especially when the dollar depreciates rapidly. An initial worsening of the current account followed by its later improvement is called the J-Curve effect. . . ." [Congressional Budget Office, 1989, p. 20.]

[3] See the implied parameter estimates from various large scale econometric models surveyed in Bryant, Hooper, and Holtham [1988], specifically Annex II-5.

[4] Serial correlation of residuals refers to the correlation over time of the unexplained portion of the dependent variable. It is often diagnosed by the Durbin-Watson statistic for first-order cases [Pindyck and Rubinfeld, 1981, pp. 158–61) or the Box-Pierce Q statistic more generally (pp. 549–50). For examples see pp. 230–40.

variables are related to a deterministic time trend, or whether they drift upward with random shocks permanently incorporated. If the former applies, then the traditional approach is appropriate. If the latter applies, then one should take a second step of checking if the variables of interest are drifting upwards together (a concept called "cointegration"). If they are not, then regressions in the first difference are appropriate. If they are cointegrated, then one should run the regression in differences *and* lagged levels, a specification called an error-correction model (ECM).

The theoretical rationale for this new approach will be developed in the next section.[5] Then a series of case studies will be presented, followed by a general algorithm for applying this alternative approach.

THEORETICAL REVIEW

Unit Roots

The econometric analysis of macroeconomic time series has followed the procedure of decomposing a particular time series into two components: "trend" and "cycle." Traditionally, the trend (or permanent) component has been considered deterministic, perhaps depending on time, while the cyclical component is stationary.

Stationary means that the process has a constant average and a stable variance, loosely speaking.[6] Usually, this stationary component can be thought of as the consequence of transitory shocks. In the context of the economy, these shocks correspond to an increase in the money supply, or a temporary increase in government spending. The shock may be purely random ("white noise"), or it may have some correlation over time, which is called "serial correlation." Such a combination of a deterministic trend and stochastic cycle constitutes a "trend stationary" (TS) process. Since TS processes do tend to revert to the trend, they are not unit root processes.

In general, statistical analysis conducted by running regressions of this TS process on some other stationary time series will produce reliable results. All one needs to do is to include time as one of the independent variables. However, a serious problem arises if the permanent component is better described as a "random walk." A simple random walk is a process wherein today's level is just yesterday's level, plus some random shock. A "random walk with drift" is a similar process, except that it includes a constant so that today's level is yesterday's, plus a constant as well as the random shock. The combination of this alternative view of the permanent component with a stochastic cycle yields a "difference stationary" (DS) process—one that is stationary only after one transforms the data by subtracting off the lagged value of the

[5] See the Technical Appendix for a formal treatment of these issues. For an excellent and accessible discussion of this section, see Stock and Watson [1988]. Technical discussions can be found in Granger and Newbold [1986], Section 6.4; Granger and Engle [1987]; and Sims, Stock, and Watson [1990].

[6] By way of contrast, note that the permanent component does *not* have a constant mean. As time $t \to \infty$, the mean of the permanent component goes to infinity also. Hence the trend component is not stationary. More generally, a variable is *stationary* when it has a statistical distribution that does not depend on time. Thus stationary variables have a constant conditional mean, constant variances, and stable autocorrelation functions.

variable (this is called taking the "first-differences" of the time series). DS series are often called integrated processes of order one, or I(1) for short, because it takes one single differencing to convert the nonstationary series to a stationary one. Note that DS processes are unit root processes, because the series has no tendency to revert to a trend.

However, either explicitly detrending the data by subtracting off an estimated time trend and then running the regression, or implicitly detrending by including time as one of the regressors, will lead to the following:

1. Induced serial correlation in what are *thought* to be deviations from a trend, even when the true deviation is not serially correlated [Nelson and Kang, 1981].
2. Nonsensical estimates of the parameters of interest. The correlations occur by chance, and are not stable over different sample periods.
3. Forecasts that appear to be more "certain" (or have a smaller standard error) than they actually are.

Cointegration

The previous section contrasted the behavior of DS and TS time series. While the appropriate econometric procedure is fairly simple for regressions involving independently drifting DS series, the appropriate procedures are more complex when two or more series are integrated, but *not* drifting independently. If two series are integrated, but they are drifting together, then they are "cointegrated." Technically, this condition holds if a linear combination of the variables is *not* integrated, but rather stationary. One interpretation of cointegration, although not the only, is that variables that exhibit a long-run equilibrium relationship, such as consumption and income, should be cointegrated. Their ratio cannot grow infinitely large or small, or in log-levels, drift arbitrarily far away from each other.

When one encounters cointegrated variables, there are several approaches one can take. The most common is to specify an ECM, which relates the first difference of the dependent variable to the first differences of the independent variables *and* the lagged levels of all the variables. In fact, according to Engle and Granger [1987], every cointegrated system can be rewritten as an ECM. One interpretation of this specification is that the change in the dependent variable is a function of changes in the independent variables *and* the amount of disequilibrium between the levels of the variables. Hence the term: The system corrects some of the disequilibrium, or "error," each period.[7]

There is another approach: to run the regression in levels. Unfortunately, there are some rather specific conditions that must be met before these regressions can yield valid results. Moreover, one cannot apply the usual tests of statistical significance, so this approach must be used with care [see Sims, Stock, and Watson, 1990]. One interesting result is that not all the analyses done in the past on integrated series are necessarily wrong in their conclusions. However, to the extent that the "correct" statistical inferences were made, they were made by accident—a rather sobering thought. Moreover, the

[7] The "disequilibrium" here does not necessarily translate into the economic idea of disequilibrium, such as the existence of excess demand. It is better thought of as a statistical construct.

estimated parameters are now properly interpreted as long-run coefficients, rather than as instantaneous.

