TRENDS AND CYCLES: HOW IMPORTANT ARE LONG- AND SHORT-RUN RESTRICTIONS? THE CASE OF MEXICO*

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Resumen: Se presenta una prueba para identificar la existencia de restricciones válidas de corto y largo plazo (tendencia común-ciclo común) en la dinámica de un conjunto de variables macroeconómicas de México. Estas restricciones se imponen en un VAR para descarticular las series tanto en su componente permanente como transitorio. El análisis muestra que la magnitud de choques transitorios (nominales) es subestimada cuando dichas restricciones no se consideran. Adicionalmente, encontramos que las fechas y la duración de los periodos de recesión y expansión son más acertadamente estimadas cuando la descomposición tendencia-ciclo se realiza incorporando restricciones de cointegración (largo-plazo) y de componente común (corto-plazo).

Abstract: The document presents a test for the existence of binding long- and short-run (common trend-common cycle) restrictions in the dynamics of a set of Mexican macroeconomic variables. These restrictions are imposed in a VAR to decompose the series into their permanent and transitory components. The analysis shows that the magnitude of transitory (nominal) shocks is underestimated when such restrictions are not considered. In addition, we find that the timing and duration of recession and expansion periods are more accurately estimated when the trend-cycle decomposition is conducted with the imposition of cointegrating (long-run) and common feature (short-run) restrictions.

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1. Introduction

The decomposition of time series into their permanent and transitory components is an exercise that has occupied economists for decades. However, most of the work has been performed using data from developed economies, from the US in particular. In the case of developing countries, empirical analysis of macroeconomic variables that identifies the importance of permanent and transitory components in time series is scarce.

Aside from the bulk of applications on the subject, a certain number of papers form the core of methodologies developed to analyze this topic. In their 1981 seminal paper, Beveridge and Nelson introduced a general procedure to decompose non-stationary time series into their permanent and transitory components and applied it to the measuring and dating of business cycles. As Blanchard and Quah (1989) indicate, however, the earlier attempt to measure trend and cyclical components did not consider the dynamic effects of permanent and transitory shocks. To address this shortcoming, Blanchard and Quah proposed a methodology that restricted the impact of transitory, or nominal shocks, on the permanent component of the series. That is, they appended to the neutrality of nominal shocks theory a further restriction: that nominal shocks have zero impact on real variables in the long run. The authors find that demand (nominal) shocks have a short-lived effect on output while supply (real) shocks affect output permanently. Although the methodology employed in that paper provided valuable tools to further evaluate the importance of transitory shocks, cointegration and the short-run relationships among the variables examined were not considered. In 1991, King *et al.* performed an analysis that explicitly imposed cointegrating restrictions in the decomposition of time series. Using a *Vector Error Correction Model*, VECM, to include such restrictions, the authors showed that nominal shocks were, in general, more important (of greater magnitude) than previously thought. This finding indicated that nominal shocks, which include the instrumentation of monetary and fiscal policy, significantly influence the magnitude and duration of business cycles.

More recently, Vahid and Engle (1993, VE hereafter) and Issler and Vahid (2001) highlighted the importance of considering common cyclical components when performing trend-cycle decomposition of cointegrated time series. The authors show that when common cycle (short-run) restrictions are imposed on a system of variables, nominal shocks are even greater in magnitude compared to that found in King *et al.* They conclude that there are efficiency gains when a VECM is estimated imposing short-run restrictions relative to the case when the VECM is estimated without such restrictions.[1]

In this document we follow VE and Issler and Vahid (2001) in analyzing the importance of trend and cyclical components of Mexican macroeconomic series. We choose Mexican Gross Domestic Product, GDP, aggregate consumption, and real credit granted by commercial banks to conduct the analysis. Recently, these three series have been the subject of study in various papers, generating a quite interesting debate. On the one hand, contrary to what most economists would expect, some studies find that private consumption and the Mexican GDP do not cointegrate. In response, other studies have shown that if the conditions of the credit market are considered, then it is possible to find cointegration between consumption and the GDP.[2] Using the VE methodology, we show that the series not only cointegrate, but that they also share a common cycle. In addition, we find that the magnitude of transitory shocks when considering short and long run restrictions is larger than when such restrictions are not accounted for. This result is particularly interesting for purposes of monetary and fiscal policy, since the instrumentation of both might be perceived as nominal shocks.

