

Sector-Level Disaggregate Stochastic Trends in Mexico's Real Output

Antonio E. Noriega*

Fecha de recepción: 10 de junio de 2002; fecha de aceptación: 24 de junio de 2003

Abstract: Our aim is to examine whether sectorial production shocks have predominated in Mexico's long annual real output, and whether shocks from different sectors are correlated. We study the long-run movement and comovements of 6 production sectors, using long, low frequency data for the Mexican economy from 1921 to 1993 and Johansen's (1991, 1995) method to test for cointegration, that is, the possibility of common stochastic shocks driving growth among sectors. Under cointegration, the idiosyncratic sectorial shocks cancel out and vanish, giving rise to a (possibly multiple) stochastic growth component common to all (some) sectors. We show that the sources of permanent innovations in Mexico's real output are more likely to come from sector-group-specific sources rather than from either independent sector-specific technological shocks, or common aggregate permanent innovations.

Keywords: Sectorial Production, Sequential Unit Root Testing, Cointegration, Common Trends

Resumen: Nuestro objetivo es examinar si han predominado choques sectoriales en la producción real anual en México, y si esos choques de diferentes sectores están correlacionados. Estudiamos el movimiento y co-movimiento de largo plazo de 6 sectores productivos, usando datos de baja frecuencia para la economía mexicana de 1921 a 1993, y el método de cointegración de Johansen para verificar la posibilidad de choques estocásticos comunes que impulsen el crecimiento entre sectores productivos. Bajo cointegración, los choques sectoriales idiosincráticos se cancelan, dando lugar a un componente de crecimiento estocástico (posiblemente múltiple) común a todos (o algunos de) los sectores.

* Department of Econometrics, Escuela de Economía, Universidad de Guanajuato, Calzada de Guadalupe s/n, Centro, Guanajuato, Gto. 36000, México. Phone and Fax 52-(4)7320105, e-mail: noriegam@quijote.ugto.mx. With thanks to Fred Wallace for making part of the data set used in this study available, to Luara Vargas for excellent research assistance, and two anonymous referees.

Mostramos que las fuentes de innovaciones permanentes en la producción real de México provienen de grupos de sectores, más que de choques tecnológicos sectoriales independientes, o choques agregados.

Palabras clave: producción sectorial, pruebas de raíz unitaria secuenciales, cointegración, tendencias comunes.

