Explaining Long- and Short-Run Interactions in Time Series Data

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In this article, I extend the concept of separate cointegration to include the common-feature trend-cycle decomposition approach. This combined approach operates a reduction of the parameter space and permits the identification of the time series long- and short-run constituent factors. A careful assessment of their reciprocal relations, in turn, allows for the answering of potentially interesting economic questions. To show the usefulness of the proposed methodology, I apply it to the study of the relationships between the international business cycle and trade flows.

KEY WORDS: International business cycle; Separate cointegration; Trade interdependencies; Trend-cycle decomposition.

There are numerous cases in economics in which groups of variables interact among each other differently from the way variables interact within each group. Consider, for example, real variables and monetary variables. The two groups are, in a way, logically distinct; the variables from the different groups are more dissimilar than those within each group. Moreover, there are both theoretical reasons and a wealth of empirical findings suggesting that, although what happens in the monetary sector has a short-run influence on the real sector, the long-run behavior of the latter is largely independent from the former (Konishi and Ramey 1993).

As a further illustration, consider the likely relationships between international aggregate outputs and international trade flows. Although the presence of long- and short-run relationships among these variables is ultimately an empirical question, there are economic reasons that would indicate the nature of these links: Cointegration within a group of national products may follow from the presence of convergence forces, and cointegration among pairwise international trade flows may also exist because of long-run balance-of-payments constraints. Short-run dynamics are likely within each group of variables, in the form of an "international business cycle" and, perhaps, of a "trade cycle." Outputs and trade flows, although probably not linked by long-run cointegration relationships, are obviously connected by other types of ties.

In this article, I propose an econometric methodology to deal with the general case of separate groups of cointegrating variables interacting in the short run. Our purpose is to allow for a careful accounting of the variables' long- and short-run constituent factors and of their relationships therein. This task is accomplished by extending the "separate cointegration" approach of Konishi and Granger (1992) to incorporate the "common-trend–common-cycle" approach of Vahid and Engle (1993). I choose the latter as a permanent–temporary component decomposition for the ease with which it allows for a useful naming of the relevant factors and, also, for—certainly disputable—aesthetic reasons.

Note, however, that other decomposition techniques, such as the one proposed by Gonzalo and Granger (1995), would do just as well. In fact, Proietti (1997) showed that the two techniques are very similar and in some instances provide identical results. Moreover, Granger and Haldrup (1997) provided the necessary representation for the Granger and Gonzalo decomposition within separate cointegration.

There is a further motivation for our work. The vector autoregressive (VAR) modeling methodology is often affected by a "curse of dimensionality"—too many parameters to estimate with too little data. One of the approaches used to tackle the problem, in the reduced-rank regression tradition, is through the definition of (canonical correlation maximizing) linear combination of the data, or of their transformation, that allow for an effective reduction of the parameter space, as argued, among others, by Tsay (1989) and Velu, Reinsel, and Wichern (1986).

Cointegration (and common-feature) analysis, by defining such linear combinations as economically meaningful, permits the use of economic theory to improve estimation efficiency. For this reason, the methodology that I here propose, in carrying forward the search for empirically tested and economically meaningful restrictions, is within the broader reduced-rank regression modeling philosophy.

To demonstrate the usefulness of our methodology in at least one case, we propose an application of the latter of the two examples illustrated previously. Using annual data for the U.S., the Japanese, and the European economies, we analyze the complex relationships between permanent and temporary components of aggregate international outputs and international trade flows. As in many empirical applications, the unconstrained empirical problem is characterized by a large parameter space with respect to the available data. We restrict its dimension by imposing both separate cointegration and common-cycles restrictions to conclude that the interplay between long- and short-run components of output and trade is rich, that this analysis is informative, and that the econometric methodology here proposed is a useful tool for such an assessment.

The article is structured as follows. Section 1 describes the proposed econometric methodology. The empirical exercise follows. Some final considerations conclude.

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1. AN ECONOMETRIC FRAMEWORK

The purpose of the proposed econometric methodology is the careful definition of a set of admissible links between two or more groups of variables. Let us consider two groups of variables described by a VAR error-correction model (VAR-ECM) assuming that they interact in three different ways.

First, the same shock is allowed to influence both groups of variables. In a VAR model, this means that we allow for contemporaneous correlation between the shocks of the two types of variables. Second, the past history of variables in one group is allowed to influence the variables in the other group. This implies letting lagged differences of variables from one group to enter the relation explaining the first differences of variables from the other. Last, the short-run dynamics of variables in one group could be helpful in explaining variables from the other group. In an error-correction model (ECM), we would let the lagged error-correction term(s) of one block enter the equations of the other. Not necessarily all these links have to be present at the same time. Given an empirical problem, statistical testing can determine which one(s) of the three types of link is active and also whether those three channels are all that are needed to characterize the relations between the two blocks of variables.

The concept of separate cointegration, introduced by Konishi and Granger (1992), allows exactly for these restrictions on the data. Consider a k 1 vector X of nonstationary I(1) components, and its partition $X' = (X_1' \mid X_2')$, where X_1 and X_2 are the k_1 1 and k_2 1 vectors corresponding to the two blocks of variables, with $k_1 + k_2 = k$. There is separate cointegration when X_1 and X_2 are linked (at most) through the three channels listed previously and when there are no cointegration relationships involving variables from both groups. Moreover, if the lagged error-correction term(s) from one block do(es) not enter the equations for the other block of variables, then we have what Konishi and Granger (1992) called "complete" separation between the two blocks.