Although showing that the series share short and long run components, and that transitory shocks explain a significant portion of their variation, are interesting in and of themselves, the analysis we conduct in this document may be used for more practical purposes, such as forecasting, for instance. In particular, consider the case when two series are shown to share a common cycle. If the release of one anticipates the release of the other, then information contained in the former may help in forecasting the behavior of the latter, most of all the upcoming turning point. Also, the decomposition methodology we employ here can be used in any model that includes in its analysis a trended series or a gap between a series and its trend. For example, one could employ this methodology to estimate the output gap in an inflation model. Obviously, this methodology can be employed in the traditional analysis of determining the magnitude and duration of business cycles. As will become evident, the results of the trend-cycle decomposition obtained when short- and long-run restrictions

[1] Parallel to the advances in the study of decomposition methods for non-stationary series, Engle and Kozicki (1993) developed common feature analysis of stationary variables based upon an instrumental variables technique.

[2] For the former argument see for instance Gonzalez Garcia (2000), for the latter Garcés (2001) and Castillo (2001).

are imposed are more efficient than other decomposition methods.

The paper is organized as follows. Section 2 outlines the methodology employed in the analysis. In section 3 we present the data along with a series of tests to identify their stochastic properties. Also, we conduct the common trend-common cycle tests and the permanent-transitory decomposition of the series. In section 4 we perform some estimations to measure the importance of nominal shocks on the variations of real series. Section 5 concludes.

2. Methodology

2.1. *Fundamentals*

The methodology used to identify the permanent and transitory components of a series is, in general, as follows: consider a vector y_t of n variables integrated of order 1 (I(1)) and whose first difference, Δy_t, follows an autoregressive process. It is said that the variables in y_t are cointegrated if there exists $r(< n)$ linear combinations of them that are integrated of order 0 (I(0)). Such combinations can be grouped in a matrix β of dimension $n \times r$. The rank of this matrix is r and it defines the cointegration space.

According to Engle and Kozicki (1993), the elements of Δy_t share serial correlation common features if there exists a linear combination of them that represents an innovation with respect to the information available prior to period t (i.e. that removes the serial correlation pattern in Δy_t). These linear combinations are denoted *cofeature combinations* and Engle and Kozicki demonstrates that, conditional upon the presence of cointegration among the variables included in y_t, there can only exist $s(< n)$ such combinations and $r + s \leq n$. These cofeature vectors can be grouped in a matrix $\widetilde{\alpha}$ with dimension $n \times s$ where $\widetilde{\alpha}\Delta y_t$ represents an innovation. The rank of the matrix $\widetilde{\alpha}$ defines the subspace of all possible cofeature vectors.

Given that both, the cointegration and the cofeature subspaces may project the full space spanned by the complete set of variables in y_t, and given that, by definition, the cointegrating (r) and the cofeature (s) relationships are linearly independent and unique when they exist, there can exist a maximum of $n - r(\geq s)$ cofeature vectors. Therefore it is possible to decompose the elements in y_t into their permanent and transitory components (à la Beveridge - Nelson) taking into account these structural restrictions.

The most widely applied technique in this kind of analysis is the one proposed by King *et al.* (1991), where the restrictions included in the model consider the cointegration space leaving the short run movements unconstrained. Ignoring short run comovements between time series when they exist, however, induces efficiency losses (Vahid and Engle, 1993; and Issler and Vahid, 2001). The losses arise because of the use of limited information methods (short-run parameters unconstrained when they should be restricted) in the estimation of such models.

Issler and Vahid show, by considering the same set of variables as in King *et. al*, that the out-of-sample forecast error is lower in a full information environment (considering short run restrictions) than in a limited information setting (taking into account only cointegration restrictions).

Given the efficiency gains obtained by including common trend-common cycle restrictions, it is possible to assess accurately the importance of transitory shocks to real variables.

2.2. *Common Cycles Test*

Following VE, the purpose of the present exercise is to find, conditional on the existence of cointegration, a linear combination of the first differences of the variables in such that the serial correlation pattern in the variables is eliminated. Once the cointegration and short run restrictions are identified, we can proceed to construct the common trend and common cycle components of the series.

We briefly describe the methodology to identify the existence of a common cycle. Let $\hat{\alpha}'\Delta y_t$ be any linear combination of first differenced variables. A statistical measure of the correlation between this combination, and the relevant past is $T \times R^2$ of the regression of $\hat{\alpha}'\Delta y_t$ on the variables that represent the history of past observations. Then, a natural candidate to be a cofeature vector is the linear combination that minimizes $T \times R^2$.

