COINTEGRATION VERSUS TRADITIONAL ECONOMETRIC TECHNIQUES IN APPLIED ECONOMICS

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INTRODUCTION

For more than a decade, cointegration techniques have been a dominant force in applied macroeconomics. Part of their attraction appears to be related to the conviction of many applied researchers that they play a useful role in identifying, with minimum prior theoretical analysis, long-run economic relationships that are buried in trended data. Cointegration techniques seem to be ideally matched with the many economic theories that are couched in long-run equilibrium terms [McKenzie, 1997]. This match applies, *a fortiori*, to the analysis of growth issues that have moved to center stage in macroeconomics over the last ten years after having been on the sidelines for several decades.

Rather than supplying another survey of cointegration techniques [Muscatelli and Hurn, 1992], this paper highlights some of the well-known problems with cointegration analysis in order to provide some perspective on the usefulness of cointegration techniques in applied economics. To better gauge the relative effectiveness of cointegration techniques, the paper compares them to traditional econometric time-series techniques of the autoregressive distributed lag type (ADL) as summarized, for example, by Hendry et al. [1984]. The comparison is based on a number of simple, easy-to-replicate Monte Carlo experiments with a widely used regression package (TSP 4.4).

The paper is organized as follows. The next section summarizes the basic idea of cointegration. The subsequent part details some key problems that cointegration analysis faces in economic applications. It also offers some numerical illustrations of these problems and a comparison to traditional econometric time-series techniques. The paper ends with a brief summary of the main points and their implications for using cointegration techniques.

THE ESSENCE OF COINTEGRATION

In what follows, cointegration is discussed independently of the available estimation techniques to focus on the *idea* of cointegration. Assume for that purpose that two variables, a variable y and a variable x, are of interest. Both variables are driven

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by a stochastic trend and a random error. To be more specific, let y be determined by the following two equations,

$$y_t = \mu_t + \epsilon_{y,t} \qquad \epsilon_{y,t} \sim \mathrm{NID}(0, \sigma^2_{\epsilon y}), \qquad t = 1, ..., T \text{ and}$$

$$\mu_t = \mu_{t-1} + \eta_{y,t} \qquad \eta_{y,t} \sim \mathrm{NID}(0, \sigma^2_{\eta y}), \qquad t = 1, ..., T,$$

where μ is a random walk, and where ϵ_y is a random error. The error term of the random walk (η_y) is assumed independent of the random error ϵ_y.

Now consider variable x, which is driven, in complete analogy to y, by the following two model equations,

$$x_t = \rho_t + \epsilon_{x,t} \qquad \epsilon_{x,t} \sim \mathrm{NID}(0, \sigma^2_{\epsilon y}), \qquad t = 1, ..., T \text{ and}$$

$$\mu_t = \mu_{t-1} + \eta_{y,t} \qquad \eta_{x,t} \sim \mathrm{NID}(0, \sigma^2_{\eta x}), \qquad t = 1, ..., T,$$

where μ is a random walk, and where ϵ_x is a random error. The error term of the random walk (η_x) is independent of the random error ϵ_x.

It is apparent that y and x follow stochastic trends. Both variables are non-stationary in levels but stationary in first differences or $I(1)$. The two variables y and x are cointegrated if the two random walk errors, η_y and η_x, are linearly dependent; that is, if their correlation coefficient is unity. In practical terms, if the stochastic trend innovation for variable x is α and the stochastic trend innovation for variable y is a linear function of α, then x and y are cointegrated. Another way of expressing this is to say that the two random walk errors have a common factor (α). Linear dependence or a common factor among the two random errors implies that the rows (columns) of the variance-covariance matrix of the random walks μ and ρ are linearly dependent. Hence, the covariance matrix is not of full rank. As is well known, this fact can be used to estimate the linear relationship between x and y, which is also known as the cointegrating vector for x and y.