Caveats

It is important not to read too much into the apparent presence of unit root processes. For instance, just because one is unable to reject the hypothesis that the real exchange rate follows a random walk does not mean that one *accepts* that hypothesis (see the Technical Appendix for details). Many analysts have this "failure to reject" as an objective – since it is consistent with their maintained theoretical hypothesis.[8] This approach can be questionable in certain circumstances. In the case of the real exchange rate, the failure to reject a random walk is common for time series spanning the floating rate period; Frankel and Meese [1987] only find mean reversion in the U.K.-U.S. rate *in over a hundred years of data.* This particular example points out the difficulties in differentiating between no trend reversion, and very slow reversion.

The thrust of this paper is not to take the apparent presence of unit roots as proof for or against a specific model of the world. Rather, unit root tests are important diagnostic tools, to be used in making accurate inferences about interesting parameters, such as elasticities and multipliers.

EXAMPLES AND CASE STUDIES

The following examples of applications illustrate the diverse areas of econometric policy analysis in which unit root processes have been found to be important.

Finance. Unit roots were first widely recognized in the finance literature. The efficient markets hypothesis implies that stock prices should follow an approximate random walk. Early references include Cootner [1964] and Fama [1970]. They asserted that the efficiency of the stock market implied that stock price changes were unpredictable, that the best guess of tomorrow's price was merely today's price. This translated into a "random walk" characterization, which was supported by early statistical work. Analysts have come to realize that the tests of the efficient market hypothesis were "weak" because it was hard to distinguish between unpredictable and slightly predictable prices.

More recently, focus has shifted from unpredictability to the issue of whether stock prices over the long run are linked to "fundamentals," such as dividend payments [Campbell and Shiller, 1987; Cochrane and Sbordane, 1988].[9] The evidence here is not supportive of the efficient markets hypothesis, although there is no clear consensus yet. If it does turn out that the stock market's valuation of financial assets deviates from the underlying values (i.e., is inefficient), then there is a potential role for government intervention.

The findings about stock prices apply to asset prices in general. Because exchange rates are also asset prices (comparing the aggregate assets of two

[8] Such an approach is common in what is called the "Equilibrium-Rational Expectations approach." Jeffrey Frankel [1990, p. 118] has called this tendency the "Zen" of modern macroeconometrics, that is "the search for perfect nothingness."

[9] Cochrane and Sbordane use Cochrane's Variance Ratio statistic, which is a nonparametric test for unit roots. See Cochrane [1988].

countries), they should also share these characteristics of unpredictability, and also perhaps cointegration. Hence, it should not be surprising that unit roots have also been found in nominal exchange rates [Meese and Singleton, 1982]. The disturbing result is that there is no evidence of cointegration with the conventionally definded fundamentals: money, income, and interest and inflation rates [see Boothe and Glassman, 1987; Meese and Rogoff, 1988; Meese and Rose, 1991]. This result means that the international sectors of many large macro models are misspecified, since expected real depreciation is often assumed to be a function of the real interest differential.

Consumption. Hall [1978] introduced integrated processes to macroeconomics in the form of random walk consumption. More recent work has focused on the cointegration between consumption and income [Stock, 1988]. Cointegration implies that there is a long-run relationship between consumption and income, but that the relationship is not as "tight" as implied by standard Keynesian consumption functions, implicit in some macroeconomic models.

Money. Hendry [1979; 1991] uses the ECM to model U. K. money demand. For the U.S., Engle and Granger [1987] find that although the measure of money known as M2 is cointegrated with nominal GNP, M1 (currency and checking deposits), M3, and broader measures of liquidity are not; this finding constitutes one explanation for the lack of "stability" in velocity that traditional monetarists have pinned their arguments on.

Energy. Hunt and Manning [1989] find that U.K. energy consumption is cointegrated with GNP. This means that they can estimate an ECM of energy consumption, real energy prices, and GNP that yields income elasticities substantially different from those derived from previous models estimated in levels.[10]

Some Microeconomic Variables. Given the examples cited above, one is tempted to dismiss the entire unit root issue as one restricted to macroeconomic phenomena. To help dispel that notion, I have analyzed some variables at random that are of interest to policy analysts in various fields: the costs of medical services, nonfinancial corporate profits, plant and equipment expenditures, net farm income, airline passenger miles traveled annually, automobile collision deaths, automobile miles traveled, and total new PhDs. In only two cases—corporate profits and air passenger-miles—could the null hypothesis of a unit root be rejected.[11] Unit roots appear to be a pervasive phenomenon.

Trend and Cycle in GNP

Nelson and Plosser [1982], among others, have found that U.S. GNP is best characterized as difference stationary, rather than trend stationary. There is, that is, a unit root in real GNP. Hence, regressions of the level of GNP on other theoretical determinants of GNP, such as government spending and the money supply, are likely to yield spurious correlations because such time series are all trending upwards over time as the economy grows.

Their conclusions have consequences for one's beliefs in large-scale, neo-

[10] While their long-run price elasticity is in the midrange of previous estimates, the income elasticity is definitely at the lower end of the range.

[11] At the 10% significance level. These results are based on the Dickey-Fuller [1979] statistics. All variables have been deflated and expressed in terms of natural logs. See the Data Appendix.

Keynesian macroeconometric models used by both businesses and governments for forecasting and policymaking. I have in mind here models such as those produced by Data Resources, Inc. and Wharton Econometrics, as well as multilateral and government agencies such as the Organization for Economic Cooperation and Development (OECD), Congressional Budget Office (CBO), and the Federal Reserve Board. Such models are systems of numerous simultaneous equations, many of which have been estimated under the assumption that the relevant time series were trend stationary. Even when there is no explicit assumption of trend stationarity in the way the various equations were estimated, TS behavior may sneak in when long-run forecasts assume TS productivity growth. Econometric critiques of such models will assert that the parameter estimates embodied in such models are likely to be next to useless for policy purposes. For example, assume a tax increase induces a once-and-for-all productivity decline. A TS model will predict a temporary effect, but if GNP is really DS, then the economy may or may not revert to the preshock trend.