Following the notation in VE, let X be a matrix of transposed first differences and Z the corresponding matrix of error correction terms. Define the past history with the matrix $W \equiv \{X_1, ..., X_p, Z_{-1}\}$ and let P_w represent the orthogonal projection to the history space. Hence, the cofeature vector $\widetilde{\alpha}$ minimizes the following expression

$$Q(\hat{\alpha}) = \frac{\hat{\alpha}'X'P_W X\hat{\alpha}}{\hat{\alpha}'X'X\hat{\alpha}}$$

VE show that the solution to the previous expression is the *Limited Maximum Likelihood*, LIML, estimator of the regression of one of the elements in Δy_t with the rest of them taken as instruments of the past history (W). In addition, the authors show that the LIML estimator of $\hat{\alpha}$ is the canonical covariate corresponding to the smallest canonical correlation between X and W.

By defining the cofeature vectors as the canonical correlations that are not significant, VE derive a test for the number of linearly independent canonical correlations that are statistically equal to zero. When there are more than two variables in the system, the number of not-significant canonical correlations between X and W defines the dimension of the cofeature space.

The statistic for the test of the null hypothesis that the cofeature space is at least s (in other words, that there are no more than $n-s$ common cycles) is:

$$C(p,s) = -(T-p-1)\sum_{i=1}^{s}\log\left(1-\lambda_i^2\right)$$

where $\lambda_i^2 \forall i = 1, ..., s$ are the s smallest canonical correlations between X and W. Under the null hypothesis, this statistic is distributed x^2 with $s^2 + snp + sr - sn$ degrees of freedom; where n is the dimension of the system, p is the number of lags in the differences (which is one less than the number in levels) and r is the number of cointegration vectors in the system.

3. Empirical Exercise

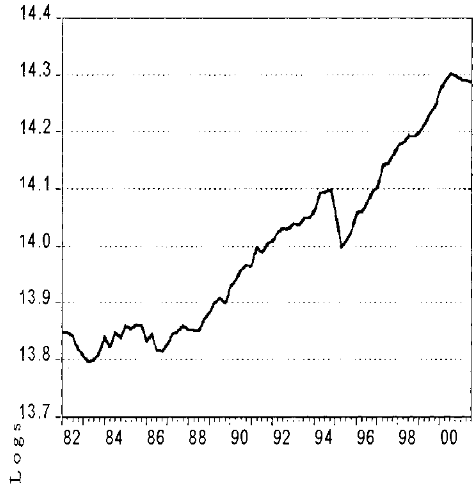
In this section, we apply the previous methodology to the seasonally adjusted series corresponding to the Mexican GDP, private aggregate consumption, and the credit granted by commercial banks to the non-banking private sector from the first quarter of 1982 to the thlrd quarter of 2001. The source of the data is the system of economic information of Banco de México (SIE-Banxico).

3.1. *Stochastic Properties of the Series*

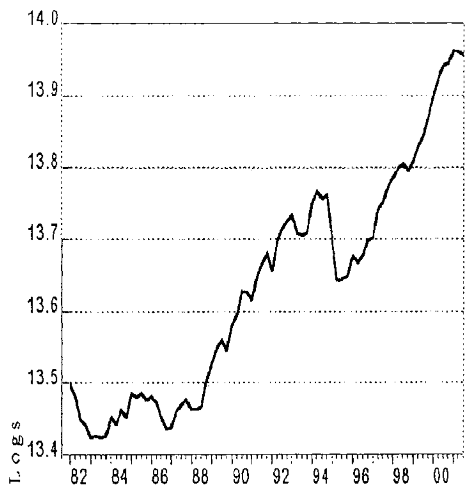
First, we examine the stochastic nature of the series. The logarithms of the GDP, consumption and credit series are presented in graphs 1, 2, and 3 respectively.

The series present a trend and hence, it is likely that a unit root characterizes their *Data Generating Process*, DGP. To test for this possibility we implement the *Augmented Dickey Fuller*, ADF, and Phillips-Perron, PP tests. The results are presented in table 1.