Consider the VAR-ECM representation of the two blocks of variables X_1 and X_2 under these hypotheses:

$$
\begin{aligned}
\Delta X_{1,t} &= \Gamma_1^{11}\Delta X_{1,t-1} + \quad + \Gamma_{p-1}^{11}\Delta X_{1,t-p-1} \\
&\quad + \Gamma_1^{21}\Delta X_{2,t-1} + \quad + \Gamma_{p-1}^{21}\Delta X_{2,t-p-1} \\
&\quad + \Pi_{11}X_{1,t-p} + \Pi_{21}X_{2,t-p} + \varepsilon_{1,t} \\
\Delta X_{2,t} &= \Gamma_1^{12}\Delta X_{1,t-1} + \quad + \Gamma_{p-1}^{12}\Delta X_{1,t-p-1} \\
&\quad + \Gamma^{22}\Delta X_{2,t-1} + \quad + \Gamma_{p-1}^{22}\Delta X_{2,t-p-1} \\
&\quad + \Pi_{12}X_{1,t-p} + \Pi_{22}X_{2,t-p} + \varepsilon_{1,t}, \qquad (1)
\end{aligned}
$$

where $\Pi_{11} = \alpha_1'\beta_1$, $\Pi_{22} = \alpha_2'\beta_2$ are the usual "Π" matrices in cointegration analysis, and Π_{12} and Π_{21} describe the influence of the error-correction term(s) of one block on the other. β_1 and β_2 are the k_1 r_1 and k_2 r_2 matrices containing each the r_1 and r_2 independent cointegrating vectors of the two blocks of variables. Within this representation, the growth rates of each block of variables depend on their lagged growth rates and error-correction term(s) and also on the lagged growth rates and the error-correction terms of the other block of variables. The matrix that describes the cointegration space of $X' = (X_1' \mid X_2')$ has the following structure:

$$
\beta = \begin{bmatrix} \underset{r_1 * k_1}{\beta_1'} & \underset{r_1 * k_2}{0} \\ \underset{r_2 * k_1}{0} & \underset{r_2 * k_2}{\beta_2'} \end{bmatrix}.
$$

That is, there are no stationary combinations of the data that require variables from both blocks.

To further clarify this point, note that if there is separate cointegration, with cointegrating relations present in each block, it is always possible to define a linear combination of variables from both blocks that is also stationary, the simpler case being the sum of all the linear combinations that have been detected. This is true because linear combinations of stationary time series are also stationary. However, in this case, it is not the pooling of variables from the two blocks what makes the overall linear combination stationary. In this sense, with separate cointegration, variables from both blocks are not "required" to form stationary linear combinations of the data. A different way of looking at the problem is by noting, as Konishi and Granger (1992) did, that separate cointegration means that the two blocks of variables do not share any common trends.

In their work, Konishi and Granger (1992) developed different testing procedures to determine whether the restrictions imposed on the relationship between the two blocks are supported by the data and an iterative procedure to estimate the cointegrating space. The latter is based on the observation that, to estimate the cointegrating space of X_1 in (1), the cointegrating space of X_2 must be known, and vice versa. We report details on this procedure, drawn from Konishi and Granger (1992), in Appendix A.

Testing for separate cointegration can be easily accomplished by comparing the sum of the cointegrating ranks of X_1 and X_2, $r_1 + r_2$, with the cointegrating rank of the unconstrained system, r. Under the null hypothesis of separate cointegration, $r = r_1 + r_2$; that is, considering the unconstrained system does not lead to the discovery of further bases of the cointegrating space. Konishi and Granger (1992) showed that the test can be executed by computing the maximum eigenvalue test familiar in Johansen's (1988) cointegration analysis, where H_0: $r = r_1 + r_2$ and H_1: $r = r_1 + r_2 + 1$. For completeness, note that Konishi and Granger (1992) proposed two more testing techniques that I do not consider here.

Separate cointegration can be combined with common-feature analysis (Engle and Kozicki 1993; Vahid and Engle 1993), to generate the desired statistical framework. Consider a multivariate version of the Beveridge–Nelson trend-cycle decomposition (Beveridge and Nelson 1981) of an I(1) multivariate series X_t:

$$
X_t = C(1)\sum_{s=0}^{\infty}\varepsilon_{t-s} + \widetilde{C}(L)\varepsilon_t,
$$

where $C(1)$ derives from $C(L)$, a moving average polynomial in the lag operator with $C(0) = I$, $\sum_{j=1}^{\infty} j|C_j| < \infty$, $\widetilde{C}_0 = I - C(1)$, and $\widetilde{C}_i = -C_i - C_{i+1} -$ for $i > 1$. The first part of the right side of the equation is an infinite summation of random shocks multiplied by a constant matrix and is thus nonstationary; I call it the *trend* of the decomposition. The second part is a moving average and as such is stationary; I call it the *cycle* of the decomposition. It can be shown (see Engle and Granger 1987) that, if X_t is cointegrated with cointegrating rank r, then the r cointegrating vectors are such that $\beta' C(1) = 0$. Then, $\beta' X_t = \beta' c_t = \beta' \widetilde{C}(L)\varepsilon_t$, a linear combination of stationary components. It can also be shown (Vahid and Engle 1993) that the vectors β^* that have the property that $\beta^{*'} \widetilde{C}(L) = 0$ are the common-feature vectors of ΔX_t, where the feature of interest is serial correlation. From the definition of β^*, we obtain that $\beta^{*'} X_t = \beta^{*'} C(1) \sum \varepsilon_{t-s}$, that can be shown to be equal to $\beta^{*'} \sum \varepsilon_{t-s}$.

Vahid and Engle (1993) argued that, when cointegration and common-feature relations of this sort are present, the data contain "common trends" and "common cycles." More precisely, if r is the cointegrating rank and s the cofeature rank (i.e., the number of orthogonal cofeature vectors), then there are $k - r$ common trends, and $k - s$ common cycles. These common trends and common cycles can be thought of as "factors," each one built as a linear combination of the data that, together, account for the variation of X_t. A general and useful interpretation of why cointegration and serial correlation common features are appropriate indicators, respectively, of comovements among integrated and stationary time series was provided by Vahid (1993).

The estimation and testing procedure proposed by Vahid and Engle (1993) has two stages: First, the cointegrating space is estimated using Johansen's (1988) technique; then common cycles are detected by estimating the canonical correlations between ΔX_t and a dataset composed of the relevant lags of ΔX_t and the lagged error-correction term(s).

The separate cointegraton framework can be easily extended to accommodate Vahid and Engle's two-step procedure. I am interested in studying the common dynamic behavior of each block of variables. Once the cointegrating space has been estimated using Konishi and Granger's method, the presence of common cycles within each block can be detected using canonical correlation analysis. In this case, however, the first differences of each block of variables depend not only on its lagged values and on the lagged error-correction term(s) of that block but also on the same variables for the other block. The common-factor vectors for the two blocks are then the result of canonical correlation analysis between $\Delta X_{i,t}$ and $\{\Delta X_{1,t-1}, \ldots, \Delta X_{1,t-q}, \Delta X_{2,t-1}, \ldots, \Delta X_{2,t-q}, \mathrm{EC}_{1,t-1}, \mathrm{EC}_{2,t-1}\}$, $i = 1, 2$, where q is the relevant number of lags for the differenced data and EC_1 and EC_2 are the error-correction terms for the first and second blocks of variables. I call s_1 and s_2 the dimensions of the cofeature spaces in the first and second blocks of variables, respectively. Thus, although the cofeature space of a given block is defined in terms of its variables only, its estimation also depends on the two separate cointegrating spaces, which, as we have seen, are jointly determined.