Presumably, the respective analysts are aware of the unit root issue, but feel it is of minor consequence to their policy conclusions. Given the importance ascribed to short-term forecasts in *most* policy analyses, they are probably correct. After all, the conduct of monetary policy is determined from meeting to meeting of the Federal Open Market Committee. And as for fiscal policy, the salient concern is to meet the upcoming fiscal year's Gramm-Rudman-Hollings budget deficit target. However, the longer the forecast horizon, the greater the importance of accounting for unit roots. As Kamlet, Mowery, and Su [1987] show, a simple ARIMA (with the emphasis on the "integrated," or difference stationary, component) model performs as well or better over long periods. One possible interpretation for the relative optimism of the Office of Management and Budget (OMB) and CBO forecasts as compared to a simple ARIMA is that GNP is following a DS process when the large-scale models implicitly assume a TS process.[12]

Figure 1 illustrates why in the short-term, TS forecasts are not likely to be different from DS forecasts, but are likely to diverge over longer time periods. In the DS forecast, a shock is permanently incorporated into GNP, while in the TS forecast a economy reverts to the pre-shock trend. In reality, of course, there are probably other short-term dynamics, but they do not affect the best guess of the economy's level of GNP far in the future.

A final implication of DS behavior is that uncertainty about the future level of the GNP grows linearly with time. While at the "gut" level most people think this is the case, TS processes do not imply this condition.[13,14]

[12] The record is far from clear on the general performance of large macro models versus ARIMA (or univariate time series) models [McNees, 1988]. Moreover, this assertion abstracts from political pressures on the forecasting process.

[13] The issue of unit roots and GNP is far from resolved, however. Skeptics Christiano and Eichenbaum [1989] ask whether "we know, and do we care" about unit roots in GNP. Their answers are no, and maybe not.

[14] I am also sidestepping a voluminous literature that debates whether the presence of a unit root in GNP can be interpreted as a validation of "New Classical" or "Real Business Cycle" models. See the symposium in the Summer 1989 issue of *The Journal of Economic Perspectives*. My own opinion is that the debate cannot be resolved using univariate time series methods.

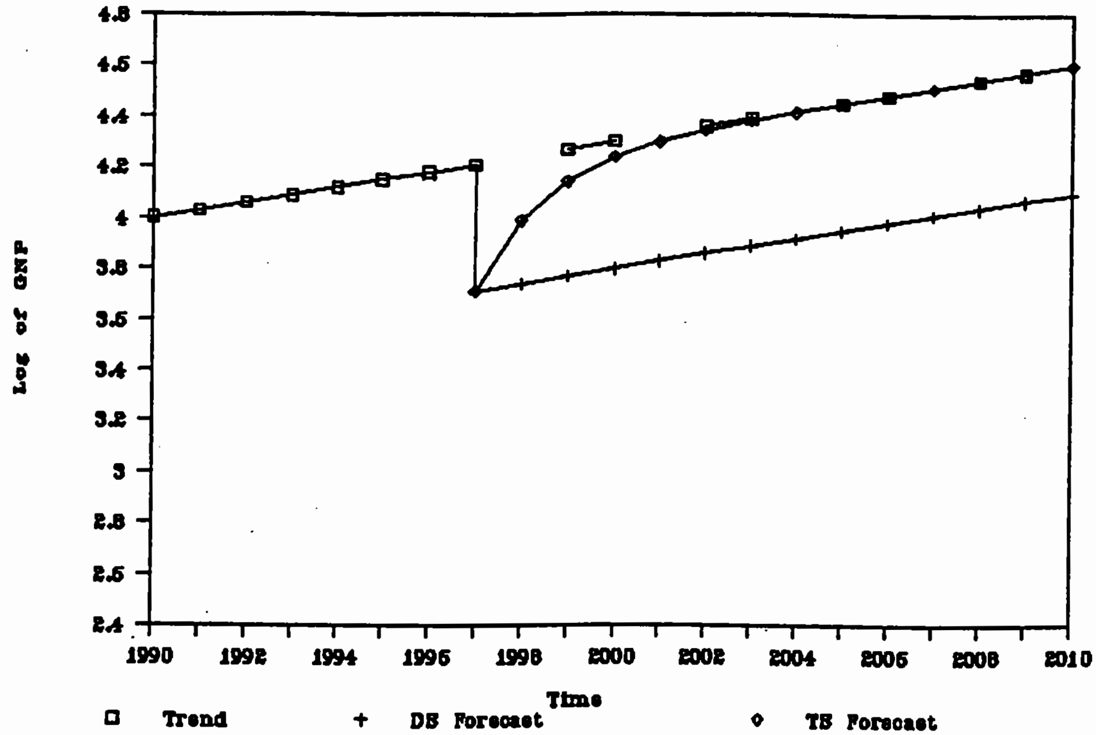

Figure 1. DS vs. TS variables.

Electricity Consumption Forecasting

The implications of DS GNP behavior extend well beyond the confines of macroeconomics. Suppose one is concerned about modeling the consumption of electricity, with a special reference to forecasting. During the early 1980s there was a substantial debate over whether the U.S. would be facing a shortage of electricity production capacity in the subsequent decades. Such anxiety was the impetus for the Department of Energy's Electricity Policy Project [DOE, 1983; see the debate in the U.S. House of Representatives, 1984].

At the risk of oversimplification, one can describe the manner in which some of the analyses were conducted as follows: The supply side was forecasted by totaling up the *planned* capacity available at any given time; the demand side was predicted using exogenously given values for fuel (input) prices and regulated electricity prices and GNP. If demand exceeds capacity, then a shortage is forecasted and additional capacity would have to be planned now, since the lead time on electric generating plants is quite long. This approach is appropriate for certain policy purposes, such as when the model is being used for capacity planning, or when one feels that the market can be dichotomized (perhaps because prices are regulated).[15]

[15] Not all models operate this way. For example, DOE's FOSSIL2 model has explicit price endogeneity. Werbos [1990] provides a general survey of energy forecasting models.