Graph 1
GDP, 1982 - 2001



Graph 2
Consumption, 1982 - 2001



Graph 3

Credit, 1982 - 2001

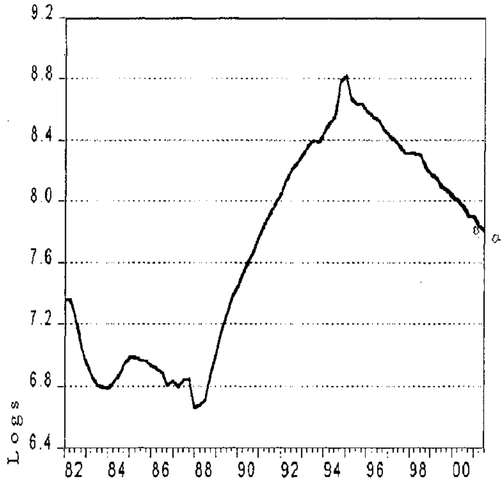


Table 1

Unit Root Tests: GDP, Consumption and Credit

Series	*ADF*	*Critical Value**	*PP*	*Critical Value**
GDP	-2.73	-3.46	-72.76	-3.46
DGDP	-7.61	-2.90	—	—
Consumption	-2.41	-3.46	-57.69	-3.46
DConsumption	-7.00	-2.90	—	—
Credit	-1.04	-2.90	-0.83	-2.90
DCredit	**-3.50**	**-1.94**	**-4.43**	**-1.94**

* At 5%.

The ADF and PP results indicate unambiguously that the credit series is integrated of order 1. In the case of GDP and consumption, however, the results are contradicting. The ADF test suggests that the series is integrated of order 1, while the PP test indicates an integration order of 0. Nonetheless, relying on the results of the ADF test results and the results of various documents that test for stationarity on consumption and GDP, including Castillo Diaz (2002) and Garcés (2001), we will assume that both series are integrated of order 1.

3.2. *Trend-Cycle Decomposition*

Since the methodology for analyzing trends and cycles is conditional on the number of lags chosen, we first determine this number by evaluating the series in an unconditional *Vector Autoregression*, VAR, following the multivariate *Akaike Information Criterion*, AIC.[3] The results of the test are presented in table 2, and suggest that the optimal number of lags for the variables in levels is 2. Hence the optimal number of lags for the variables in first differences is 1, that is, $p = 1$.

Table 2
Multivariate Akaike Information Criterion from an Unrestricted VAR in Levels GDP, Private Consumption and Credit (seasonally adjusted series) 1982:1 - 2001:3

No. of Lags	*AIC*
1	-14.00
2	-14.10
3	-13.94
4	-13.93
5	-13.91
6	-13.67

[3] The AIC is defined in this case as

$$ln\left(\left|\hat{\Omega}\right|\right) + \frac{2pn^2}{T} + n\left(1 + log\left(2\pi\right)\right)$$

Next, we perform the cointegration and common feature tests. We apply the methodology suggested by Johansen (1991) and the test suggested by VE, respectively.[4] The results, presented in table **3**, indicate that the GDP, consumption and credit series share one cointegrating relation and one cofeature vector at conventional significance levels. Based on Johansen's trace statistic we reject the null hypothesis of no cointegration at 5 percent significance level, but could not reject the null of one cointegrating vector (table **3**). The evidence found by applying the cofeature test developed by VE, constrained to the existence of one cointegrating relationship, shows that the null of no common feature between these variables is rejected at 5 percent significance level, but we could not reject the presence of one cofeature vector at the same level (five last rows in table **3**).

Table 3

Common Trends and Common Cycles Tests: GDP, Consumption and Credit, 1982:1 - 2001:3

*Cointegration Test**	*Number of Cointegrating Vectors (r)*		
Null hypothesis	$r = 0$	$R \leq 1$	$r \leq 2$
Trace test	29.85	8.31	0.11
95% Critical value$^{\varsigma}$	29.68	15.41	3.76
Cofeature Test	*Number of Cofeature Vectors (s)*		
Null hypothesis	$s > 0$	$S > 1$	$s > 2$
Squared correlations	0.049	0.133	0.423
$C(p, s)^{\dagger}$	4.075	15.660	60.194
Degrees of freedom	2	6	12
p-value	0.130	0.0157	$\approx$0.00

*Johansen's (1991) trace statistic test, $^{\varsigma}$ Taken from the tables contained in Osterwald-Lenum (1992), † Statistic represented in equation (1) with $p = 1$.

The coefficients estimated for the cointegrating and the cofeature vectors are presented in table 4. Given that they are maximum likelihood estimates, the normalization procedure does not involve any distortion in the presentation of results. For the cointegrating relation

[4] We thank Joao Victor Issler for providing us with the Gauss code for performing these estimations.

we normalize on consumption. We find that the long run elasticity of consumption with respect to GDP is 0.52, and with respect to the credit variable is 0.14.

The cofeature vector (i.e. the linear combination of the variables in the system which eliminates the serial correlation pattern present in the first differences of these series) normalized on the credit variable indicates that its short run fluctuations are a combination of 0.74 times the one period changes in GDP and 0.65 times those of consumption. This is only a representation of the short run dynamics of the system normalized on one of its variables (credit).