As an extension, consider the case where the stochastic trend model for both y and x allows for a drift in the random walk that is driving the stochastic trend. The model for y could then be written as

$$y_t = \mu_t + \epsilon_t \qquad \epsilon_t \sim \mathrm{NID}(0, \sigma^2_\epsilon), \qquad t = 1, ..., T,$$

where the stochastic trend component is specified as

$$\mu_t = \mu_{t-1} + \beta_{t-1} \qquad \eta_t \sim \mathrm{NID}(0, \sigma^2_\eta), \qquad t = 1, ..., T$$

$$\beta_t = \beta_{t-1} + \xi_t \qquad \xi_t \sim \mathrm{NID}(0, \sigma^2_\xi), \qquad t = 1, ..., T.$$

In this case, β is the drift parameter of the random walk μ. It is assumed to develop over time as a random walk itself. An analogous set of equations can be specified for x.

This case differs from the earlier one in that both y and x are integrated to order two rather than one. The first differences of x and y are cointegrated if the error terms that are driving the drift parameters in the two models are linearly dependent; that is, if they have a common factor. This, in turn, implies that the variance-covariance matrix of the error terms driving the drift parameters is of less than full rank.

The above description can be extended to more than two variables. Irrespective of the number of variables involved, cointegration remains to be tied to linear restrictions (common factors) among the random errors that drive the stochastic trends. However, what is different from the case of two variables is the number of linear dependencies (common factors) that may arise among the error terms. In the case of three variables, there may be two linear dependencies (common factors) and, therefore, two cointegrating vectors, and so forth for systems with more variables.

Further extensions of the basic model are possible to allow for cointegration of seasonal or cyclical components, as described, *inter alia*, by Engle et al. [1989] and Boswijk and Franses [1995]. Cointegration has also been extended to non-linear relationships [Granger et al., 1997]. In all cases, however, cointegration reduces to common factors in the error terms that drive the respective stochastic processes.

What does the knowledge of cointegration and cointegrating vectors provide us with? First, the estimation of a multivariate system of cointegrated variables can make use of the reduced rank of the variance-covariance matrix, and will therefore raise the efficiency of the parameter estimates. Second, if one has predicted one of the variables in a cointegrated system, then the long-run trend values of the other variables can be derived using the cointegrating vector. But there is also something that cointegration techniques cannot provide. Since cointegration is a purely statistical concept, tied to common factors of stochastic disturbances, the technique does not guarantee that any of the common factors that may exist among the variables are economically meaningful.[1] As a corollary, cointegration does not, by definition, imply that a component of the underlying economic structure has been identified.

SOME PRACTICAL LIMITATIONS OF COINTEGRATION ANALYSIS

Cointegration Analysis When a Relationship is Spurious

Hardly any paper that uses cointegration techniques for empirical exploration fails to mention why they use the cointegration methodology: to avoid spurious regression results. That has been the key statistical motivation behind cointegration analysis since its inception. In practical applications, however, not all commonly used cointegration techniques have a unique edge over standard regression techniques in identifying spurious economic relationships. To illustrate this point, consider three independent random walks, X, Y, and Z, with 99 observations each.[2] By their construction, any association among them is purely spurious.

Let us assume that one approaches the association between X, Y, and Z in a traditional manner by starting out with a fourth-order autoregressive-distributed lag model (ADL) with X as the dependent variable and tests this model down to a more parsimo-

TABLE 1
Unit Root Tests for Levels of Variables

	X	Y	Z
Augmented Weighted-Symmetric[a]	0.776	0.135	0.639
Augmented Dickey-Fuller[b]	0.018	0.313	0.003
Phillips-Perron[b, c]	0.187	0.198	0.036

Probability values (p-values) are provided for the null hypothesis of a unit root. See Note 2 in the text for the construction of the variables.
a. See Pantula et al. [1994].
b. p-values come from MacKinnon [1994].
c. Phillips and Perron [1988].

nious form [Gilbert, 1986; 1989].[3] One may arrive at a specification such as the following,

$$X_t = \underset{(-1.4)}{-0.734} - \underset{(-1.5)}{0.075}\, Y_{t-1} + \underset{(1.87)}{0.200}\, Z_t - \underset{(-2.58)}{0.377}\, Z_{t-1} + \underset{(2.17)}{0.233}\, Z_{t-2} + \underset{(16.96)}{0.878}\, X_{t-1}$$