Separation in common cycles can be easily tested. If cycles are correctly identified within each block of variables, then their total number should not increase when the whole unconstrained system is considered. Under the null hypothesis of separation in common cycles, then, $s = s_1 + s_2$, where s is the dimension of the unconstrained cofeature space. That is, under the null hypothesis, considering the unconstrained system does not lead to the discovery of further bases of the common-feature space. The alternative hypothesis of the test is $s = s_1 + s_2 + 1$.

Vahid and Engle (1993) also showed that, when the number of cointegrating relations and the number of cofeature relations add up to the dimension of the data space, then it is possible to easily recover the trend and the cycle component of each individual time series. In the context of separate cointegration, when $r_1 + s_1 = k_1$ and $r_2 + s_2 = k_2$, it is possible to recover trend and cycle for each series in each block in a very easy way. The derivation of such a decomposition is available in Appendix B.

An interesting case occurs when r_i or s_i is equal to the number of variables less 1 $(k_i - 1)$. In the first instance, when $r_i = k_i - 1$, the ith block of the data is characterized by only one common trend; that is, only one factor explains its long-run behavior. In the second case, when $s_i = k_i - 1$, the data are characterized by only one common cycle; that is, the short-run dynamics of the data can be effectively summarized by only one shared transitory component. In the latter case, it can be shown that the unique common cycle corresponds to the error-correction term. For further details, see Vahid and Engle (1993).

This decomposition is also useful to derive factor representation of the data, where each variable is explained by a series of common factors. To allow for comparisons of the magnitudes of factor-loading coefficients, it is advisable to consider factors with normalized variance.

2. AN EMPIRICAL APPLICATION—THE INTERNATIONAL BUSINESS CYCLE: DOES TRADE MATTER?

In this section I provide an empirical application of the methodology by focusing on the relationships between the international business cycle and the short- and long-run comovements of trade flows.

Comovement of the outputs of different economies is a well-established economic stylized fact. Outputs seem to move together across countries both in the long run, possibly because of the pressure to converge to a common growth path, and also at business-cycle frequencies. Comovement of output is self-evident when we consider the momentous events that have shaped the economic history of the last century, such as the crisis of the 30 or the oil shocks of the 70s. These events affected economic activity virtually in all countries. Even in more normal times, however, business-cycle peaks and troughs tend to be roughly synchronized across countries, a phenomenon that has already been noted in the pioneering study on the business cycle by Burns and Mitchell (1946). Evidence of comovement at business-cycle frequencies within a cointegration framework has been found, among others, by Kozicki (1992).

"Economic integration," loosely defined, is often cited as the explanation for this state of affairs. Economic integration is a catch-all term, comprising trade interdependence, integration of the financial markets, technological interdependence, and political and even cultural integration. With a few exceptions—such as the work of Dellas (1986) and Canova and Dellas (1993)—not much attention has been dedicated to the effort of narrowing down the concept of economic integration to a more meaningful list of well-defined factors that matter for the comovement of business cycles across countries.

Often, different factors receive different emphasis in explaining international output comovement according to the occasion and to the a priori beliefs of the writer. The old tradition of the macroeconometric modeling of the world economy, for example, gives a prominent role in the transmission of the business cycle to trade flows between countries, within a framework where aggregate activity is largely determined by aggregate demand (e.g., Dornbusch 1980). The international real business-cycle literature focuses instead on the importance of shocks that in part are common across countries, in some instances spill over abroad through diffusion processes, and in general are transmitted via variations in the accumulation path of capital (e.g., Backus, Kehoe, and Kydland 1992; Baxter 1996).

Different views on why economic activity seems to be synchronized across countries have strikingly different economic policy implications. If cycles are common because shocks in one country are transmitted abroad—for example, through trade interdependencies—then trading partners face a problem of economic policy coordination. On the other hand, if common shocks are responsible for the international business cycle, then economic policy coordination would not help. A better understanding of what exactly explains the international business cycle and of which aspects of economic integration matter would improve our knowledge of how the international economy works, and it would allow us to make better informed economic policy recommendations.

To apply my methodology to this problem, I first conjure up a list of possible links between the different variables involved. With respect to the output variables, there are reasons to believe that they are bound by long-run relationships. Bernard and Durlauf (1995) argued that the neoclassical long-run convergence theory implies that international outputs are cointegrated; several outputs should then share a single common trend or have a cointegrating rank equal to the number of outputs considered less 1. Bernard and Durlauf (1995), for a number of Organization for Economic Cooperation and Development countries, rejected the hypothesis of convergence (one common trend) but found substantial cointegration, denoting the presence of “a set of common long-run factors which jointly determine international output growth” (p. 97).

The presence of long-run relationships among international output variables does not seem to be linked to the nature of the trade interdependencies, in the sense that the latter should not be relevant in determining the cointegrating properties of the former. As I have argued, short-run relationships are also present among outputs across countries. Both common trends and common cycles in international output, in the Vahid and Engle (1993) sense, were detected by Kozicki (1992).

There are also reasons why trade flows between countries should be characterized by the presence of both long- and short-run relations. If the trade flows considered add up to total world trade, a long-run equilibrium is simply given by the accounting identity that equates total world imports to total world exports. Often, individual countries are worried by their trade imbalances with other individual trading partners. The political and diplomatic pressure that follows such imbalances, if effective, would result in long-run bilateral trade equilibrium.

International trade flows, moreover, are subject to shocks that are, to a great extent, common across countries. Terms of trade shocks, while affecting trade flows asymmetrically, are such an example. The same can be said of technological shocks and of the trade diversion effects that follow the creation of free trading areas: In all cases, the trade of many countries is affected, although in different ways. These shocks, permanent or temporary in nature, can have both permanent effects, as they cause the trade flows to move to a new path, or temporary “cyclical” effects as the trade flows, after having been perturbed, return to their previous path.

On the other hand, stable long-run relations between output and trade, even more so between output and pairwise trade flows, seem to be very unlikely. Technological relations are not fixed but change over time as technological progress takes place and as input substitution occurs because of movements in relative prices. Moreover, bilateral trade typically includes a vast array of (differentiated) products. The demand for these goods depends on relative prices, on possibilities of substitution with other goods produced in third countries, and on product life-cycle considerations. The observed variations of these determinants do not seem to be compatible with long-run relationships between individual trade flows and outputs.