Table 4
Cointegration and Cofeature Vectors: GDP, Private Consumption and Credit, 1982:1 - 2001:3

	GDP	*Consumption*	*Credit*
Cointegrating Vector	-0.52	1.00	-0.14
Cofeature Vector	-0.74	-0.65	1.00
	Trends		
	GDP	*Consumption*	*Credit*
GDP	1.00	-0.93	0.50
Consumption	1.00	-0.93	0.50
Credit	2.61	0.36	1.00

VE show that, when the number of cointegration and cofeature relations are equal to the number of variables in the system ($r+s=n$), it is possible to represent the decomposition of y_t in the Beveridge-Nelson form, that is, as the sum of a permanent and a transitory component (Vahid and Engle, 1993; and Issler and Vahid, 2001).[5] In the current analysis, however, there exists one cointegrating vector ($r=1$) and one cofeature vector ($s=1$) (presented in table 4). Since they are orthogonal, we cannot construct a base to project the

[5] In fact, Issler and Vahid (2001) show that when $r+s=n$ the trends and cycles of a series can be recovered as a linear combination of the cointegrating and cofeature vectors. For our own purposes, it would had been quite interesting to have found a group of series such that $r+s=n$. In that case, we could have also used the Issler and Vahid decomposition technique. This is an exercise that we leave for future research.

space that spans the variables in the system ($n = 3$). Thus, we cannot perform the decomposition as suggested by VE. Nonetheless, in the case when $r + s < n$ there exist alternative methodologies to perform the trend-cycle decomposition, including King *et al.* (1991) or Gonzalo and Ng (2001).

We choose to implement the methodology suggested by King *et al.* In particular, we consider the long run restrictions imposed by the cointegrating vector and estimate a VECM from where we obtain the permanent and transitory components of the series.[6] Following this methodology, we find two common trends. In other words, we find that two random walks guide the stochastic common trends for the variables considered in the system.[7]

Graphs 4-6 show the stochastic trends that best fit each of the analyzed series. In particular, it is evident that one of the trends closely follows the GDP and consumption series, whereas the second trend better fits the credit series. Note that the common trend series we obtained is not smooth. At first, this result may appear somewhat puzzling. After all, one would expect that a trended series would not present pronounced peaks and valleys. However, we believe that part of the gains in estimating the trended series using the present methodology is that the series obtained more accurately represent the magnitude of transitory shocks, which, since we use seasonally adjusted series, are more likely to be the factors that cause the fluctuations in the estimated series.

The actual level of GDP for the second part of the period examined (1999:01 - 2000:03) is above the estimated trend, and it is below for the rest of the period of analysis (graph 4). This last result captures well the recession observed in Mexico and worldwide during 2001.

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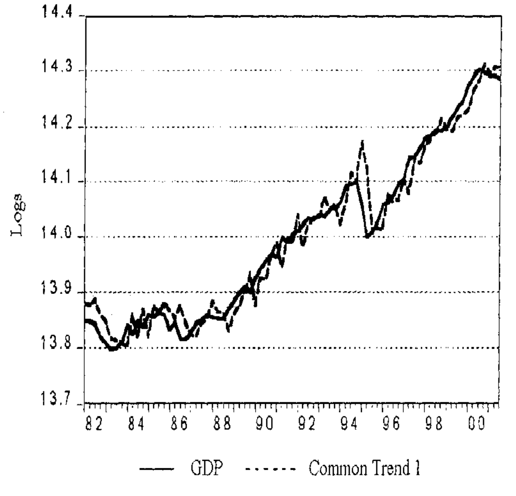
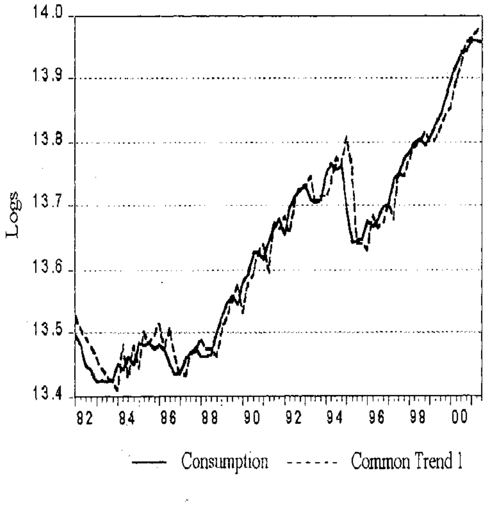
[6] As is well known, the VECM has two representations: autoregressive and moving average (Engle and Granger, 1987). By imposing the restrictions presented in the upper part of table 4 in the autoregressive form of the VECM, one can recover the moving average representation of the system including those restrictions. After an algebraic manipulation of the moving average form it is possible to find the trend-cycle decomposition of the variables included in the VECM. For details we refer the interested reader to the original paper (King *et al.* 1991).