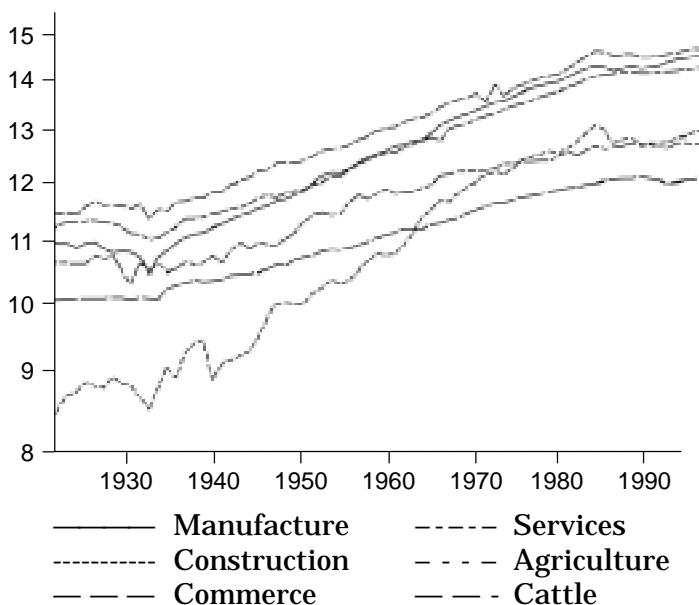
Introduction

The econometric techniques developed during the last twenty years to analyze long-run behaviour of time series data, have helped in understanding the nature of the nonstationary behaviour of macro aggregates¹. In more recent years, these techniques have been applied to disaggregated data. For instance, Norrbin (1995) finds evidence of multiple common stochastic trends in disaggregated US industrial production data, implying that there are industry-specific sources of growth in the industrial production aggregate, and that production at the industry-specific level should not be modelled as an independent integrated process. As Norrbin argues, these implications in turn affect theoretical research, which should focus on more than a single stochastic source of output growth. More recently, Cheung and Westermann (2003), recognize that sectorial data offers a good opportunity to illustrate the idiosyncratic elements of different economic sectors, and to compare different views on the sources of sectorial growth. Sectorial data for Mexico, for instance, reveals heterogenous long-run behaviour among some sectors. In particular, during most of the twentieth century (1921-1993), the highest growth rate corresponds to manufacturing (5.7%), while the lowest goes to cattle (3.2), the difference being quite dramatic. On the other hand, others have observed similar growth rates: cattle and agriculture (3.5), or commerce (4.9) and services (4.8). Figure 1 divides the natural logarithms of Mexico's disaggregated real gross domestic product into six sectors². As can be seen, some sectors tend to move together in the

¹ The literature on the econometric analysis of non-stationary data, i.e., integration and cointegration, is already vast. Recent surveys are Phillips and Xiao (1998) and Maddala and Kim (1998).

² The data consists of disaggregated production at the sectorial level: agriculture, cattle, manufacturing, construction, commerce, and services. It was constructed from two sources. Data for the period 1921-1970 come from the appendix in Cardenas (1998), while that for the period 1971-1993 from the Instituto Nacional de Estadística, Geografía e Informática, INEGI (1996).

Figure 1



long-run, such as the manufacture and construction, and commerce services. A common trend seems to also apply to the group manufacture, construction and commerce. On the other hand, the construction sector's long-run behaviour is quite different from other sectors. This illustrates the possibility of both idiosyncratic as well as common elements across sectors.

In order to guide sectorial economic policy, it is important to know whether idiosyncratic sectorial production shocks have predominated in Mexico's real output, or whether shocks from different sectors are correlated. This is equivalent to investigating if the conventional assumption of a stochastic trend in real gross domestic product can be represented as a common source, or if permanent, long run movements are sector-specific, or sector-group specific. Following the lines of Cheung and Westermann (2003), one cannot rule out the possibility of a common long-run trend among sectorial output, since different economic sectors in a national economy share a common pool of labor and operate in a similar macro-environment. Therefore, reallocation of resources (including labor) across sectors in the wake of sectorial shocks is likely to occur in the long-run, although factor mobility may

not be perfect in the short-run. They also argue, that “The effects of technology changes will diffuse across sectors and improve overall efficiency, albeit in varying degrees, in different sectors” (p. 142).

In this paper, we study the long-run movement and co-movements of 6 production sectors, using long, low frequency data for the Mexican economy from 1921 to 1993. In order to examine whether idiosyncratic sectorial production shocks have predominated in Mexico’s real output, or whether shocks from different sectors are correlated, we utilize Johansen’s (1991, 1995) method to test for cointegration, that is, the possibility of common stochastic shocks driving growth among sectors. Such shocks can in principle be the result of endogenous technological change, due to any of the reasons developed in the new growth literature, or can be regarded as exogenous innovations. Under cointegration, the idiosyncratic sectorial shocks cancel out and vanish, giving rise to a (possibly multiple) stochastic growth component common to all or to some sectors. In order to address these issues, we disaggregate real output into the following sectors: agriculture, cattle, manufacturing, construction, commerce, and services. We show that the sources of permanent innovations in Mexico’s real output are more likely to come from sector-group-specific sources rather than from either independent sector-specific technological shocks, or common aggregate permanent innovations. Along the lines of Norrbin (1995), this evidence points to a need to model the permanent innovations affecting real aggregate output as disaggregated, sector-group specific, technological innovations.

The following section presents the econometric methodology to analyze the possibility of common stochastic trends, while section II reports the empirical results. The last section concludes.

I. Common Stochastic Trends

Assuming that Real Gross Domestic Product, (RGDP) has a single stochastic trend (a unit root), it can be represented by a time series autoregressive model of the following form:

$$\Delta Y_t = \mu + \sum_{i=1}^{p-1} \phi_i \Delta Y_{t-i} + \varepsilon_t \quad (1)$$

where ΔY_t represents the first differences of real output and ϕ_i is a vector of propagation parameters. The constant μ is included to allow for a deterministic linear trend in the data.