$R^2 = 0.9636$ p-values: td = 0.82, bg1 = .65, bg4 = .92, chow = 0.19, white = 0.80, reset = .07

where t-values are reported in parentheses below the estimated coefficients and where probability values (p-values) are provided for all statistical adequacy tests.[4] The equation shows a surprisingly good statistical fit, with high R^2 and acceptable test statistics. In addition, the equation is dynamically stable. However, the equation lacks long-run economic content because the implied long-run multipliers ($\partial X/\partial Z = 0.461$ and $\partial X/\partial Y = -0.617$) have t-values of 1.06 and -1.48, respectively, and are, therefore, not statistically significant at the five percent level.[5]

Now consider a typical cointegration analysis of the relation between X, Y, and Z. As is fairly standard practice, the analysis commences with unit root tests for all three variables. The results are given in Table 1. All three unit root tests indicate that variable Y is $I(1)$[6], but the evidence on the other two variables is less clear. Such ambiguity is fairly common for unit root tests. The analysis proceeds on the assumption that all three variables are $I(1)$ as suggested by the first test reported in Table 1, which is arguably the most reliable of the three unit root tests [Pantula et al., 1994].

The tests for cointegration are next. The Engle-Granger procedure [Engle and Granger, 1987] cannot reject the null hypothesis of no-cointegration among the three variables at any common level of statistical significance.[7] This is the result that one would expect from a cointegration test on three independent random walks. By contrast, the Johansen [1991] cointegration trace test rejects the null hypothesis of zero rank ($r = 0$) with a p-value equal to 0.006 and the null hypothesis of rank one or less ($r \leq 1$) with a p-value equal to 0.023.[8] Even testing at the one percent level results in one statistically significant cointegrating vector, not what is expected from a very popular cointegration test. Yet these results are not atypical.[9] Repeating the above tests 1,000 times confirms that, at the five percent level of significance, the Johansen trace test rejects the null hypothesis of zero cointegrating vectors in about 17 percent of all cases. This is not much different from the results that one can obtain by testing for statistically significant long-run multipliers within the context of an ADL regression. At the five percent level, an unrestricted fourth-order ADL finds statistically significant long-run coefficients in about 20 percent of all cases.[10] The Engle-Granger procedure, by contrast, does significantly better: at the five percent level, it rejects the null of no-cointegration in less than four percent of all cases. Hence, when a spurious relationship actually exists, the Engle-Granger procedure appears to be quite good at identifying it. It is appreciably better than either the more popular Johansen cointegration technique or the traditional approach that relies on an ADL model.

Cointegration Analysis When a Meaningful Long-Run Relationship Exists

Avoiding a type I error, that is finding cointegration when the relationship among the economic variables under consideration is in fact spurious, is only one issue for cointegration techniques. The companion issue is to avoid a type II error, that is finding no cointegration when, in fact, a meaningful relationship exists among the variables considered. It is suggested that neither the Johansen nor the Engle-Granger technique performs significantly better in this respect than standard regression techniques based on the application of an ADL model. The relative performance of these techniques is illustrated for three potential problem cases of practical relevance: omitted variables, structural change, and simultaneous equations bias.

The Problem of Omitted Variables. By now, it is well established that the success rate of finding a cointegrating relationship, even when one is known to exist, depends critically on what variables are included or excluded from the analysis [Melnick, 1995]. The early belief among practitioners that cointegration analysis somehow provides an easy way of finding meaningful long-run economic relationships without much need for economic theory has turned out to be ill founded. Careful economic theorizing and familiarity with the data remain prerequisites for sensible results, whether one uses cointegration or traditional regression techniques.