[7] Since the cointegration relationship eliminates one stochastic trend from the system.

Graph 4
GDP and its Trend

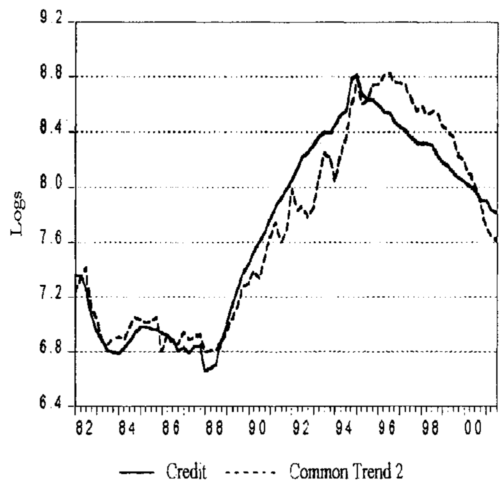


Graph 5
Consumption and its Trend



Similarly, the observed level of consumption for the period 1995: 03 - 2000:03, with the exception of four quarters, was also located above the first common trend (graph 5). Beginning in the fourth quarter of 2000, however, it has remained below the common trend.

Graph 6
Credit and its Trend



In the case of the credit series, the observed level remained above the trend from the first quarter of 1989 to the second quarter of 1995, a fact that is consistent with the "credit boom" experienced during this period (graph 6). From the third quarter of 1995 to the second quarter of 2000, the level remained below the trend consistently. Only in recent periods does there appear to be a rebound in the level of the credit series.

3.3. *Methodology Comparison*

In graphs 7-9 we compare the cycles obtained using the King *et al.* methodology with those obtained using the commonly used Hodrick-Prescott, HP filter.[8] Note that the magnitude of the cycles obtained

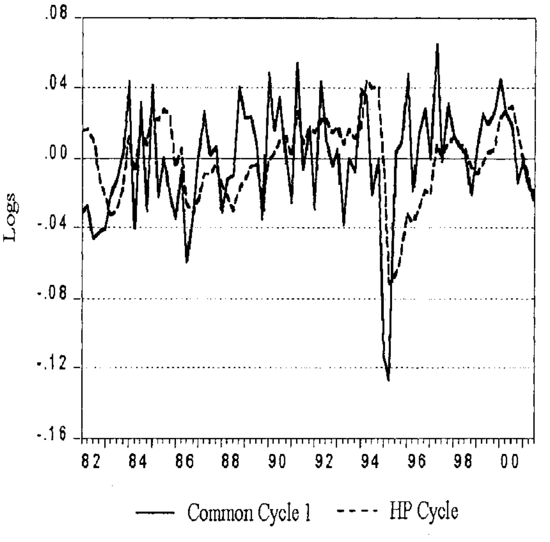
[8] First, we filtered the seasonally adjusted series and then obtain the logarithmic difference between the original and the filtered series.

with the methodology used in this document is greater than that of the cycles obtained with the HP filter.[9] In addition, we find that the expansion and recession[10] dates suggested by the two cyclical series do not precisely coincide.

With the HP methodology, we find that GDP was above its trend between the third quarter of 1999 and the fourth quarter of 2000 ("positive" cycle), while from the first quarter of 2001 to the end of the sample period, we find that it was located below its trend (graph 7). On the other hand, the trend we obtained applying the King *et al.* methodology shows that the previously mentioned first cycle on the GDP series, appears before it does when using the HP filter.

Graph 7

Cycle in GDP: Common Cycle 1 vs. HP Filter



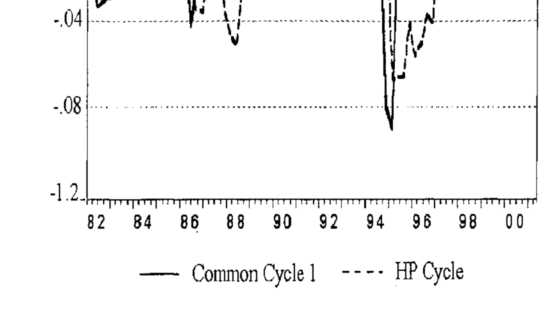
[9] It is not surprising to find this result, since the trended series we estimated presents pronounced peaks and valleys, in contrast with the trended series estimated with the HP methodology. As we argued in the text, we believe that the common trend series is so volatile is because it estimates the magnitude of transitory shocks more accurately, and not because of seasonal factors, since we are using seasonally adjusted series.