One of our main goals is to characterize how trade flows and output variables interact in the short run at business-cycle frequencies. There seem to be at least three channels through which this can happen. First, the same shock may affect both output and trade flows. An oil shock, for example, may at the same time decrease output of nonoil-producing countries and, because of import substitution, decrease their imports from other nonoil-producing countries. In a VAR framework, allowing for this possibility means to allow for contemporaneously correlated disturbances. Second, the past history of output could be significant in explaining trade flows, as in familiar import or export equations, and the past history of trade, through the income identity, could be significant in explaining output. In an ECM representation of the two blocks of variables, one would allow for the lags of the differences of one type of variables to enter the regressions of the other type. Third, the short-run dynamics of one type of variables could help explain the other. In the ECM, one would let the lagged error-correction term(s) for one block enter the equations for the other. The three channels that I have just listed are obviously the same allowed for by the separate cointegration approach.

I have analyzed the international business cycle and the trade links of three economies—the United States, Japan, and Europe—defined as the sum of its four biggest economies—Germany, France, the United Kingdom, and Italy. The United States, Japan, and Europe together represent a considerable share of world output, and their reciprocal trade flows are an important part of total world trade. Figures 1 and 2 show,

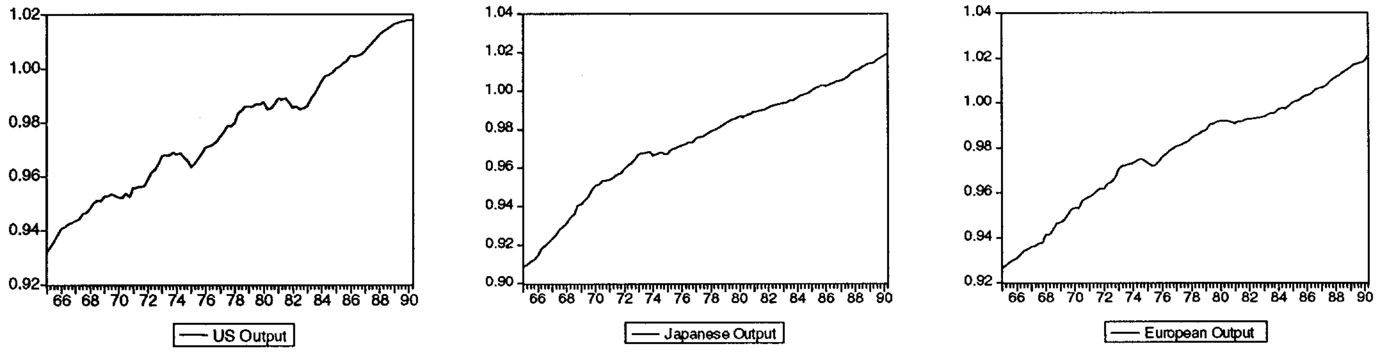

Figure 1. The International Outputs (index numbers).

respectively, the output and the trade data. A description of the data is in Appendix C.

The right columns of Table 1 show the results of separate cointegration analysis for the two blocks of variables. In reading the results, note that two lags of the variables have been considered in the ECM; qualitative results do not change if three lags are considered instead. Moreover, a linear time trend has been included in the ECM, and its significance has been tested and found significant for relevant dimensions of the cointegrating space.

Both output and trade seem to be linked by one long-run relation. In the whole VAR system composed of the nine output and trade variables, once separate cointegration has been imposed, there are two error-correction terms. The first one is a linear combination of the output variables only; the second term is a linear combination of the trade variables only.

Although there are reasons for there being separate cointegration among the variables, the validity of the implied restrictions is largely an empirical question. The test statistic for the null hypothesis $H_0 : r = 2$ versus the alternative $H_1 : r = 3$ is equal to 36.108 and well below any conventional significance-level critical value. The constraints implied by the identifying hypothesis introduced in Section 1 and imposed by separate cointegration are not rejected by the data. The two cointegrating vectors are shown in Table 2.

Table 3 shows the correlations of the disturbances of the ECM under the restrictions implied by separate cointegration [Eq. (1)]. These correlations indicate how common the shocks affecting output and trade are across countries. They are moderately and (mostly) positively correlated within each block of variables.

Innovations to output are positively correlated between the United States and Europe and, to a smaller degree, between Japan and Europe. Innovations to Japanese and U.S. output are the least correlated. Correlations of the shocks to the two trade flows between each pair of countries are all positive: If a shock increases imports from one country, on average it also increases exports to that country. Since shocks to output are positively correlated, if a shock causes a pair of economies to do well, trade in both directions will also benefit. Observe that pairwise trade innovations are more correlated between, say, Europe and the United States, whose output shocks also have higher correlation, than between Japan and the United States, whose output shocks are nearly orthogonal.

Imports to one country are for the most part positively correlated with its output. A possible explanation could be that a higher expected income, as expressed by positive innovations to output, increases imports.

European output is positively correlated with European exports and Japanese output with Japanese imports from Europe, possibly indicating that stronger than expected exports are the source of stronger than expected growth; however, the same positive correlations are not found in the other cases.

Table 1 also shows common-cycle analysis for the output and for the trade variables considered separately. The dimension of the cofeature space is 2 for the output variables and 5 for the trade variables. Separation in the cofeature space has been tested, as illustrated in Section 1, by considering the dimension of the unconstrained cofeature space. The null hypothesis that such a space is of dimension 7, equal to the sum of the estimated dimensions for the constrained spaces, has not been rejected with a P value equal to .518.