If specification uncertainty is a problem for the relationship that is being modeled, one typically faces the potential for an omitted variables problem. It is suggested that traditional regression techniques offer a more constructive modeling environment in this situation than cointegration techniques. To illustrate this point, consider the relationship $W = 5 + 1.5\,X + 0.5\,X^2 + \epsilon_y$, which is non-linear in variable X.[11] Assume that the non-linearity in X is ignored initially. Starting with a fourth-order ADL and testing down to a more parsimonious form, leads to the equation

$$W_t = \underset{(2.0)}{1.54} + \underset{(14.8)}{0.940}\, W_{t-1} - \underset{(-0.54)}{0.035}\, W_{t-4} + \underset{(3.07)}{1.30}\, X_t - \underset{(-3.5)}{2.03}\, X_{t-1} + \underset{(2.2)}{0.907}\, X_{t-2}$$

$R^2 = 0.8861$ p-values: td = .81, bg1 = .40, bg4 = .56, chow = .00, white = .00, reset = .97

where the implied long-run multiplier $\partial W/\partial X$ is equal to 1.87. With a p-value of 0.054, this long-run multiplier is not significantly different from zero at the five percent level. In addition, the equation does not pass standard tests for structural stability and heteroskedasticity. Overall, this equation would be unacceptable on the basis of standard regression techniques.

Cointegration tests for the variables W and X lead to p-values of 0.707 for the Engle-Granger test and 0.059 for Johansen's trace test. Hence, both tests reject cointegration at the five percent level. However, no guidance is offered by either test as to what could be wrong with the equation. Is there truly no economically meaningful relationship between W and X or is the relationship only misspecified?

Repeating the above experiments 1,000 times, one finds the following results. There is only a five percent chance that an unrestricted fourth-order ADL will not be rejected for the mis-specified model by either the test statistics for heteroskedasticity or structural stability at the five percent level or better. If one's work is guided by these statistical adequacy tests, there is little chance that one would accept a wrong model. The results of the Johansen technique are less convincing. In about 43 percent of all cases, the Johansen trace test rejects the null hypothesis of no-cointegration at the five percent level of significance. The equivalent rejection rate for the Engle-Granger technique is 17 percent.

How is the fact to be interpreted that cointegration techniques identify with a non-negligible probability a cointegrating vector (CIV) even when there is an omitted variable problem? On the positive side, finding cointegration correctly suggests that a long-run relationship exists. On the negative side, the researcher is likely to accept a numerically wrong CIV if one assumes some degree of collinearity exists among the included and excluded variables.

Since omitted variables may play an important role for cointegration analysis, any researcher employing these techniques would be well advised to spend sufficient time to fully develop the underlying economic theory and to consider possible deviations from it before embarking on cointegration tests.[12] It certainly makes little sense to approach cointegration analysis similar to a short-run VAR-based forecasting exercise, that is, with only a minimal amount of economic theorizing.

The Problem of Structural Change. To detect common factors among the stochastic trends of variables requires a sufficient number of observations so the stochastic trends can reveal their unique characteristics. This requirement entails a fundamental problem for cointegration analysis in economics. The longer the time horizon that is considered, the higher is the probability that the underlying economic structure changes and the linear relationship among the trend innovations is likely to change over time. As a consequence, no unique CIV will emerge. The implications for cointegration analysis are rather unfavorable. As the sample is expanded toward the past, one comes closer to the ideal testing environment for cointegration analysis. Yet at the same time, the problem of structural change emerges, which in turn leads to a breakdown of cointegration analysis. In other words, the facts of economic reality fundamentally conflict with the statistical requirements of cointegration analysis.[13]

This fundamental contradiction is expressed in the large literature on structural breaks and how to handle them in cointegration analysis. Starting from early work by Perron [1989], and Hamilton [1989] to more recent contributions by Campos et al. [1996], Gregory et al. [1996], Gregory and Hansen [1996], and Perron [1997], the problem of structural breaks has been subjected to intense scrutiny. Although the work in this area displays considerable ingenuity, it is generally based on the assumption that structural change is a rare occurrence in a world that is inherently stable. Experience in applied economics suggests the contrary: structural change is a permanent and key feature of economic reality. Not surprisingly, the work on cointegration and structural change[14] appears to be moving ever closer to the same types of techniques, such as rolling regressions, that are commonplace in traditional time series econometrics. However, accepting the identification of cointegrating regressions that may only hold for certain, and possibly rather short, subsets of the data, effectively discards the spirit and basic idea of cointegration, which is to accept only relationships that survive the test of time. In that case, cointegration is starting to compete with methodologies that may be better suited to the type of structural change that is so common in economic applications.[15]