Now consider real output disaggregated into sectorial production. Let Y_{st} denote the production of sector s at time t , where $t = 1, 2, \dots, T$ and $s = 1, 2, \dots, S$, with T and S denoting the sample size, and the total number of sectors, respectively. Since Y_t represents the sum of the production of all sectors, then it is implicitly assumed in equation (1) that there is a single, aggregate stochastic trend affecting all sectors.

In order to model permanent innovations arising from sector-specific sources, we utilize, as did Norrbin (1995), a Vector Autoregressive (VAR) model. The underlying VAR model for equation (1), comprising all S sectors, takes the following form:

$$\Delta Y_t = \mu + \sum_{i=1}^p A_i \Delta Y_{t-i} + \varepsilon_t \quad (2)$$

where ΔY_t , μ , and ε_t are $(S \times 1)$ vectors, and A_i are $S \times S$ matrices of unknown parameters. If each sector follows a random walk process, then the vector ΔY_t in (2) would be $I(1)$. Thus, the unit root in real *aggregate* output from (1) should be understood as arising from S , independent permanent stochastic shocks, one for each sector. This comes as no surprise, since, following arguments in Granger and Newbold (1986), it is generally true that a linear combination of $I(1)$ series will also be $I(1)$. It is natural to ask, however, whether these stochastic trends hitting each sector are correlated, or whether they are truly independent from each other. Under the latter, aggregate growth sources should be found in the analysis of idiosyncratic, sector-specific technology shocks. Under the former, technology shocks in one sector will spur growth into other sectors, as discussed in Durlauf (1989)³. In order to examine the potential correlation between shocks from different sectors, we utilize Johansen's (1991, 1995) methods to test for cointegration. To proceed, we reparametrize the VAR in (2) to obtain the Vector Error Correction Model (VECM), as follows:

³ A theoretical model in which aggregate output growth depends on links among production sectors is presented in Startz (1998).

$$\Delta Y_t = \mu + \Pi Y_{t-1} + \sum_{i=1}^k \Gamma_i \Delta Y_{t-i} + \varepsilon_t \quad (3)$$

where $\Pi = \sum_{j=1}^p A_j - I_S$, $\Gamma_j = -\sum_{j=i+1}^p A_j$, and $k = p-1$. When the variables in Y_t are cointegrated, and there are, say, $r < S$ cointegrating vectors, then the matrix Π has reduced rank r . In this case, there exist $S \times r$ matrices α and β each with rank r such that $\Pi = \alpha\beta'$, and the Error Correction Mechanism (ECM) $\beta' Y_{t-1}$ is stationary. The columns of β represent the cointegrating vectors.

If the S stochastic trends are independent from each other, the matrix Π has rank zero, implying that all sectors are hit by independent unit root shocks. In other words, the S sectorial production variables are not cointegrated. In this case the appropriate procedure is to estimate equation (3) excluding the lagged level of the dependent variable, that is, a VAR in the first differences of the data, in order to eliminate the stochastic trends. On the other hand, under the possibility of r stable long-run relationships among the sector's stochastic trend components, namely cointegration, then the sectorial production variables share r common aggregate shocks, and the rank of Π is r , $0 < r < S$. In this case, specifications such as (2) are misspecified, due to a missing variable bias.

In order to test for cointegration, the Johansen's (1991, 1995) method consists in estimating the matrix Π (using maximum likelihood) in an unrestricted form, and then testing whether the restrictions implied by the reduced rank of Π can be rejected. In testing for cointegration, it is necessary to determine the lag length of the autoregressive component, k , and the structure of deterministic elements, which describes the long-run movement of the data (intercept and/or trends for each series) and the long-run *c*o-movement of the involved variables (intercept and/or trend in the ECM). In order to guide the determination of both the lag length and the deterministic components, we use the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC).