However, if one's objective is to forecast, say, electricity *consumption* (rather than demand), then an alternative approach is necessary. One cannot necessarily model the system supply and demand separately, since each will feed into the other via prices (in other words, simultaneity is relevant). An alternative approach is described below. Moreover, potential GNP (from which trend electricity consumption is predicted) is usually modeled as trend stationary in these exercises.[16]

I have examined the time series properties of annual electricity consumption for the period 1960–88. I find that one cannot reject the null hypothesis that log electricity consumption is integrated of order one—I(1). A plausible preliminary conclusion is that the best forecast of electricity consumption should be some ARIMA with drift. This conclusion, however, is counterintuitive, if one believes that GNP and electricity consumption cannot drift infinitely far apart. However, while log GNP is also I(1), it does not appear to be cointegrated with electricity consumption. Yet policy papers still speak of electricity-GNP correlations and trends as if they were cointegrated [e.g., National Research Council, 1986, pp. 22–24]. In fact, the unit root issue is rarely, if ever, mentioned.

I find that only after including real electricity and fossil fuel prices in the cointegrating relationship does it appear that the four variables share a common stochastic component (i.e., they move together in the long run). Then an ECM can be written that should be able to outpredict a simple random walk.[17] And as log as the inputs into the model are correctly forecasted, as I(1) processes, then these forecasts should be superior to those provided by other techniques. The improvement should be more pronounced the longer the forecast horizon, on average.

In historical simulations, an ECM outpredicts a forecasting equation based only on levels of the exogenous variables (root mean squared error 0.069 vs. 0.079). It also performs better than either a model based only on the first differences of the exogenous variables (0.189), or a simple univariate (IMA [1,1]) model at 0.152.[18] This result illustrates the fact that ignoring the long-run proportionality implied by cointegration, and implicit in an error-correction specification, leads to inferior forecasts.

What policy implications can one draw from this exercise? If on average better forecasts are provided by more accurate estimates of critical elasticities, then it would appear that one might more readily accept ECM elasticities

[16] See the DRI long-term forecast [DRI, 1988] for an example. Potential GNP is modeled as a function of demographic factors and productivity.

[17] It is important to recognize the peculiar institutional features of the electricity market, the most critical involving state and Federal regulation of electricity-generating utilities. Given extensive price regulation in the past, it is difficult to interpret electricity prices as moving in response to supply and demand factors in the short to medium run [see Navarro, 1985, for an extensive discussion of this issue]. However, as long as electricity prices *in the long run* respond to such market pressures, then an ECM is appropriate. Alternatively, one can view the ECM as merely a statistical representation implied by the finding of cointegration.

[18] The regressions used for the forecasts were based on annual data from 1960–80 (see the Data Appendix), and the *ex post* forecasts were conducted over the 1981–88 period. The independent variables were log real electricity prices, log real fossil fuel prices, and log real GNP. Log real fossil fuel prices enter in because higher alternative prices induce substitution towards electricity consumption, but also tend to increase electricity prices since they enter into the cost function.

than those derived from levels specifications. It turns out that the short-run ECM elasticities are higher (0.32) than most estimates, implying that to induce a reduction in electricity consumption requires, for instance, only slightly higher prices.

The Trade Balance

Theoretically, changes in the real exchange rate will induce expenditure-switching, and all large-scale macroeconometric models have in their trade equations at least one variable that looks something like a real exchange rate. Indeed, the real exchange rate does enter significantly into most estimated regressions of the level of the trade balance on the level of the exchange rate (and other variables).

However, the failure of the recent dollar depreciation to reduce drastically the U.S. trade deficit has led to speculation as to whether the structural trade equations, represented in large-scale econometric models, shifted over the early 1980s. Such a view was buttressed by the apparent failure of two empirical phenomena to recur in the latest appreciation and depreciation of the dollar: the J-curve and the pass-through relation.

As noted in the introduction, from 1985–87, the dollar depreciated in real terms by about 40%, and yet the trade balance continued its course of record deficits until 1987. This constituted a period much longer than the conventionally accepted six months to a year lag. Moreover, only slight improvement in the trade deficit was made in 1988, to about $112 billion. Various arguments were forwarded to rescue the J-Curve. "Cascading" J-Curves, more rapid growth in the U.S. compared to the rest of the world, or market-share targeting by foreign firms, were but some of the arguments.[19] The purpose here is not to evaluate such arguments, but merely to cast doubt on the J-curve as an empirical regularity.

A second artifact of international macroeconomics is the "pass-through" relationship between the exchange rate and nominal import or export prices. One might be tempted to posit a one-for-one relationship between the two variables (i.e., when the exchange rate depreciates 1%, import prices rise 1%), especially over the long run. In most studies, the sum of the pass-through coefficients seldom approached one. However, the estimated degree of pass-through in the most recent episode was even less than usual.[20]

These problems with quasistructural models suggests that the problem could be, once again, spurious correlations in inappropriate regressions involving integrated variables. In an exhaustive study of the J-Curve, Rose and Yellen [1989] conclude that the statistical evidence that the real exchange rate affects trade flows is actually quite weak, after taking into account issues of nonstationarity.

[19] "Cascading" J-Curves refer to the continuous, rather than discrete, nature of the dollar depreciation. See Meade [1988] for an examination of the 1985–87 depreciation and the J-curve effect.

[20] An empirical pass-through study is Hooper and Mann [1989]. See also the long-run price–exchange rate elasticities in Bryant, Holtham, and Hooper [1988], Annex VI. Any number of industrial organization/imperfect competition models can yield less than complete and constant pass-through [Mann, 1986; Dornbusch, 1987; Knetter, 1989]. Hence, the shifts in the pass-through relation may be due to omitted variables in the conventionally estimated equations, such as manufacturing capacity or domestic absorption, or due to aggregation problems [Melick, 1990]. These effects could be modeled as time-varying parameters [see Kim,1990].