[10] The term "expansion" ("recession") refers to the case when the level of the observed variable is located above (below) the level of the trended series

In the case of the consumption series, the "expansion" periods found with the HP filter appear at a later date compared with those identified with the methodology we employed (graph 8). The HP filter shows that the last expansion period began by the end of 1999 and finished in the third quarter of 2001. In contrast, our results show a sustained expansion (with two or three outliers) from the second half of 1995 until the third quarter of 2000.

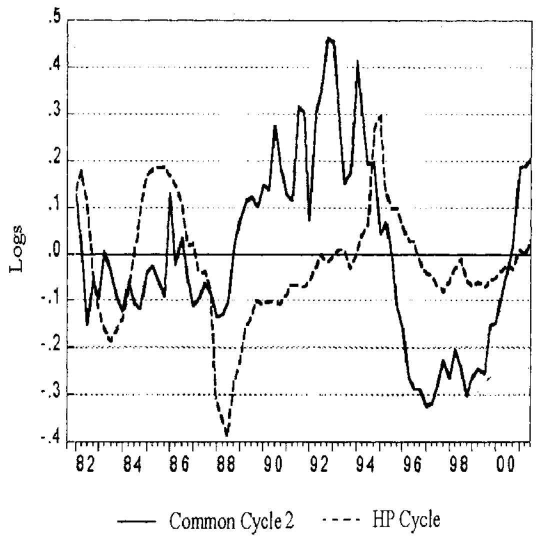
In the case of credit (graph 9), we also obtained contrasting evidence for the "recession" and "expansion" dates and the magnitude of the cycles when using both methodologies. For the credit expansion period (1988-1994), the HP methodology finds that the level is below the trend (negative gap), a result that is clearly counterintuitive. So in this case the advantage of including structural restrictions instead of using numerical methods to estimate the business cycles in macroeconomic variables is clear.

Graph 8
Cycle in Consumption: Common Cycle 1 vs. HP Filter



Once we have shown the significant influence of transitory shocks on the time series we consider, the relevant issue becomes identifying the factors that cause the shocks. Evidently, this is not a trivial task, since it is difficult for anyone to properly identify all the variables that may influence the behavior of any time series. As an exploratory exercise, in the next section we evaluate the importance of some nominal variables in explaining the variation of GDP, consumption and credit. In particular, we estimate several bivariate structural vector autore gressions that include a nominal variable and one of the real variables previously mentioned.[11]

Graph 9
Cycle in Credit: Common Cycle 2 vs. HP Filter



4. Nominal Shocks

The relative importance of nominal shocks can be evaluated implementing a VAR. As it is well known, to solve a VAR it is necessary to impose identifying restrictions.

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11 It would also be possible to estimate a multivariate VAR in order to determine the importance of the transitory shocks. However, we are primarily interested in showing how each individual nominal factor affects each individual real variable.

There exist various procedures for identification. Blanchard and Diamond (1989, 1990), for instance, used *a priori* assumptions of structural parameters. The commonly used Cholesky factorization can also serve as an identifying methodology. In this document, nonetheless, we follow the identification procedure suggested by Blanchard and Quah (1989). This methodology has been extensively used in studies that analyze nominal and real shocks, including that of exchange rates between the US and some of its major trading partners.[12]

The Blanchard and Quah identification procedure requires a long -run restriction of the nominal shock. That is, assuming long-run neutrality, the effect of the nominal shock on the real variable is constrained to be zero in the long run. This condition is imposed by restricting the moving average representation of the VAR.[13]

The long-run neutrality restriction is imposed in a VAR considering the real and nominal variables and a structural VAR, (SVAR), is estimated. The real variables we consider are those examined in the previous section. The nominal variables are interest rates of treasury bills at 28 days, CETES28, the *Consumer Price Index*, INPC, and the money aggregate $M1$. For the interest-rate variable and the INPC, we obtained quarterly data by averaging monthly observations. In the case of $M1$ we used the end of the period observation. The results of the SVAR's are presented in tables 5-7.