II. Empirical Results

Testing for cointegration assumes that the variables in the vector Y_t are $I(1)$, that is, each has a unit root. In Dickey and Pantula (1987), it

was observed empirically that the probability of rejecting the null hypothesis of one unit root (denoted H_1) against the alternative of stationarity (H_0) increases with the number of unit roots present. Therefore, in testing the stationarity of each variable, we follow the methodology suggested by Pantula (1989), which consists of an asymptotically consistent sequential procedure for testing the null hypothesis H_r : exactly r unit roots, against the alternative H_{r-1} : exactly $(r - 1)$ unit roots, with $r = m, \dots, d+1, d$, where m is an assumed maximum number of unit roots present in the data, and $d =$ true number of unit roots present in the data. Pantula suggests that the hypotheses must be tested sequentially in the order H_m, H_{m-1}, \dots, H_d . This procedure is based on Augmented Dickey-Fuller (ADF) tests. We assume that it is known a priori that the maximum possible number of unit roots present in the data is three. Based on Pantula's results, the hypotheses must be tested sequentially in the order H_3, H_2 and H_1 . We perform unit root tests downwards, starting with a test of the null hypothesis H_3 : exactly three unit roots (or a unit root in the second differences of the data). If the null H_3 is rejected, then we test the null H_2 : exactly two unit roots, against the alternative H_1 : one unit root in the autoregressive representation of the series. If both H_3 and H_2 are rejected, we test H_1 against H_0 . Specifically, we test the significance of a_r , using the following ADF-type regression model (see Pantula, 1989, for details):

$$\Delta Y_t = \mu + \beta t + a_r \Delta^{r-1} Y_{t-1} + \sum_{j=1}^k b_j \Delta Y_{t-j} + \varepsilon_t; \quad r = 3, 2, 1 \quad (4)$$

Table 1. Order of Integration of sectorial production variables, Mexico (1921–1993)

<i>Variable</i>	$H_3(\mu = \beta = 0)$	$H_2(\beta = 0)$	H_1
<i>Agriculture</i>	-6.8433* (5)	-10.4460* (0)	-1.9890 (1)
<i>Cattle</i>	-10.7442* (1)	-6.8073* (0)	-1.5855 (0)
<i>Manufacturing</i>	-8.8023* (2)	-6.6147* (0)	-2.6812 (1)
<i>Construction</i>	-8.7433* (2)	-7.8894* (0)	-1.5226 (0)
<i>Commerce</i>	-11.7464* (1)	-5.3759* (1)	-2.2334 (1)
<i>Services</i>	-10.0645* (1)	-3.6665* (1)	-2.6461 (1)

Note: *stands for significance at the 1% level.

Since all of our series in levels indicate the presence of strong upward trends, regression equation (4) is run without restricting the value of both μ and β for $r = 1$. However, for $r = 2$, we impose the restriction $\beta = 0$, since the data in first differences does not have a linear trend, but just a non-zero intercept. For the case $r = 3$, we impose the restriction $\mu = \beta = 0$, since the second differences of the data do not seem to contain neither a trend nor a constant. Table 1 summarizes the time series properties of the variables for Mexico.

In Table 1, the second column reports ADF statistics for testing the null H_3 against the alternative H_2 where no constant or linear trend are allowed in the auxiliary regression. Columns 3 and 4 have a similar interpretation. The numbers in parenthesis correspond to the order of the autoregressive approximation, following Perron's (1997) k -max criterion.⁴ As can be seen, the ADF tests strongly reject the presence of three and two unit roots for all variables. The last column indicates that it is not possible to reject one unit root in the AR representation for each series, implying that our vector of sectorial production series, Y_p , is integrated of order one.

We proceed to test for cointegration, using the Johansen test.⁵ Table 2 reports the number of Error Correction Mechanisms (ECM , the cointegrating rank) resulting from applying both the trace and maximum eigenvalue tests, denoted λ_{trace} , and λ_{max} , respectively, together with the corresponding values of the Akaike and Bayesian Information criteria (AIC and BIC), for values of k , the lag length in the $VECM$, ranging from 0 to 4.⁶ All test results reported in the table correspond to the assumption of linear trends in the individual variables.