Table 1. Estimates of U.S. export and import elasticities (1967.1-89.4).

Exports		Imports		
Income (+)	Price (−)	Income (+)	Price (+)	Description (a priori coeff. sign)
−0.02	−0.06	0.92	0.24*	Partial adjustment model
[−11.24]	[−35.88]	[2.80]*	[0.73]*	in levels
−0.02	−0.20*	1.54*	0.29*	Partial adjustment model
[−0.34]	[−0.80]*	[4.10]*	[0.78]*	in levels with time trend
0.05	−0.16	1.81*	0.13	First differences[a]
[0.13]	[−0.57]	[3.35]*	[0.54]	
0.01	−0.18	2.05*	−0.03	Error-correction model
[na]	[na]	[2.77]*	[0.71]	(unconstrained dynamic)[b]
0.21	−0.19	2.11*	−0.06	Error-correction model
[na]	[na]	[2.73]*	[0.58]*	(two-step procedure)[b]

Notes: Figures are short-run elasticities. Bracketed figures [.] are long-run elasticities. * denotes significance at the 5% level for the null hypothesis that the parameter equals 0. Estimates are from quarterly data 1967.1-89.4. All regressions include seasonal indicator variables.

Sources: Data for econometric analyses from Citibase databank (Jan. 1990) and Federal Reserve Board (provided by Janet Yellen). The real exchange rate is a multilateral G18 trade weighted rate. The foreign activity variable is rest of world GDP. Imports are merchandise net of oil. Exports exclude services. See the Data Appendix for details.

[a] Regression on current and four lags of independent variables. The short-run elasticity is the parameter on contemporaneous variables. The long-run elasticity is the sum of the coefficients on all lags.

[b] Export error correction term(s) have nonsensical estimates; short-run elasticities are sum of current and lagged coefficients on the difference terms.

I provide some additional evidence to this effect in Table 1. The parameter estimates of the import and export functions are quite different, depending upon the specification. It should be noted that the purpose of this table is not to argue in favor of *one* particular specification, or parameter estimate; rather the purpose is to illustrate the uncertainty surrounding our understanding of the various magnitudes of effects.

Certain parameter estimates vary over as wide a range as those exhibited by the large-scale macroeconometric models examined in the Brookings symposium on empirical macro modeling [Bryant, Holtham, and Hooper, 1988, Annex II-A]. For instance, the short-run income elasticity of export demand ranges from 0.4 to 0.7 for three large macro models (that of Data Resources, Inc., the Fed's Multi-Country Model, and the OECD's). The range for the various specifications examined below is −0.02 to 0.21, despite the fact that the same data is used in each of the export demand regressions reported.

A general characteristic of the models in which nonstationarity is expected to be more completely accounted for (first differences and error correction) is that the price elasticities are either lower than those estimated in levels, or are not statistically significant. In contrast, those price elasticities derived from the import specifications in levels and levels with a time trend *appear* to be highly significant.[21]

[21] Notice that the ECM for exports fail to produce reliable results. In fact, I fail to find evidence of cointegration between exports, ROW activity, and the exchange rate, at the 10% level. One possible explanation is that the cointegrating vector should include a measure of the Latin American debt crisis. It is therefore not surprising that the estimated ECM yields nonsensical estimates since the specification is not justified by the data.

The next natural step is to ask if this unit root behavior is important for policy. In fact, the difficulty in finding cointegration is consistent with the hypothesis of hysteresis in trade. *Hysteresis* is the property of a variable not to return to its original condition after a temporary shock. In the context of the 1984–85 dollar overvaluation, the return of the dollar to its original level is not in itself sufficient to restore the trade balance to its pre-shock level. There are several possible reasons the trade balance might exhibit such behavior.[22]

The most important issue involves import penetration during a period of exchange rate overvaluation. Once foreign firms gain a larger market share—thereby setting up marketing networks and establishing customer relationships—the return to the original exchange rate is not sufficient to restore the pre-overvaluation situation because of the sunk costs involved in entering the market.[23]

Krugman and Baldwin [1987] find that in some empirical investigations, there is little evidence of hysteresis. Unfortunately, the analysis was performed on undifferenced data, so no set conclusions are available. Baldwin [1988] performs a more sophisticated analysis, using first differenced data, and concludes that shifts *have* occurred, in the posited direction.[24] Additionally, Rose and Yellen [1989] find no evidence of cointegration between the trade balance and income, a finding consistent with the presence of hysteresis.

These theoretical models imply that large exchange rate changes have qualitatively different effects on trade flows than small changes. The natural policy conclusion is that one should avoid large exchange rate fluctuations, it one believes resource reallocations are not without cost.[25] How tightly does one need to keep them restricted? Using plausible parameter values, Dixit [1989] finds that the exchange rate "bands" need not be too tight.

A NEW PROCEDURE

The discussion in this section focuses on taking time trends and lag structures seriously. Consequently, it abstracts from other important econometric prob-

[22] Some explanations not explored here include (1) loss of capacity, where the loss is not easily recovered due to either inefficient capital markets, or adjustment costs; (2) the demonstration effect of new imports on consumer tastes.

[23] A bit more insight might be useful here. In general, these models posit firms that operate in imperfectly competitive markets, but for which a fixed initial cost, or "sunk" cost, is necessary in order to enter and operate in that market. Under such conditions, small changes induce normal firm responses—increases or decreases in output and prices. However, if the exchange rate changes are sufficiently large, then either foreign firms may enter the domestic market, or vice versa. Hence large shocks yield qualitatively different effects from small ones, since the entry (or exit) of firms alters market demand elasticities; pricing behavior in monopolistic competition depends on such parameters, and so pricing behavior also changes. When the large exchange rate shock is reversed, then, if the magnitude of reversal is not at least equal, the entry (or exit) of foreign firms will not be reversed. That is because the new firms will not find it profitable to exit (enter) given sunk costs and the future uncertainty about the exchange rate.