It may be noted that long time series cause a problem for cointegration analysis in applied economics not only because parameters vary, but also because data definitions are more likely to change. Such changes in definitions are not surprising. They reflect the changes to the structure of the economy.

To illustrate the problem of structural change, consider the following relationship between W and X. For observations 2 to 30 the equation is assumed to be $W = 5 + 1.5X + \epsilon_y$, where X is the random walk defined earlier and where the innovation ϵ_y is the one underlying the construction of random walk Y (Note 2). For observations 31 to 100, the equation is specified as $W = 8 + 1.2X + \epsilon_y$. There is a structural break in the equation at observation 31 that changes both the intercept and the slope parameter.

Starting from a fourth-order ADL and testing down to a simpler form results in the equation

$$\underset{}{W_t} = \underset{(3.2)}{1.71} + \underset{(5.2)}{0.453}\, W_{t-1} + \underset{(3.9)}{0.290}\, W_{t-2} + \underset{(11.0)}{1.53}\, X_t - \underset{(-5.0)}{0.950}\, X_{t-1} - \underset{(-2.4)}{0.220}\, X_{t-4}$$

$R^2 = 0.9711$ p-values: td = .15, bg1 = .76, bg4 = .39, chow = .19, white = .05, reset = .01

where the implied long-run multiplier $\partial W/\partial X$ is equal to 1.40, with associated p-value equal to 0.00. A statistically significant long-run multiplier exists, but since the equation does not pass all statistical adequacy tests, the equation is not acceptable based on traditional regression methodology.

Consider now the cointegration methodology. Cointegration tests on W and X cannot reject the null hypothesis of no-cointegration for either the Engle-Granger (p-value = 0.80) or the Johansen technique (p-value = 0.17) at the five percent level of significance. Again, the standard cointegration methodology does not indicate a lack of cointegration.

The above experiment is repeated 1,000 times to get a better idea of how the structural break affects traditional regression methodology versus cointegration analysis. For the particular example at hand, the Engle-Granger and Johansen techniques reject the null hypothesis of no-cointegration at the five percent level 27 and 76 percent of the times, respectively. For an unrestricted fourth-order ADL, a statistically significant long-run multiplier is found in 93 percent of all cases. However, at least one of the statistical adequacy tests signal rejection of the model assumptions in all cases at the five percent level of significance.

The Monte Carlo evidence supports earlier work that a structural break can fairly easily lead to the conclusion of no-cointegration for the Engle-Granger methodology. By contrast, the Johansen technique appears to be less affected by a structural break. How to evaluate this empirical evidence is not clear cut. The finding of no-cointegration is undesirable because there is a meaningful underlying relationship, albeit one with a structural break. However, rejection of the null of no-cointegration is also undesirable because it leaves the researcher with a cointegrating vector that is not correct and with no indication that something may be wrong with it.

The traditional regression techniques provide a more useful outcome. They correctly identify the existence of a statistically significant long-run relationship. Yet, at the same time, they signal that the equation has a statistical problem, which forces the conscientious researcher to investigate further. In a sense then, the traditional approach offers a more constructive modeling environment than standard cointegration techniques.

The Problem of Simultaneity. If the variables that form part of the cointegration analysis are simultaneously determined in the sense of the Cowles Commission, then cointegration analysis may have little to offer relative to such venerable techniques as two-stage least squares. In fact, Hsiao [1997a; 1997b] has shown that in the context of dynamic simultaneous equation systems and no identification problem one can all but ignore the time series properties of the variables and instead use the received techniques without being worse off.