As can be seen from the table, the Akaike information criterion is minimum when there are three cointegrating vectors in a $VECM$ with 4 lags of the differenced data (which implies a $VAR(5)$ model in levels). This lag order selection applies to the case of a constant plus linear

⁴ We start with a maximum value for the autoregressive component of $k = 5$, and reduce the length of lag if the t -statistic on \hat{b}_k was significant at the 5% level (instead of the 10% level used by Perron). In all cases we check the resulting correlogram to verify that there is no remaining autocorrelation in the residuals using the estimated k , reported in the Table.

⁵ Calculations were carried out in EViews 3.0. The procedures are presented in detail in Johansen (1995).

⁶ Note that the maximum value of $k = 4$ in the first differences of the data implies that the highest lag in level is 5. Although such a selection is somehow arbitrary, it is based on the fact that the Johansen procedure suffers from substantial size distortions in the tests for the second and subsequent cointegrating vectors when the sample size-number of parameters ratio is small (see Maddala and Kim, 1998).

Table 2. Number of Error Correction Mechanisms, r . (Johansen's λ_{trace} and λ_{max} tests)

Lag order	constant	in	ECM	cons + trend	in	ECM
	λ_{trace} λ_{max}	AIC	BIC	λ_{trace} λ_{max}	AIC	BIC
k=0	4	-17.34	-15.64	2	-17.64	-16.64
	1	-17.39	-16.82	2		
k=1	1	-17.46	-15.74	1	-17.59	-15.83
	0	-17.29	-15.96	1		
k=2	0	-17.21	-14.72	1	-17.48	-14.55
	0			1		
k=3	0	-16.95	-13.26	1	-17.20	-13.09
	0			0	-16.95	-13.26
k=4	4	-17.52	-11.06	3	-17.74	-11.57
	2	-17.51	-11.83	3		

trend in the ECM. Furthermore, both λ_{trace} and λ_{max} concur. This formulation is referred to as *stochastic* cointegration (see for example Campbell and Perron, 1991). The BIC, on the other hand, selects a more parsimonious model, reaching an overall minimum for a VECM with zero lags (which implies a VAR(1) model) with one cointegrating vector, and a constant in the ECM. Since increasing the lag order typically results in a modest decrease in power, but a substantial decrease in size distortions (see DeJong *et al.*, 1992), we prefer to rely on the AIC, which indicates a richer lag structure. Furthermore, results from an LM test (not shown) indicate significant residual serial correlation for the model selected under the BIC. On the other hand, the same LM test on the VECM with four lags shows no indication of residual autocorrelation. This comes as no surprise, since the role of the dynamics is precisely to whiten the error. Indeed, as noticed in Banerjee *et al.* (1993), "...It is not clear that the use of the Schwarz criterion, which penalizes the addition of lags strongly, will prove optimal in this context" (p. 286).

Our results indicate that the sectorial production variables are stochastically cointegrated, with three cointegrating relationships. This means that there are three (independent) linear combinations of sectorial production that are stationary. The variables involved in those three stationary linear combinations share a common stochastic trend

(see Stock and Watson, 1988). Therefore, the six sectorial unit root processes can be reduced to 3 common ones, implying that real GDP appears to be a weighted average of 3 different permanent components. Hence, permanent movements in Mexico's Real Gross Domestic Product are not driven by a single permanent component, as is usually assumed, but by three, sector-specific, common stochastic trends. As argued above, this could be the result of either resource reallocation across sectors following sectorial shocks, or technology diffusion across sectors, or both.⁷

We do not develop an economic interpretation of the main results from the estimation of the vector error correction model. It is important to note that Johansen's method is a-theoretical: it is a purely statistical procedure, in the sense that the estimated cointegrated vectors may not have any economic meaning. This is so because the identification of the long-run relationships (the number of cointegrating vectors) is determined without imposing any economic structure on the underlying VECM.⁸ This is specially true in the case of multiple cointegrating vectors, as in our case. The parameter estimates of the resulting VECM are thus not reported, since they depend on the normalization used, and there is no clear indication as to which sector should act as the "dependent variable". However, from the estimation results, which are available from the author, it could be of some use to say that in the three identified cointegrating vectors, there is a positive long-run relationship between all sectors. In other words, the long-run elasticities show a positive effect (although not always significant) from each sector's output to the rest. That is, in the steady state, the effects of technology changes in one particular sector will diffuse across sectors and improve overall efficiency.