[24] The hysteresis need not be manifested only in the quantity of exports. Little [1989] finds evidence of hysteresis in export sector *employment*. Such behavior is attributed to an upward ratcheting in automation and off-shore sourcing.

[25] It is true, however, that the theoretical treatments have not yet analyzed the normative welfare implications of hysteresis in trade.

lems of simultaneity (what happens when the independent variables are not exogenous), measurement errors, omitted variables (leaving out important factors), and "incredible identifying" assumptions in general [Sims, 1980].

With the above limitations in mind, one can proceed through the following steps:

1. Determine whether the time series to be analyzed are stationary by visual inspection of time series plots (are they trending upwards or downwards?). If they are stationary, then analysis can proceed as usual.

2. If they trend upwards, then one must determine whether the series are trend stationary or difference stationary. The standard test is the Dickey-Fuller [1979] test with a time trend in the equation.[26] If the series are trend stationary, one can proceed with a time trend in the regression equation.[27]

3. If the series are drifting upwards stochastically (i.e., are integrated), then one should test whether the relevant series are cointegrated. A rule of thumb is that the adjusted R^2 is greater than the Durbin-Watson statistic in a regression involving the relevant time series, then spurious correlation is likely [Granger and Newbold, 1986, p. 205]. Formal tests of cointegration are provided in Engle and Granger [1987] and Engle and Yoo [1987].

4. If the series are not cointegrated, then either the regression should be run on the first differences of all the variables, or the model should be reassessed and additional variables considered. The resultant parameters can be interpreted as both the short-run and long-run parameters. Observe, however, that there is no long-run relationship between the *levels* of the variables in this instance.

5. If the series are cointegrated, one should run the regression(s) in the error-correction specification.[28] There are two ways to proceed at this juncture: (1) run a single regression of the first difference on the right-hand-side (RHS) variable against the first differences of the left-hand-side (LHS) variables and lagged levels of the RHS and LHS variables; or (2) implement the Engle-Granger [1987] two-step procedure, in which one first estimates the long-run relationship to obtain the "disequilibrium error" or error-correction term, and then runs a regression involving the first differences and the lagged error-correction term. From either of these, one can obtain the short- and long-run parameters (see the Technical Appendix). Policy can then be formulated based on these estimated parameters.[29]

For forecasting purposes, one has two choices as to how to proceed: (1) estimate each variable as a function of lagged values of itself and lagged

[26] Further references include Phillips [1987] and Perron [1988].

[27] If a univariate prediction is desired, one could use an ARIMA model or an ARMA model with a time trend, depending on which one appeared to fit better *out-of-sample*. Even though a series may appear DS in-sample, TS models sometimes outperform DS models out-of-sample. There is no clear resolution to this paradox. See Meese and Geweke [1984]. If a DS process is assumed, for forecasts with very long horizons one may wish to use the Beveridge-Nelson [1981] decomposition. For a simple exposition, see the Appendix to Stock and Watson (1988).

[28] It is possible to just run the cointegrating regression, which will yield consistent estimates of the long-run parameters. See Stock and Watson [1988, pp. 165–67].

[29] In general, one will have many more decisions to make about lag lengths and constraints. One way to assess the relative performance of several specifications is to subject the forecasting equations to historical *ex post* simulations. This involves performing the estimations on a subsample of data, and then using actual values of the exogenous variables (post-sample) to predict the endogenous variable. See Pindyck and Rubinfeld [1981, pp. 354–414] for discussion. An example of various forecasting comparison techniques applied to exchange rates is in Chinn [1991].

values of the other variables in the cointegrating relationship, and forecast recursively (what they term an Unrestricted Vector Autoregression); or (2) use the estimated cointegrating relation in an ECM to forecast recursively (the Engle-Granger 2-step procedure). Engle and Yoo [1987] describe these procedures and in a small simulation study find that procedure (1) out-performs procedure (2) for short time horizons (5 periods or less). However, the E-G 2-step procedure dominates at all longer horizons.

6. Depending upon the policy question at hand, one may or may not attempt to infer behavior from the statistical results. Usually, aggregate time series results cannot "prove" a particular model is correct; they can only provide results that are consistent (or inconsistent) with the preferred model.

For instance, apparent lack of cointegration between exports, the real exchange rate, and the rest-of-world economic activity lends support to the idea of hysteresis in trade, but it neither proves it nor isolates the particular mechanism by which hysteresis occurs.[30] Despite this limitation, the statistical results may still provide useful evidence on which to base policy decisions.

SUMMARY AND CONCLUSIONS

Policy analysts should pay much more attention to the possibility that time series data under analysis are characterized by unit root processes. This article has reviewed the meaning of a unit root process and explained the problems that arise with traditional estimation methods that do not account for it. In examining many areas of policy for which econometric estimates and forecasts are used, I have identified numerous instances in which inappropriate techniques are used and result in substantially different policy implications than those resulting from the more modern estimation methods described herein. Without suggesting that the policy implications are settled matters, the examples suggest the following: (1) a reduced faith in the rationality of the stock market; (2) less support for monetary policies that rely on the stability of the income velocity of narrow money; (3) slower U.K. energy consumption growth than previously thought; (4) more pessimistic forecasts for long-term growth in the face of supply shocks; and (5) greater support for policies that restrict exchange rate fluctuations.

I have also presented some evidence to suggest that unit root processes are present in time series data of numerous microeconomic variables; thus policy analyses using them, but failing to account for the presence of unit roots, deserve reexamination.

The techniques for taking proper account of unit root processes are not complicated, as the guidelines in the previous section suggest. I hope the importance of using them is now obvious to a wider audience than before.

DATA APPENDIX

- Data for variables cited in "Examples and Case Studies" (all annual).