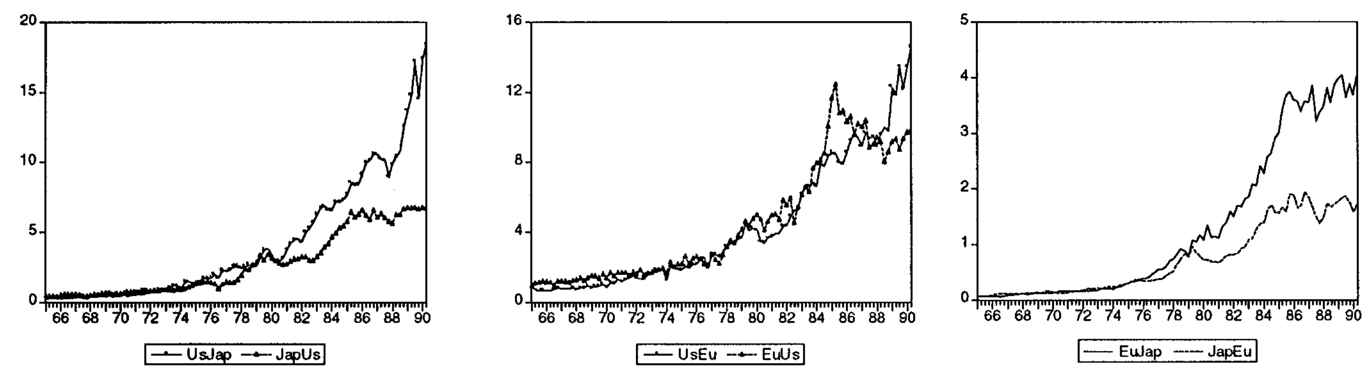

Figure 2. The Trade Flows (billions of 1985 U.S. dollars).

Table 1. Separate Cointegration and Common-Feature Analysis

Separate cointegration analysis		Common-feature analysis		
Trace test statistic	*5% critical values*	*Canonical corr.*	*P values*	*r*
Output variables				
.19	3.74	.84	.00	2
6.09	18.17	.69	.47	1
35.08	34.55	.60	.76	0
Trade variables				
.56	3.74	.84	.02	5
6.63	18.17	.74	.28	4
24.03	34.55	.72	.53	3
43.90	54.64	.68	.78	2
69.44	77.74	.65	.91	1
110.59	104.94	.47	.99	0

NOTE: Separate cointegration test—null hypothesis: H_0: rank $\Pi \le r$ versus H_1: rank $\Pi > r$; Johansen's method. Critical values are from Osterwald-Lenum (1992). Common-feature test—test χ^2 on the null hypothesis that the current and all the smaller canonical correlations are jointly 0, after imposing the restrictions implied by separate cointegration.

The estimated dimensions of the cointegrating and the cofeature spaces imply that the three outputs have one common cycle and two common trends and that the trade variables have one common cycle and five common trends. In this case, as indicated in Section 1, the short-run behavior of each block of variables is described by one common cycle only. We have thus verified that indeed international output has one "international business cycle" that drives the national business cycles. Moreover, trade flows are characterized by a high degree of short-run commonality, which can be summarized by only one "trade cycle." Note that the interpretation of an error-correction term as the cycle is possible if, as in the present case, $r_i = 1$ and $s_i = k_i - 1$. More generally, as shown by Vahid and Engle (1993), a cycle would be a linear combination of the error-correction terms.

The two cycles are shown in Figure 3. Note that the international business cycle presents the expected swings around the negative world-economy downturns of the mid-70s and of the early 80s. The trade cycle seems to be unrelated to the business cycle. We will see how a more careful analysis of the relations between these two cycles provides useful insights on the economic problem at hand.

Table 4 shows the estimated coefficients of the ECM, together with the results of several significance tests. Note that in the test equations both error-correction terms are present and that these are linear combinations of the same data for which we are testing significance. P values on the joint significance of the two lagged values of a given (differenced) variable are between parentheses under the estimated coefficients ("Test A"). Trade flows are mostly nonsignificant in explaining output, with the exception of Japanese output, which is significantly explained by most lagged trade flows. U.S. and Japanese outputs are significant in explaining trade flows, respectively, in three and two cases out of six. Lagged European output is significant in only one case.

At the bottom of Table 4, I report the P values on the joint significance of all the lagged output variables ("Test B") and of all the lagged trade variables ("Test C"). Jointly considered, lagged trade flows are significant in explaining output in only one case. Lagged output, jointly considered, explains trade in three cases out of six.

We now turn our attention to the error-correction terms. Recall that EC1, the error-correction term of the output block, represents the international business cycle and EC2 stands for the trade cycle. The output cycle is significant for both U.S. and European output and not very far from being significant at conventional significance levels for the Japanese output as well. Most important, EC2, the trade cycle, is significant in explaining all three output variables. That is, lagged trade variables are mostly nonsignificant in explaining the variations of output, but the only stationary linear combination of trade is. The lagged trade cycle effectively "summarizes" the information contained in the trade data relevant in explaining output, and the short-run dynamics of trade do matter to explain output. In the trade block, the error-correction terms are significant in explaining trade flows only in two cases.

To get a better grasp of the dynamic properties of the output and of the trade data, we consider their constituent factors, normalized to have unit variance to allow for comparison of the loading coefficients. The derivation of the constituent factors, in the present context, where $r_i + s_i = k_i$, is illustrated in Appendix B. Table 5 shows those factor-loading coefficients.

Table 2. The Cointegrating Vectors

	YUS	*YJAP*	*YEU*	*UsJap*	*UsEu*	*JapUs*	*JapEu*	*EuUs*	*EuJap*
EC1	1	.997	−1.510	0	0	0	0	0	0
EC2	0	0	0	1	.084	3.592	−.566	−.244	−.998

NOTE: EC1 (EC2): The output (trade) cointegrating vector; normalized weights of the linear combinations.

Table 3. The Constrained ECM: Correlation Between Innovations

	YUS	YJAP	YEU	UsJap	UsEu	JapUs	JapEu	EuUs	EuJap
YUS	1								
YJAP	.054	1							
YEU	.307	.222	1						
UsJap	.004	−.109	.228	1					
Useu	.137	−.042	.272	.384	1				
JapUs	−.078	−.002	−.003	.189	−.032	1			
JapEu	.063	.099	.193	.032	−.100	.352	1		
EuUs	−.048	−.070	.176	.137	.425	.184	.060	1	
EuJap	.220	.141	.200	.115	.151	.216	.267	.272	1

NOTE: The estimated equations [Eq. (1) in the text]:
$\Delta X_{1,t} = \Gamma_1^{11}\Delta X_{1,t-1} + \quad + \Gamma_{p-1}^{11}\Delta X_{1,t-p-1} + \Gamma_1^{21}\Delta X_{2,t-1} + \quad + \Gamma_{p-1}^{21}\Delta X_{2,t-p-1} + \Pi_{11}X_{1,t-p} + \Pi_{21}X_{2,t-p} + \varepsilon_{1,t}$
$\Delta X_{2,t} = \Gamma_1^{12}\Delta X_{1,t-1} + \quad + \Gamma_{p-1}^{12}\Delta X_{1,t-p-1} + \Gamma^{22}\Delta X_{2,t-1} + \quad + \Gamma_{p-1}^{22}\Delta X_{2,t-p-1} + \Pi_{12}X_{1,t-p} + \Pi_{22}X_{2,t-p} + \varepsilon_{1,t}$
YUS: U.S. output; YJAP: Japanese output; YEU: European output—UsJap: U.S. imports from Japan and so forth. Variables are in logs. For details on the data, see Appendix C.