The important message at this stage is, in any case, that the production sectors do share common stochastic trends. The long-run evolution of the different sectors is linked through equilibrium

⁷ We also tested for cointegration among subgroups of the original 6 sectors vector, and found that the presence of cointegration weakens as we drop sectors from the analysis. Cointegration is rejected in 6 cases (out of 15 possible combinations) when the testing involves pairs of variables. When considering three sectors, cointegration is rejected in 4 cases (out of 20). There is a single rejection when using combinations of 4 sectors, and no rejections with (6) combinations of five sectors. This is the result of the effect of omitted variables on cointegration tests (see Maddala and Kim, 1998).

⁸ For a discussion of identification in cointegrated systems see Hsiao (1997), Johansen (1995) and Johansen and Juselius (1994). A recent survey can be found in Maddala and Kim (1998, section 5.6).

conditions. Economic theory is usually introduced at this stage, once one knows the results of the empirical (statistical) investigation. In this respect, there are some recent works studying different links among sectors in the production process. For instance, Startz (1998), introduces a transmission mechanism in a two sector model of growth with dynamic endogenous comparative advantages among sectors. Following Durlauf (1989), the presence of cointegration among sectors can be attributed to the possibility that innovations (technology shocks) that spur growth in these sectors are correlated. Our findings are consistent with those of Cheung and Westermann (2003), who find evidence of cointegration between (seasonally unadjusted) sectorial data for Germany. They also fit well with both the usual economic intuition, and the underlying ideas of some endogenous growth models.

It should be noted that our results might be sensitive to the presence of structural breaks in the variables, as is well known that unit root tests are biased towards non rejection under the presence of permanent deterministic changes in the long-run trend of the variables. If in fact the orders of integration of the variables would be reduced by the presence of structural breaks (as in Perron, 1997, Clemente *et al.*, 1998, Noriega and de Alba, 2001, among others), results on testing long-run affinities in sectorial output would point to different conclusions. If by the inclusion of an appropriate number of breaks it were possible to reject the unit root hypothesis at a high level of confidence for the sectorial output series, then there would be no need for cointegration analysis. This means that it would not be a case that a group of unit root-nonstationary variables moves together in the long-run, but that variables are stationary around broken trends, and that what may be left to do is to test for co-breaking, in order to identify long-term affinities amongst groups of stationary variables subject to individual, or most probably interrelated, structural breaks. The theory and testing of co-breaking is presented in Hendry and Mizon (1998), Clements and Hendry (1999, chapter 9) and Krolzig and Toro (2000). From an economic theory point of view, the possibility of segmented trends in real output has been analyzed by Startz (1998), through a transmission mechanism which allows sufficiently large shocks (to either technology or preferences) to induce multiple growth states, the theoretical counterpart of the broken trend models of Perron (1989). We hope to report results in this direction in a future paper.

III. Conclusions

We first showed that Mexico's disaggregated production at the sectorial level (agriculture, cattle, manufacturing, construction, commerce, and services) is driven by a stochastic trend. That is, each one of the six sectorial production series has a unit root in its autoregressive representation. We then verified the presence of cointegration, in order to investigate whether these six permanent shocks are correlated across sectors. As a result, three of the six idiosyncratic sectorial shocks cancel out, leaving three stochastic growth components common to all sectors. This means that the secular component of real output does not seem to be determined by a single aggregate stochastic trend, or by idiosyncratic independent innovations, but by three common stochastic trends, coming from disaggregated sources at a sectorial level. In other words, the sources of permanent innovations driving growth in Mexico's real output are more likely to come from sector-group-specific sources rather than from independent sector-specific technological shocks, or from common aggregate permanent innovations. Our results can be interpreted along the lines of Cheung and Westermann (2003), i.e., technological progress in one sector improves long-run overall efficiency, through reallocation of resources across sectors following sectorial shocks. This evidence points to a need to model the permanent innovations affecting real aggregate output as disaggregated (sector-group specific) technological innovations.