Cost of medical services: Log of CPI for medical care services (1982–84 = 100) deflated by CPI-all, for 1947–89. Source: *Economic Report of the President, 1990,* Table C-60.

[30] In fact, the lack of cointegration among the selected variables may imply omission of a crucial integrated variable.

Plant and equipment expenditures: Log of business plant and equipment expenditures, all industries, deflated by PPI for capital equipment (1982 = 100) for 1948–88. Source: *Economic Report of the President, 1990,* Tables C-54 and C-63.

Net farm income: Log net farm income in 1982$ (deflated by implicit GNP deflator) for 1940–88. Source: *Economic Report of the President, 1990,* Table C-95.

Nonfinancial corporate profits: Log nonfinancial corporate profits including inventory valuation adjustments and corporate capital allowances, in billions of dollars, deflated by CPI-all (1982–84 = 100) for 1947–89. Source: *Economic Report of the President, 1990,* Table C-88.

Airline passenger-miles: Log of total airline revenue–passenger-miles flown domestically (in millions) for 1938–88. Source: FAA, *Statistical Handbook of Aviation,* various issues.

Automobile collision deaths: Log of motor vehicle deaths (in thousands) in collisions with other motor vehicles for 1930–86. Source: National Safety Council, *Accident Facts,* 1987 Edition.

Automobile car miles driven: Log of automobile (including motorcycles) travel (in billions of miles) for 1937–87. Source: Federal Highway Administration, *Highway Statistics Summary to 1985;* and Department of Commerce, *Statistical Abstract of the United States, 1989.*

Total new PhDs: Log of total PhDs awarded in thousands, for 1930–88. Pre-1957 data is by calendar year; subsequently by fiscal year. The 1957 datum is found by log-linear interpolation. Sources: Department of Commerce, *Historical Statistics of the U.S. to 1970,* for data up to 1970; Department of Commerce, *Statistical Abstract of the United States,* 1976, 1982/83 and 1989, thereafter.

- Data for electricity consumption analysis (all annual).

Electricity consumption: Log electricity consumption (in billions of kWh). Source: Energy Information Administration, *Annual Energy Review, 1988.* [DOE/EIA-0384 (88)], Table 84.

Price of electricity: Log of real price of delivered electricity deflated to 1982$ by implicit GNP deflator (in cents per kWh). Source: Energy Information Administration, *Annual Energy Review, 1988.* [DOE/EIA-0384(88)], Table 92.

Price of fossil fuels: Log of composite index of fossil fuel prices in 1982$. Source: Energy Information Administration, *Annual Energy Review, 1988.* [DOE/EIA-0384(88)], Table 27.

GNP: Log of real GNP in 1982$. Source: *Economic Report of the President, 1990,* Table C-2.

- Data for the trade balance analysis (all quarterly).

Real exchange rate (UAGTSW): Log real G-18 multilateral trade weighted value of the dollar. Source: Federal Reserve Board database, and IMF, *International Financial Statistics,* series rec.

Exports (GEXM82): Log of real exports of merchandise (1982$). Source: Citibase, Jan. 1990 disk.

Imports (GIMNP82): Log of real imports on non-oil merchandise (1982$): Source: Citibase, Jan. 1990 disk.

GNP (GNP82): Log of real GNP (1982$), seasonally adjusted, at annual rates. Source: Citibase, Jan. 1990 disk.

Rest of world economic activity (GPRW82): Log of index of rest of world real GDP. Source: Citibase, Jan. 1990 disk.

TECHNICAL APPENDIX

This appendix describes the econometric issues involved in unit roots, trend versus difference stationarity, and cointegration. To discuss these issues, we must first define the trend and difference stationary processes.

Suppose y_t is a time series. A convenient example of a time series is log real GNP. Let y_t be composed of two parts—a trend and a cycle:

$$y_t = y_t^P + y_t^S \qquad \text{(A1)}$$

The *P* superscript denotes the permanent (trend) component; the *S*, the stationary (cyclical). A stationary process is one with a constant mean and variance. A common characterization of the stationary component is

$$y_t^S = \varepsilon_t \qquad \varepsilon \sim iid(0, \sigma_\varepsilon^2) \qquad \text{(A2)}$$

This means that the stationary component is a random error, and has constant mean of zero, and variance of $\sigma_\varepsilon^2 < \infty$. While this is not easily thought of as a cyclical component, it can be simply generalized to one, e.g.,

$$y_t^S = \phi y_{t-1}^S + \varepsilon_t \qquad \varepsilon \sim iid(0, \sigma_\varepsilon^2), |\phi| < 1 \qquad \text{(A3)}$$

This process is called a first-order autoregressive [AR(1)] process. It has some persistence and so corresponds to one's idea of a cycle as a somewhat persistent deviation from a trend.

In the past, y_t^P has typically been conceived of as deterministically related to time:

$$y_t^P = \alpha + \beta t + u_t \qquad u \sim iid(0, \sigma_u^2) \qquad \text{(A4)}$$

If the data are annual, and $\beta = 0.03$, then the growth in trend or potential GNP is 3% per year. The rationale for such a specification is that potential output depends on the stocks of labor, capital, and technology that presumably grow exponentially.

Combining (A2) and (A4) yields the time series representation

$$y_t = \mu + \beta t + u_t + \varepsilon_t \qquad \text{(A5)}$$

(A5) is a "trend stationary" process.

If one thinks of y_t^S as

$$y_t^S = \phi y_{t-1}^S + \Theta z_t + \varepsilon_t \qquad \text{(A3')}$$

where z_t is an exogenous variable (or vector of variables), then regressing y_t on an exogenous variable(s) (z_t) and a time trend should yield unbiased estimates of all the parameters. This is how conventional macroeconometrics has been implemented. There is some evidence that a better characterization of the permanent component of many macroeconomic time series is

$$y_t^P = \delta + y_{t-1}^P + u_t \qquad u \sim iid(0, \sigma_u^2) \tag{A6}$$

Equation (A6) is called a "random walk with drift," and δ is called the drift parameter.[31] Notice that any random error (or innovation), u_t is *permanently* incorporated into the variable. Hence such time series processes have infinite and complete memories. One can also think of (A6) as a nonstationary AR(1) process where the autoregressive parameter is unity. A random walk process, therefore contains a "unit root." Stock and Watson [1988] call processes with at least one unit root "variable trends."