EC1 and EC2 refer to the output and the trade cycle, respectively; FT1 and FT2 are the output trend factors, and FT3 to FT7 are the trade trend factors. Remember that these factors are linear combinations of either the output or the trade variables: Each variable is completely explained by the factors of its group. This explains why not all factors are used to explain output or trade variables. However, as I have shown in Section 1, the relevant linear combinations from one block also depend on the qualities of the other block's data.

The output variables all have the same signs on the same factors, denoting similar dynamic behavior. The trade variables, with the exception of European imports from Japan, are characterized by the same sign on the loading coefficient for their cyclical common factor. This indicates that the cyclical behavior of trade is largely shared by the different trade flows. The most affected by it is the bilateral trade flow between the United States and Europe. On the other hand, trade variables seem to be characterized by a greater diversity with respect to their common trend factors. Only FT4 is loaded with the same sign on all the trade-flow variables.

To better understand the relationship between trade flows and international output short-run dynamics, I compare the respective common cycles, depicted in Figure 3. First, note that they are nearly orthogonal, their correlation being equal to −.051. In other words, the trade cycle, which we have

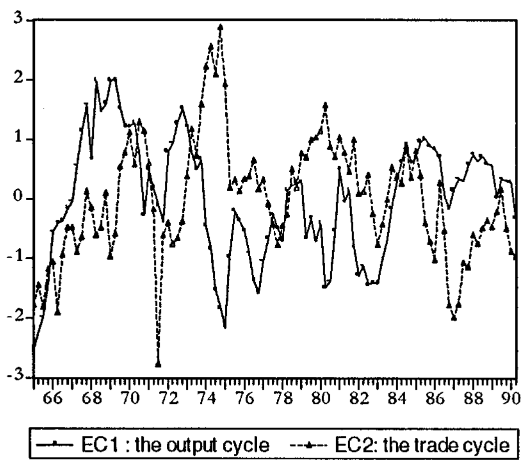

Figure 3. The Error-Correction Terms, or Cycles."

already found to be significant in explaining international outputs, seems to be unrelated to the output cycle. This may be so because the determinants of the international business cycle and of the trade cycle are either different or, while being common, they interact with trade and with output in different ways.

The availability of the time series constituent factors also permits a Granger causality analysis between them that we have carried out including two lags of the relevant variables. The most interesting results of such an analysis are the following. Surprisingly, the output cycle does not Granger-cause the trade cycle at conventional significance levels (the P value of the F test is equal to .42), but the trade cycle does cause the output cycle: Trade short-run dynamics are important in explaining output short-run dynamics. An explanation of this result could be that some variables affect output through their effect on trade.

3. CONCLUSIONS

I have proposed an econometric framework that, by combining the concepts of separate cointegration and of common features, allows for a careful assessment of the long- and short-run constituent factors of two (or more) blocks of variables and of their relationships.

I have applied this combined methodology to the problem of determining the relationship between international output and international trade. The overall conclusion is that trade does have an effect on the international business cycle. Trade short-run dynamics are important in explaining output variations, and they provide valuable information to account for the international business cycle.

A particular role is played by the trade cycle—that is, by the unique stationary combination of the trade data that well summarizes their cyclical behavior. The trade cycle also effectively summarizes the role of trade in determining output, and it is significant in explaining future swings of the international business cycle. Not surprisingly, I also find that output matters to explain the dynamics of trade.

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Table 4. The Constrained Error-Correction Models

Dependent variable		Independent variable: YUS	YJAP	YEU	UsJap	UsEu	JapUs	JapEu	EuUs	EuJap
YUS	lag 1	.17	.05	.04	2.31	2.33	.27	−.71	.20	−2.70
	lag 2	.19	−.00	.15	1.12	1.22	.56	.02	.98	1.53
	Test A	(.09)	(.85)	(.18)	(.01)	(.01)	(.77)	(.63)	(.54)	(.00)
YJAP	lag 1	.05	.12	.01	−1.47	−2.21	−1.79	−1.92	−1.77	−3.16
	lag 2	.12	−.28	.06	.10	2.19	1.19	−1.52	−.07	−.69
	Test A	(.75)	(.03)	(.86)	(.43)	(.05)	(.16)	(.34)	(.33)	(.01)
YEU	lag 1	−.07	−.02	−.14	1.83	−.16	1.01	−.71	.88	2.20
	lag 2	.13	−.29	−.15	.41	−.73	.47	2.36	1.47	2.21
	Test A	(.69)	(.04)	(.23)	(.33)	(.84)	(.66)	(.32)	(.42)	(.03)
UsJap	lag 1	.00	.02	.00	−.17	.36	−.01	−.09	.10	.05
	lag 2	.00	.01	.01	−.07	−.01	−.16	−.37	−.17	−.05
	Test A	(.98)	(.22)	(.45)	(.37)	(.02)	(.36)	(.11)	(.22)	(.79)
UsEu	lag 1	−.01	−.02	−.00	−.11	−.63	−.03	.17	−.23	.03
	lag 2	−.01	.00	−.00	.08	−.17	.10	.16	−.02	.10
	Test A	(.70)	(.10)	(.89)	(.38)	(.00)	(.55)	(.55)	(.17)	(.66)
JapUs	lag 1	.02	−.01	−.01	−.02	.21	−.17	.04	.10	−.11
	lag 2	.02	.04	.00	−.05	.01	−.05	.42	−.01	−.02
	Test A	(.19)	(.01)	(.85)	(.89)	(.28)	(.31)	(.05)	(.75)	(.60)
JapEu	lag 1	−.00	−.01	−.00	−.16	−.11	−.05	−.20	.03	.01
	lag 2	.00	−.02	−.00	.06	.12	.13	−.02	.10	−.03
	Test A	(.75)	(.02)	(.90)	(.10)	(.15)	(.13)	(.24)	(.43)	(.91)
EuUs	lag 1	−.01	.01	.02	−.10	−.09	.36	−.23	−.20	−.13
	lag 2	−.01	−.01	.00	−.27	−.20	.06	−.09	−.15	−.06
	Test A	(.71)	(.44)	(.24)	(.13)	(.35)	(.01)	(.41)	(.22)	(.51)
EuJap	lag 1	.02	.01	.01	.19	.11	.15	.19	.09	.03
	lag 2	.00	.00	−.00	−.13	−.02	−.00	.07	−.00	.03
	Test A	(.37)	(.43)	(.67)	(.12)	(.67)	(.44)	(.53)	(.77)	(.91)
EC1 (output variables)		.09	.04	.12	.29	.00	.27	.95	.45	.61
		(.06)	(.20)	(.00)	(.36)	(.99)	(.38)	(.04)	(.18)	(.04)
EC2 (trade variables)		−.01	−.01	−.00	.02	−.00	−.06	−.09	.00	−.02
		(.00)	(.00)	(.08)	(.49)	(.88)	(.02)	(.01)	(.92)	(.36)
	R^2	.30	.40	.43	.32	.48	.40	.32	.30	.37
	Test B	(.46)	(.10)	(.41)	(.04)	(.02)	(.55)	(.47)	(.50)	(.00)
	Test C	(.58)	(.06)	(.66)	(.04)	(.00)	(.05)	(.25)	(.08)	(.92)