References

- Banerjee, A., J. J. Dolado, J.W. Galbraith, and D. F. Hendry (1993), *Cointegration, Error Correction, and the Econometric Analysis of Nonstationary Data*, Oxford University Press, Oxford.
- Campbell, J. and P. Perron (1991), "Pitfalls and Opportunities: What Macroeconomists Should Know About Unit Roots", *Macroeconomics Annual*, pp. 141-201.
- Cárdenas, E. (1992), *Historia Económica de México*, Fondo de Cultura Económica, México.
- Cheung, Y.-W. and F. Westermann (2003), "Sectoral Trends and Cycles in Germany", *Empirical Economics*, núm. 28, pp. 141-156.

- Clemente, J., A. Montañez and M. Reyes (1998), "Testing for a Unit Root in Variables with a Double Change in the Mean", *Economics Letters*, núm. 59, pp. 175-182.
- Clements M. and D. Hendry (1999), *Forecasting Non-stationary Economic Time Series*, Cambridge, Mass.: MIT Press.
- DeJong, D. N., J. C. Nankervis, N. E. Savin, and C. H. Whiteman (1992), "The Power Problems of Unit Root Tests for Time Series with Autoregressive Errors", *Journal of Econometrics*, vol. 53, pp. 323-343.
- Dickey, D. A. and S. G. Pantula (1987), "Determining the Order of Differencing in Autoregressive Processes", *Journal of Business and Economic Statistics*, vol. 5, núm. 4, pp. 455-461.
- Durlauf, S. (1989), "Output Persistence, Economic Structure, and the Choice of Stabilization Policy", *Brookings Papers on Economic Activity*, núm. 2, pp. 69-136.
- E-Views (1998), version 3.0, Quantitative Micro Software.
- Granger, C. and P. Newbold (1986), *Forecasting Economic Time Series*, Academic Press, 2nd Edition.
- Hendry, D. and G. E. Mizon (1998), "Exogeneity, Causality and Cobreaking in Economic Policy Analysis of a Small Econometric Model in the UK", *Empirical Economics*, núm. 23, pp. 267-294.
- Hsiao, C. (1997), "Cointegration and Dynamic Simultaneous Equations Model", *Econometrica*, núm. 65, pp. 647-670.
- INEGI (1996), "Banco de Información Económica", web site: <http://www.inegi.gob.mx>.
- Johansen, S. (1991), "Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models", *Econometrica*, núm. 59, pp. 1551-1580.
- (1995), *Likelihood-based Inference in Cointegrated Vector Autoregressive Models*, Oxford University Press.
- and K. Juselius (1994), "Identification of the Long-run and Short-run Structure: an Application to the IS-LM Model", *Journal of Econometrics*, núm. 63, pp. 7-37.
- Krolzig, H.-M. and J. Toro (2000), "Testing for Cobreaking and Super Exogeneity in the Presence of Deterministic Shifts", Institute of Economics and Statistics, Oxford. Mimeo.
- Maddala, G. S. and I. M. Kim (1998), *Unit Roots, Cointegration and Structural Change*, Cambridge University Press.

- Noriega, A. E. and De Alba, E. (2001), "Stationarity and Structural Breaks: Evidence from Classical and Bayesian Approaches", *Economic Modelling*, núm. 18, pp. 503-524.
- Norrbin, S. C. (1995), "Disaggregate Stochastic Trends in Industrial Production", *Economics Letters*, vol. 47, pp. 327-333.
- Pantula, S. G. (1989), "Testing for Unit Roots in Time Series Data", *Econometric Theory*, vol. 5, pp. 256-271.
- Perron, P. (1989), "The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis", *Econometrica*, núm. 57, pp. 1361-1401.
- (1997), "Further Evidence on Breaking Trend Functions in Macroeconomic Variables", *Journal of Econometrics*, núm. 80, pp. 355-385.
- Phillips, P.C.B. and Z. Xiao (1998), "A Primer on Unit Root Testing". Available on-line at: <http://korora.econ.yale.edu/phillips/papers/unit13.pdf>
- Startz, R. (1998), "Growth States and Shocks", *Journal of Economic Growth*, núm. 3, pp. 203-215.
- Stock, J. and M. Watson (1988), "Testing for Common Trends", *Journal of the American Statistical Association*, núm. 83, pp. 1097-1107.