LACEA 2001
MONTEVIDEO URUGUAY

LACEA 2001
MONTEVIDEO URUGUAY

Jorge Eduardo Carrera, joint with Ana Paula Cusolito, Mario Félis and Demian Panigo

An Econometric Approach to Macroeconomics Risk. A Cross Country Study

An econometric approach to macroeconomic risk. A cross country study

Jorge Eduardo Carrera[1] *(UNLP)*
Ana Paula Cusolito (UNLP)
Mariano Féliz (PIETTE-CONICET, UNLP)
Demian Panigo (PIETTE-CONICET, UNLP)

Esta versión: April 2001

Abstrac

A contribution to the study of volatility and country risk is made in order to achieve a successful cross-country comparison. We present a methodology for the evaluation of country risk that include endogenous detection of multiple structural breaks (also identifying its different kinds), determination of persistence of shocks through their structural-break free fractional integration order and determination of the adjusted volatility which best characterizes the economy. This methodology is applied to developed and emerging countries' GDPs (taking 9 countries from each group). Although the former have fewer structural breaks than the latter, these breaks are extremely relevant in 14 of the 18 countries. This affects the calculation of the series persistence and volatility. Comparing a traditional risk indicator to our suggested one we find that the cluster of reference of 60% of the countries changes. Most countries present fractional integration (long memory) being the distribution between both groups heterogeneous. Country volatility varies strongly if we isolate structural breaks that present a probabilistic distribution different from intrinsic GDP volatility. Clusters arrangement is different with some risk country evaluation methodologies.

Keywords: Risk, Volatility, Persistence, Structural breaks, Forescastability, Macroeconomic variables, Cross country analysis.

JEL codes: C3, C5, E3

[1] jcarrera@isis.unlp.edu.ar

The views expressed in this paper do not necessarily represent those of the institutions to which the authors belong.

An econometric approach to macroeconomic risk. A cross country study

Jorge Eduardo Carrera[2] *(UNLP)*
Ana Paula Cusolito (UNLP)
Mariano Féliz (PIETTE-CONICET, UNLP)
Demian Panigo (PIETTE-CONICET, UNLP)

Esta versión: April 2001

Contens:

Keywords: Risk, Volatility, Persistence, Structural breaks, Forescastability, Macroeconomic variables, Cross country analysis.

JEL codes: C3, C5, E3

[2] jcarrera@isis.unlp.edu.ar

The views expressed in this paper do not necessarily represent those of the institutions to which the authors belong.

An econometric approach to macroeconomic risk. A cross country study

Jorge Eduardo Carrera[3] *(UNLP)*
Ana Paula Cusolito (UNLP)
Mariano Féliz (PIETTE-CONICET, UNLP)
Demian Panigo (PIETTE-CONICET, UNLP)

Esta versión: April 2001

1 Introduction. Calculating risk from macroeconomic data

Macroeconomic risk has become a major variable in models trying to explain the performance of national economies. Hence, in the last few years several indicators and ratings have been developed which take into account such information. In such circumstances it is still relevant to remember that the rule used for the assesment of the risk of an asset should be valid for country risk. That is, we should be able to associate the macroeconomic risk of a country with the capacity to predict with the highest amount of average precision and with the minimum level of uncertainty for the variable in question. This should be true for an individual indicator such as the GDP or the exchange rate, as well as for a basket of indicators.

In the literature there are multiple approaches to approximate and calculate the risk for individual variables, such as public or private assets issued in a country, or at a global level for its use in the determination of sovereign risk by international agencies, whose activity has expanded exponentially in the last decade, especially due to the irruption of the so called emerging countries in the bond markets of the OECD (Cantor y Packer, 1995).

In the recent theoretical and empirical discussion on the subject we may find a great number of variables that help determine risk based on different econometric techniques.

As the price volatility of a financial asset is an approximation of its risk, given the difficulty in estimating with precision the future behavior (and thus expected capital gains and losses), the volatility of the economy is the synthetic indicator most commonly used to measure the risk that is associated to investing financially or physically in a country.

Besides this direct association between volatility, forecasting precision and risk, volatility in its association with an economy has been a traditional field of research. In many cases evidence has been found of the cross-country association between the effects of the volatility of variables such as GDP, nominal or real exchange rate, the current account, fiscal deficit, monetary variables, etc. and the macroeconomic evolution of the countries.

However, the analysis of the global relationship between risk and forecasting precision requires a more exhaustive use of the information from each variable and the application of the most recent advances in time-series econometrics.