NOTE: For the estimated equations, see Table 3. YUS: U.S. output; YJAP: Japanese output; YEU: European output—UsJap: U.S. imports from Japan, and so forth. Variables are in logs. EC1 and EC2 are the (once lagged) error-correction terms for the output and trade variables' blocks, respectively. Two lags of the dependent variables are included in the estimated (differenced) equations, together with the output and the trade lagged error-correction terms. The table reports estimated coefcients; *P* values are between parentheses. Test A—null hypothesis: joint signicance of once and twice lagged dependent variables; Test B—null hypothesis: joint signicance of all lagged output variables; Test C—null hypothesis: joint signicance of all lagged trade variables; *P* values below error-correction estimated coefcients relate to the standard *t* test.

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APPENDIX A: ESTIMATION OF THE COINTEGRATING SPACE UNDER SEPARATE COINTEGRATION

Consider the projections familiar in Johansesn's (1988) analysis:

$$R_{0t} = X_{t-k} - P(X_{t-k} | \Delta X_{t-1,\ldots,}\Delta X_{t-k-1})$$

and

$$R_{kt} = X_{t-k} - P(\Delta X_{t-k} | \Delta X_{t-1,\ldots,}\Delta X_{t-k-1}),$$

where $P(A|B)$ denotes the least squares projection of A on B. Similarly, call R_{0it} and R_{kit}, $i = 1, 2$, the same projections relative only to the ith block's variables; that is, $R_{0t} = (R_{01t} | R_{02t})$ and $R_{kt} = (R_{k1t} | R_{k2t})$.

The iterative procedure proposed by Konishi and Granger (1992) consists of first estimating β_1 considering X_{1t} in isolation. Then, by treating β_1 as known and equal to its estimate $\hat{\beta}_1$, $\hat{\beta}_1' R_{k1t}$ is concentrated out from the original projections by regressing R_{0t} and R_{kt} against it. This defines a new set of projections: $\widetilde{R}_{kt} = R_{kt} - P(R_{kt} | \hat{\beta}_1' R_{k1t})$ and $\widetilde{R}_{0t} = R_{0t} - P(R_{0t} | \hat{\beta}_1' R_{k1t})$. β_2 is then estimated again with Johansen's technique using the $\widetilde{R}_{0t}$ and $\widetilde{R}_{kt}$ projections to obtain $\hat{\beta}_2$. The step is reiterated; that is, the estimated β_2, $\hat{\beta}_2$, is treated as known and $\hat{\beta}_2' R_{k2t}$ is concentrated out from the the $\widetilde{R}_{0t}$ and $\widetilde{R}_{kt}$ projections to obtain another estimate of β_1.

This iterative process goes on until convergence of successive estimates is obtained. Precise convergence usually occurs after two or three iterations. Konishi and Granger (1992) showed that the results of this iterative procedure is the maximum likelihood estimate of Johansen (1988) that imposes the restrictions of separate cointegration.

Table 5. Factor Analysis

	YUS	YJAP	YEU	UsJap	UsEu	JapUs	JapEu	EuUs	EuJap
EC1	18.91	33.09	24.91						
EC2				34.57	118.45	19.91	23.27	60.19	−15.44
FT1	8.31	11.80	13.29						
FT2	−2.83	−16.82	−12.98						
FT3				−14.23	−55.14	4.93	4.00	−29.13	3.66
FT4				46.57	123.99	29.73	125.64	99.78	68.93
FT5				7.70	−3.59	−2.95	1.48	−7.78	−4.24
FT6				−10.20	−192.58	6.22	−68.70	−97.75	58.71
FT7				−19.19	−3.69	6.56	−11.40	9.94	5.31

NOTE: Factor loadings, after variance normalization. Interpretation: YUS = 18.91*EC1 + 8.31*FT1 − 2.83*FT2, and so forth.

APPENDIX B: TREND–CYCLE DECOMPOSITION WHEN $r_1 + s_1 = k_1$ AND $r_2 + s_2 = k_2$

Consider the $k * k$ matrix B, obtained by stacking the $\beta^{*'}$'s and the β''s as follows:

$$B = \begin{bmatrix} \underset{s_1*k_1}{\beta_1^{*'}} & \underset{s_1*k_2}{0} \\ \underset{s_2*k_1}{0} & \underset{s_2*k_2}{\beta_2^{*'}} \\ \underset{r_1*k_1}{\beta_1'} & \underset{r_1*k_2}{0} \\ \underset{r_2*k_1}{0} & \underset{r_2*k_2}{\beta_2'} \end{bmatrix},$$

where the β_i contains the cointegrating vectors and β_i^* the cofeature vectors of the ith block. Multiplying B times X_t, we obtain

$$BX_t = \begin{bmatrix} \beta_1^{*'} \sum \varepsilon_{1,t-s} \\ \beta_2^{*'} \sum \varepsilon_{2,t-s} \\ \beta_1' \widetilde{C}(L)\varepsilon_{1,t} \\ \beta_2' \widetilde{C}(L)\varepsilon_{2,t} \end{bmatrix},$$

since $\beta_i' X_{i,t} = \beta_i' \widetilde{C}(L)\varepsilon_{i,t}$ and $\beta_i^{*'} X_{i,t} = \beta_i^{*'} \sum \varepsilon_{t-s}$. Consider next B^{-1}, the inverse of B, partitioned as follows:

$$B^{-1} = \begin{bmatrix} \underset{k_1*s_1}{b_1^*} & \underset{k_1*s_2}{0} & \underset{k_1*r_1}{b_1} & \underset{k_1*r_2}{0} \\ \underset{k_2*s_1}{0} & \underset{k_2*s_2}{b_2^*} & \underset{k_2*r_1}{0} & \underset{k_2*r_2}{b_2} \end{bmatrix}.$$