To illustrate this point, consider the following linear dynamic simultaneous equations system consisting of two behavioral equations (demand and supply, respectively) and an equilibrium condition:

$$Q_t^d = 1 - 0.5\,P_t + 0.5Y_t + 2\,Z_t + 0.2Q_{t-1} + u_t$$

$$Q_t^s = 1 + 0.5\,P_t + X_t + 0.8Q_{t-1} + v_t$$

$$Q_t^d = Q_t^s = Q_t.$$

where the variables Y, Z, and X are random walks defined earlier, u and v are standard normal random variables,[16] and where Q and P are generated on the basis of the associated reduced-form equations.

Cointegration techniques are examined for this system under two alternative assumptions: (a) the structure of the system outside of its dynamics is known to the researcher and (b) nothing is known to the researcher outside of the variables that play a role in the system. It must be noted that the traditional Cowles Commission approach and the work of Hsiao [1997a; 1997b] assume that the structure of the system is known, at least approximately. Hence, assumption (b) is irrelevant for the traditional approach.[17]

TABLE 2
Long-Run Parameter Estimates for Simultaneous Equations System, One Equation at a Time

	Long-Run Parameters		
Demand Function	**P**	**Y**	**Z**
true parameters	-0.63	0.63	2.50
EG estimate	-0.58	0.48	2.54
JOH estimate - CIV-1	-0.69	0.53	2.48
CIV-2	0.47	0.89	1.94
2SLS - 2nd order ADL	-0.61	0.64	2.50
OLS - 2nd order ADL	-0.55	0.59	2.51
Supply Function	**P**	**X**	
true parameters	2.50	5.00	
EG estimate[a]	0.38	2.17	
JOH estimate	2.31	4.61	
2SLS - 2nd order ADL	2.11	4.43	
OLS - 2nd order ADL	1.80	4.11	

All parameter estimates are based on the same data set and are assumed to be on the right side of the equal sign, with Q being on the left side. EG stands for the Engle and Granger [1987] technique. JOH represents the method used by Johansen [1991]. CIV stands for cointegrating vector, 2SLS for two-stage least squares, OLS for ordinary least squares, and ADL for autoregressive distributed lag. See Note 2 for the construction of variables X, Y, Z.

a. Not significant at the 5 percent level.

Table 2 reports the results of the Engle-Granger and Johansen cointegration tests on the variables of each equation, but excluding the lagged dependent variable. At the five percent level of significance, the Engle-Granger technique identifies a cointegrating vector only for the demand function. The Johansen technique finds multiple cointegrating vectors for the demand function. Both OLS and 2SLS estimates are based on an unrestricted second-order ADL, true to the assumption that the dynamics of the equations are unknown. Both techniques identify the existence of long-run parameters at better than the one percent level for all variables. Comparing the estimated long-run parameters to the true ones, it is apparent that both OLS and the Engle-Granger technique have the largest bias.[18] The first cointegrating vector of the Johansen technique and the 2SLS method tend to provide better long-run parameter estimates.

The above experiments are repeated 1,000 times. For each replication, the random walks X, Y, and Z and the disturbance terms u and v are created from a new set of innovations. At the five percent level of significance, the Engle-Granger technique identifies a CIV for the demand function in 74.4 percent of all cases. This contrasts with 93.6 percent for the Johansen technique. For the supply function, the Engle-Granger technique finds a CIV in only 2 percent of all cases, while the Johansen technique does so in 99.3 percent of all cases. In 44 percent of all cases, the Johansen technique finds a second CIV for the demand function. For the supply function the percentage is about 23 percent. 2SLS establishes the existence of a long-run multiplier for each of the five variables in about 92 to 93 percent of all cases when the test is conducted at the five percent level.