Table 5
Variance Decomposition of GDP

Period	*Cetes28*	*INPC*	*M1*
1	6.1	5.4	7.4
2	8.3	9.5	8.5
3	9.4	9.0	8.3
4	9.6	9.0	8.4
5	9.6	9.1	8.4
6	9.7	9.1	8.4
7	9.7	9.1	8.4

12 Including Enders and Lee (1997), Clarida and Gali (1994) and Lastrapes (1992).

13 For a detailed description of the methodology see Lastrapes (1992).

Table 5
(continued)

Period	*Cetes28*	*INPC*	*M1*
8	9.7	9.1	8.4
9	9.7	9.1	8.4
10	9.7	9.1	8.4

Table 5 reports the variance decomposition of GDP. The change in the interest rate explains nearly 10 percent of the variance in the growth rate of GDP after 10 periods, the largest portion explained by any of the three nominal variables considered.

Table 6 presents the variance decomposition for consumption. As in the case of GDP, the interest rate explains a significant portion of the variation in the dependent variable.

Table 6
Variance Decomposition of Consumption

Period	*Cetes28*	*INPC*	*M1*
1	7.8	2.8	2.3
2	9.0	5.6	2.2
3	11.6	5.5	2.2
4	11.7	5.5	2.2
5	11.8	5.6	2.2
6	11.8	5.6	2.2
7	11.8	5.6	2.2
8	11.8	5.6	2.2
9	11.8	5.6	2.2
10	11.8	5.6	2.2

The evidence found for the credit variable, table 7, is qualitatively the same as in the previous cases. However, as could be expected, the portion of the variation in the credit variable explained by the interest rate is much higher than for GDP and consumption, up to 19 per cent after 10 periods.

Table 7
Variance Decomposition of Credit

Period	*Cetes28*	*INPC*	*M1*
1	0.0	8.8	4.6
2	15.1	8.6	6.7
3	18.8	7.3	7.0
4	19.2	7.1	7.1
5	18.9	7.0	7.1
6	19.0	6.9	7.1
7	19.2	6.9	7.0
8	19.2	6.9	7.0
9	19.2	6.8	7.0
10	19.2	6.8	7.0

The results of the variance decompositions previously estimated show that the nominal variables explain a significant portion of the variation in the real variables. The nominal interest rate is the variable that provides the highest coefficients in all cases. In the case of GDP and consumption, $M1$ is the variable that explains the least. In comparison with studies on the US, the proportion of the variation that the nominal variables explain in the cases presented above is relatively high, Enders and Lee (1997), for example, find that $M1$ explains up to 4 percent of the variation of the GDP in the US, while we find that for the case of Mexican GDP, it explains around 8 percent. These results are clearly consistent with those found in the trend-cycle decomposition analysis conducted in the previous section, that is, nominal shocks appear to explain a significant portion in the variation of real variables.

5. Conclusion

The evidence found in this paper sheds some light on the behavior of three Mexican macroeconomic series: GDP, aggregate private consumption, and bank credit granted to the private sector. The analysis shows that the data generating process guiding these variables consists of two common trends (one cointegrating relation) and two common cycles (one cofeature vector). These characteristics allows for the imposition of restrictions on the permanent-transitory component decomposition of the series. As shown in Vahid and Engle (1993), and Issler and Vahid (2001), imposing such restrictions leads to a more efficient identification of the common trends and cycles. This efficiency is mainly reflected in the estimated effects of the transitory shocks on the variables in the system. In our particular exercise, we find that the restricted decomposition provides information that improves the identification of cyclical periods. In addition, we find that the influence of nominal shocks on the previously mentioned series is important, and greater relative to the case when no restrictions are imposed on the decomposition of the series.

Although in this paper we focus mainly on presenting the trend-cycle decomposition methodology using short and long-run restrictions, it is evident that this methodology can be applied to more practical enterprises. For example, given the efficiency gains obtained when using the present methodology, it would be desirable for forecasting purposes. That is, if one conducts an exercise to identify series that share common cycles, and the series are characterized by having one of them lead the other, then one could provide an efficient forecast of the lagged variable using the information provided by the leading variable. Also, the methodology can be employed in exercises that require the derivation of gaps between variables and their trends, such as inflation models. Traditionally, the derivation of output gaps in inflation models follows less efficient methods including filters and estimations of VAR's or VEC's. As shown in this article, however, one can obtain more accurate estimates of trends when using the methodology presented in this paper. These two applications, of course, are just a few of the possible scenarios where the trend-cycle decomposition that imposes short- and long-run restrictions can be applied.

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