Premultiplying BX_t by B^{-1}, we obtain

$$B^{-1}BX_t = \begin{bmatrix} b_1^*\beta_1^{*'} \sum \varepsilon_{1,t-s} + b_1\beta_1' \widetilde{C}(L)\varepsilon_{1,t} \\ b_2^*\beta_2^{*'} \sum \varepsilon_{2,t-s} + b_2\beta_2' \widetilde{C}(L)\varepsilon_{2,t} \end{bmatrix}$$

or

$$B^{-1}BX_t = \begin{bmatrix} X_{1,t}^p + X_{1,t}^c \\ X_{2,t}^p + X_{2,t}^c \end{bmatrix},$$

where $X_{i,t}^p = b_{1,t}^p \beta_i^{*'} X_t$ is the permanent component, or trend, of the decomposition and $X_{i,t}^c = b_{1,t}\beta_i' X_t$ is its transitory component, or cycle.

APPENDIX C: THE DATA

The output is gross national product for the United States, Japan, and Germany and gross domestic product for France, Italy, and the United Kingdom. Output for Europe is a weighted sum of the output of each included European country, expressed as index numbers in local currency units and at constant prices. The weights have been computed as the share of each country's output in the sum of the four countries' output in the second quarter of 1990 (the last observation of the sample), expressed in dollars and using the average 1990 exchange rate. Other European countries could not be considered because of lack of the necessary trade data. The source for the output data is IMF-IFS.

The six corresponding pairwise trade flows are expressed in dollars and also in index form. The trade data have been taken from the IMF "Directions of Trade" (DOT) tapes. All variables are expressed in logs.

All data are quarterly and seasonally adjusted, and the sample period is from the first quarter of 1965 to the second quarter of 1990, for a total of 102 observations. The sample period has been limited to the second quarter of 1990 to avoid any overlapping of German pre- and post-unification data.

The variables are named YUS, YJAP, and YEU for U.S., Japanese, and European output; and UsJap, UsEu, JapUs, JapEu, EuUs, and EuJap for the six pairwise trade flows (where, for example, UsJap is U.S. imports from Japan).

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REFERENCES

Backus, D., Kehoe, P., and Kydland, F. (1992), "International Real Business Cycles," *Journal of Political Economy*, 101, 745–775.

Baxter, M. (1996), "International Trade and Business Cycles," in *Handbook of International Economics* (vol. 3), eds. G. Grossman and K. Rogoff, Amsterdam: North-Holland, pp. 1801–1864.

Bernard, A. B., and Durlauf, S. N. (1995), "Convergence in International Output," *Journal of Applied Econometrics*, 10, 97–108.

Beveridge, S., and Nelson, C. R. (1981), "A New Approach to Decomposition of Economic Time Series Into Permanent and Transitory Component With Particular Attention to Mesurement of the `Business Cycle,'" *Journal of Monetary Economics*, 7, 151–174.

Burns, A. F., and Mitchell, W. C. (1946), "Measuring Business Cycles," New York: National Bureau of Economic Research.

Canova, F., and Dellas, H. (1993), "Trade Interdependence and the International Business Cycle," *Journal of International Economics*, 34, 23–47.

Dellas, H. (1986), "A Real Model of the World Business Cycle," *Journal of International Money and Finance*, 5, 381–394.

Dornbusch, R, (1980), "Open Economy Macroeconomics," New York: Basic Books.

Engle, R. F., and Granger, C. W. J. (1987), "Cointegration and Error Correction: Representation, Estimation and Testing," *Econometrica*, 55, 251–276.

Engle, R. F., and Kozicki, S. (1993), "Testing for Common Features" (with discussion), *Journal of Business & Economic Statistics*, 11, 369–395.

Gonzalo, J., and Granger, C. W. J. (1995), "Estimation of Common Long-Memory Components in Cointegrated Systems," *Journal of Business & Economic Statistics*, 13, 27–35.

Granger, C. W. J., and Haldrup, N. (1997), "Separation in Cointegrated Systems and Persistent-Transitory Decompositions," *Oxford Bulletin of Economics and Statistics*, 59, 4, 449–463.

Johansen, S. (1988), "Statistical Analysis of Cointegrating Vectors," *Journal of Economic Dynamics and Control*, 12, 231–254.

Konishi, T., and Granger, C. W. J. (1992), "Separation in Cointegrated Systems," Discussion Paper 92-51, University of California, San Diego, Dept. of Economics.

Konishi, T., and Ramey, V. (1993), "Stochastic Trends and Short-Run Relationships Between Financial Variables and Relative Activity," Working Paper 4275, National Bureau of Economic Research, Cambridge, MA.

Kozicki, S. (1992), "Theory and Application of Common Features," unpublished Ph.D. dissertation, University of California, San Diego, Dept. of Economics.

Osterwald-Lenum, M. (1992), "A Note With Quantiles of the Asymptotic Distribution of the Maximum Likelihood Cointegration Rank Test Statistics," *Oxford Bulletin of Economics and Statistics*, 54, 461–472.

Proietti, T. (1997), "Short-Run Dynamics in Cointegrated Systems," *Oxford Bulletin of Economics and Statistics*, 59, 405–422.

Tsay, R. (1989), "Parsimonious Parameterization of Vector Autoregressive Moving Average Models," *Journal of Business & Economic Statistics*, 7, 327–315.

Vahid, F. (1993), "Essays on Common Dynamic Features in Multiple Time Series," unpublished Ph.D. dissertation, University of California, San Diego, Dept. of Economics.

Vahid, F., and Engle, R. F. (1993), "Common Trends and Common Cycles," *Journal of Applied Econometrics*, 8, 341–360.

Velu, R. P., Reinsel, G. C., and Wichern, D. W. (1986), "Reduced Rank Models for Multiple Time Series," *Biometrica*, 73, 105–118.