What is perhaps most interesting for these experiments is a comparison of how close the long-run parameter estimates of the Johansen technique and 2SLS are to their true values. For each replication, the better of the two estimation techniques is identified on the basis of the absolute deviation of the long-run parameter estimate from its true value, summed over all five parameters. The 2SLS technique outperforms the Johansen technique by this criterion for 69.3 percent of the 1,000 replications. These results support the point made by Hsiao [1997b]: if there is no specification uncertainty with regard to which variables enter the equations to be estimated, there is little to recommend cointegration techniques over a dynamic version of 2SLS.

According to assumption (b), specification uncertainty implies that the researcher knows the variables that enter the system of equations but does not want to assign the variables to the structural equations or to distinguish between endogenous and exogenous variables. A fairly common approach to cointegration testing in this setting is to use all variables $\{Q, P, X, Y, Z\}$ in the cointegration analysis. The results of such an exercise for the variables used at the beginning of this section are presented in Table 3. Again, multiple CIVs arise for the Johansen technique, none with any obvious economic interpretation. This suggests the existence of an identification problem. The way to proceed in this case would be to impose and test identifying restrictions as discussed, *inter alia*, by Johansen [1995] and Boswijk [1996]. It requires no further discussion that economic theory is needed to deliver these identifying restrictions. Hence, it is again obvious that cointegration analysis needs a sufficient foundation in terms of economic theory to make economic sense.

A simple way to produce identification restrictions may sometimes be to impose exclusion restrictions covering either single or multiple variables.[19] Recently, Davidson [1998] has taken the idea of exclusion restrictions and reformulated it as a search for *irreducible cointegrating relations* (ICs). From a practical point of view, such a search implies testing all possible subsets of variables for cointegration. All subsets of variables that cointegrate belong to the set of ICs. All supersets that also cointegrate are discarded as are all variable sets that do not cointegrate. As discussed in detail in Davidson [1998], this simple elimination procedure can potentially identify structural economic relationships and other useful relationships, such as reduced forms. This is borne out for the given data set (Table 3). Davidson's [1998] methodology has little trouble identifying the two structural equations and the two corresponding reduced-form equations in the current data. This is a notable advance beyond the unrestricted and uninterpretable CIVs identified by the Johansen technique. However, it needs to be kept in mind that Davidson's [1998] methodology is not immune to the problems discussed earlier. The omission of important variables in the original set of

TABLE 3
Cointegrating Vectors for Simultaneous Equations System (All Variables Used Simultaneously)

	Q	P	X	Y	Z
True Parameters					
demand function	1	-0.63		0.63	2.50
supply function	1	2.50	5.00		
reduced form P		1	-1.60	0.20	0.80
reduced form Q	1		1.00	0.50	2.00
Estimates					
EG estimate	1	-0.47	0.27	0.43	2.38
JOH estimate - CIV-1	1	-2.47	-2.96	0.79	4.32
CIV-2	1	-0.32	0.50	0.51	2.18
ICs - 1	1	-0.62		0.58	2.44
- 2	1	2.08	4.44		
- 3		1	-1.65	0.21	0.91
- 4	1		1.01	0.45	1.89

All parameter estimates are based on the same data set as those of Table 2. A 1 for P or Q identifies which of the two variables is moved to the left side of the equal sign. All other variables (parameters) are assumed to be on the right side of the equation to match Table 2 and the simultaneous equations system provided in the text. EG stands for the Engle and Granger [1987] technique. JOH represents the method used by Johansen [1991]. CIV stands for cointegrating vector, ICs stands for *Irreducible Cointegrating relations*, a term introduced by Davidson [1998] and described in the text. The irreducible form estimates are performed with the statistical package GAUSS using the program referenced in Davidson [1998]. See Note 2 for the construction of variables X, Y, and Z.

variables, structural change, and collinearity among the set of variables will negatively affect the methodology, as they will all cointegration techniques.

SUMMARY AND CONCLUSIONS

The purpose of this paper has been to provide some perspective on the usefulness of cointegration techniques in applied economics. This has been accomplished by (1) reviewing the weak spots of cointegration analysis and (2) comparing the performance of two popular cointegration techniques to the traditional autoregressive distributed lag model.