The term "unit root" deserves some comment. Technically, in such processes, one of the roots of the characteristic equation is exactly on the unit circle. Suppose one had a variable w_t, which was governed by the equation $w_t = 1.3w_{t-1} + 0.3w_{t-2} + e_t$. One could rewrite this equation with a lag operate (L), where for instance $L(w_t) \equiv w_{t-1}$ and $L^2(w_t) \equiv w_{t-2}$. This equation would be $(1 - 1.3L + 0.3L^2)\, w_t = e_t$. Setting the term in parentheses equal to zero yields what is called the characteristic equation. One can find the roots of this equation by using the quadratic formula. In this case, the roots are (1, 3.33...). Alternatively, one could have factored the polynominal to find that $(1 - 1.3L + 0.3L^2) = (1 - L)(1 - 0.3L)$, and so once again, one of the roots is unity.

Random walks are a prominent example of "integrated" processes. An integrated process of degree one [I(1)] is one that has to be first-differenced once in order to induce stationarity.[32]

It should be no surprise, then, that combining (A2) and (A6) should also yield a I(1) process:

$$y_t = \delta + y_{t-1}^P + u_t + \varepsilon_t \tag{A7}$$

If one linearly detrends y_t (or equivalently, runs a regression of y_t on a time trend and other exogenous variables), then the parameter estimates that are produced will be biased and unstable.

Notice that first differencing (A7) *does* yield a stationary process. In particular

$$(1 - L)y_t = \delta + u_t + \varepsilon_t - \varepsilon_{t-1} \tag{A8}$$

Thus the first difference $(1 - L)$ of log GNP is a constant, white noise, plus a moving average error process.

Such processes as (A7) will exhibit hysteretic behavior, which is when a variable fails to revert to its original state after removal of the force that induced the change. In this case, if there is a shock, u_t to y_t^P, then after the shock is gone, the value of y will *not* naturally revert to its pre-shock value.

Confirming that a particular time series has a unit root is, however, a difficult problem. Classical statistical methods assume that the processes

[31] If ε_t is *not* white noise, but rather exhibits higher order dependence, then the process is called a martingale. In practice, the terms *random walk* and *martingale* are often used interchangeably.

[32] Difference stationary series are "integrated" processes. If it takes a single first differencing to induce stationarity, then the process is integrated of degree one [I(1)]. If it takes two differencings, then it is I(2). A random walk is a special case of a difference stationary process. Random walks will not only be stationary after first differencing, but will also be white noise.

are stationary. In this context, stationarity requires that the autoregressive parameter must be bounded between -1 and $+1$. *Thus, current statistical techniques might fail to reject the null hypothesis of a unit root, but this is not the same as proving with some confidence that there is a unit root.* The procedures and test statistics for unit roots are described in Dickey and Fuller [1979].

Once one finds that series are integrated, if one wants to regress one on the others, one has to use the cointegration tests described in Engle and Granger [1987] and Engle and Yoo [1987]. Essentially, these tests examine whether the residual

$$u_t = y_t - \alpha x_t \qquad u_t \sim I(0)\ ? \tag{A9}$$

is integrated (where α is assumed to be known here, but can be estimated by OLS). x_t could be a vector.

One can interpret u_t as a disequilibrium error that can persist in the short run but cannot drift off to infinity. If y and x are cointegrated, the usual approach is to use an error-correction specification. The implied ECM for (A9) is (A10).

$$\Delta y_t = a_1 \Delta x_{t-1} + a_2 x_{t-1} + a_3 y_{t-1} + A(L) v_t \tag{A10}$$

Where $A(L)$ is a polynomial in the lag operator. The short-run elasticity (if the y and x are log levels) is a_1. The long-run elasticity is $-a_2/a_3$, according to this unrestricted form [Hall, 1986]. Hendry, Pagan, and Sargan [1984] provide an extensive discussion of the use of ECMs and how they "nest" other forms of autoregressive distributed lag models.[33]

An alternative two-step procedure by Engle and Granger (1987) is implemented as follows. First estimate $\hat{\alpha}$ using OLS, and generate an error-correction term, $(y_t - \hat{\alpha} x_t) = (y_t - \hat{y}_t)$. Second, estimate (A11):

$$\Delta y_t = a_1 \Delta x_{t-1} + a_3 (y_{t-1} - \hat{\alpha} x_{t-1}) + A(L) v_t \tag{A11}$$

The a_1 coefficient has the same interpretation as above, but the estimated long-run parameter is now the $\hat{\alpha}$ obtained in the first step regression.

These two procedures should yield similar results for data spanning a long period, but may produce different parameter estimates in small samples [Banerjee, Galbraith, and Dolado, 1990]. Moreover, the error-correction specification can include more lags of both the differences and the lagged levels.

One issue that has not been addressed in the text involves simultaneity. In general, problems of simultaneity (the presence of right-hand side variables that are not exogenous) have been largely been ignored in empirical applications. This is because of the asymptotic "super-consistency" characteristics of cointegrating regressions discussed by Stock [1987]—the fact that the parameter estimates in cointegrating regressions converge to their expected values even faster than in standard cases. However, in small samples, it may be important to account for simultaneity by use of instrumental variables to avoid biased estimates [see Phillips and Hansen, 1990]. Fortunately, in many cases, ECM specifications can avoid much of the bias.

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[33] If x is exogenous, then contemporaneous values of Δx can be used. Otherwise lagged values are appropriate.

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