The comparison of cointegration and traditional econometric time-series techniques suggests two conclusions. First, traditional econometric techniques have not become completely obsolete for trended data as it is sometimes suggested. In fact, for many applications they offer a sensible alternative to cointegration techniques.[20] Second, cointegration techniques need to be applied with great care. This latter conclusion has at least three dimensions. First, cointegration analysis is not a substitute for carefully developing the underlying economic theory. In particular, approaching cointegration analysis with the type of minimalist economic theory that may be sufficient for short-run VAR forecasts is likely to lead to an omitted variables problem, multiple cointegrating vectors, and incorrect inferences. Second, every researcher needs to be aware of the fact that standard cointegration techniques do not work very well for the long time series for which they are intended because of the ever present possibility of structural change in the economic environment. Third, if one or more cointegrating vectors are identified, it is highly desirable to test for identifying and/or exclusion restrictions. The procedure developed by Davidson [1998] appears to be well suited for many practical applications because it allows one to derive, in a systematic manner, cointegrating vectors with potentially sensible economic interpretations.

NOTES

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1. McNew and Fackler [1997] present a recent example in which cointegration has no obvious relation to economic theory.
2. The series are created in TSP 4.4 for observations 2 to 100, with sample observation 1 being zero for all three series. Standard normal random variables are used for their construction. The random walks X, Y, and Z are generated for the sample 2 to 100, with the following seeds for the respective error terms (starting with observation 1): $\epsilon_X = 12360$, $\epsilon_Y = 87642$, $\epsilon_Z = 64934$.
3. It is assumed that a simple regression in levels will not be seriously entertained. Such an exercise would lead to a high R^2 (0.8323) but highly significant statistics for autocorrelation, structural break, and functional form tests.
4. The abbreviation *td* stands for a likelihood ratio test of the exclusion restrictions relative to a fourth-order ADL; *bg1* and *bg4* represent the Breusch-Godfrey test [Godfrey, 1978] for autocorrelation with one and four lags, respectively; *chow* identifies Chow's [1960] test for structural break at the sample midpoint; *white* is White's [1980] test for heteroskedasticity, and *reset* stands for Ramsey's [1969] test for functional form misspecification.
5. Asymptotic t-values are calculated by the delta method. The qualitative conclusions do not change if one does not test down the fourth-order ADL to a more parsimonious form but calculates asymptotic t-values for the equation containing all four lags.
6. Unit root tests are repeated on the first differences of X, Y, and Z and reject the null of non-stationarity at all reasonable levels of statistical significance and for all three variables.
7. The associated p-value is 0.345 with two lags added.
8. The Johansen estimation procedure is the one hard-programmed in TSP 4.4. An AIC rule is used for the optimal lag length, finite sample corrections are employed according to Gregory [1994], and p-values are interpolated from Osterwald-Lenum [1992].
9. Very similar results can be found in Gonzalo and Lee [1998].
10. Fewer significant cases are typically found when the ADL is tested down to a more parsimonious form.
11. Note 2 discusses the construction of variable X and innovation ϵ_y.
12. Consider in this vein the discussion by Pesaran and Smith [1995].
13. *Prima facie*, it would appear that there are fewer such conflicts in the natural sciences where the vast majority of relationships analyzed do not change over time.
14. See Maddala and Kim [1998, Chapter 13] for a recent survey and assessment of the work on cointegration and structural change.
15. Such a methodology is *structural time series* modeling, also known as *unobserved components* modeling [Harvey 1989; 1997].
16. Random variable u is generated with seed 2223 and random variable v with seed 33322 in TSP 4.4.
17. If the model specification is only approximately known, the traditional approach would use (1) statistical adequacy tests, (2) tests for the existence of economically sensible long-run multipliers, and (3) deterministic and/or stochastic model simulations of the type described by Fair [1994] to identify the model structure.
18. The bias of the Engle-Granger technique was first pointed out in Banerjee et al. [1986].
19. There may be a problem with exclusion restrictions when some or all variables are highly collinear.
20. This conclusion is similar to that suggested by Pesaran and Smith [1998].

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