For this, additional risk factors such as the probability of an economy having extraordinary structural shocks or the persistence of shocks affecting the economy must be taken into account. This is important to optimize the use of information we may gather from an univariate process. Besides, they are a better input for a multivariate model that relates risk with a set of associated variables and for a strategy that uses adequately the co-integration relationships between the variables.

The objective of this paper is to make a contribution to the literature on macroeconomic risk, by developing a univariate multidimensional risk indicator that includes in the analysis the different risk factors that can be obtained from a time-series.

The article is structured in the following manner. After this introduction we present the different factors that affect risk (associated with the forecasting precision or the goodness of fit process used to

---

[3] jcarrera@isis.unlp.edu.ar

The views expressed in this paper do not necessarily represent those of the institutions to which the authors belong.

forecast the future behavior of a series). Then we describe the methodology we will use to estimate the significance and magnitude of each factor, giving special emphasis to the explanation of the tests used to obtain the parameters of persistence and the information that refers to the possible existence of multiple structural breaks in the series. Later we apply the methodology to evaluate the macroeconomic risk in the GDP series of 18 countries (9 developed and 9 emerging ones) to end with the conclusions and bibliography.

2 Main determinants of the risk associated to the goodness of adjustment or forecasting precision.

3 Volatility

When we deal with equity or financial assets we observe that the volatility measures the assets' total risk, whether they be systematic or not[i]. In this sense, volatility is the correct measure for the owner of a diversified portfolio and it is very important to estimate the value of option, warrants, convertible obligations and the array of financial assets with options included. If the volatility of an asset is high this means that its future value will differ greatly from its expected value. In other words, the volatility is a coefficient that measures the total risk of an asset as a function of the historical deviations with respect to its mean value. Technically, the calculation of volatility consists in obtaining the annualized standard deviation of the returns from an asset. The volatility also relates to the beta, which is the calculation of the covariances of the market return and the asset return under study.

At an aggregate level we can establish that a countries' macroeconomic risk is related to the forecasting uncertainty for future growth rates. From an extreme point of view if in a country there were no volatility we would know the GDP level of any other macroeconomic variable in the long run. As volatility increases our uncertainty about future growth rates increases too, as well as the uncertainty about the future level of GDP or any other variable or group of variables that approximates risk.

In econometric terms, there exists a direct relationship between the volatility of a series, the forecasting capacity and the associated risk. The greater the volatility, the lower the precision and the greater the risk.

The justification for this relationship between volatility, forecasting precision and risk comes from the existence of distortions in the financial market. An increase in the volatility of the GDP or other macroeconomic variable (such as the real exchange rate, the fiscal deficit, etc.), increases the difficulties and cost of monitoring (verification of the different states of nature) and also the probability that *ceteris paribus* the debtor of this country enters in default for macroeconomic reasons. Thus, the international financial markets require a greater premium when there is greater volatility.

Additionally, Aizenman and Powell (1997) stress that, under some conditions[ii], volatility exerts a significant negative influence on production, employment and welfare, which then can be seen as a complimentary factor of risk.

Other empirical studies (Pindyck y Solimano (1993), Hausmann y Gavin (1995) y Aizenman y Marion (1996)) have also found adverse first order effects of the GDP volatility on private investment and growth.

IDB (1995) and Hausmann and Gavin (1995) highlight the importance of macroeconomic volatility in explaining the poor performance of Latin-American countries in comparison with SouthEast Asians or developed countries.

A common denominator in these recent papers (which are representative of the relationship between volatility and comparative macroeconomic performance) is that they measure volatility between two regions as the standard deviation without taking into account adequately the existence of structural breaks. If a region had an extraordinary shock and another didn't, we would be inferring wrongly the effects of volatility when in reality these effects are caused by the extraordinary events. Obviously, the policies recommended for the reduction of the effects of country risk are, in each case, different: structural policies to correct or dampen a permanent shock versus a regimen or institutions that will minimize the volatility of the economy.

Imagine two countries A and B with equal volatility in the control variable ($\sigma_A = \sigma_B$) to which we apply a permanent shock that produces a permanent change (or at least a very persistent one) in the long run trend. With the traditional measurement of volatility we will have that one region would have higher volatility than the other would and, thus, the policy recommendation from the IAD would be for the first economy to copy the other country's institutions and economic policy regime. However, if we had measured the volatility correctly, why should have to apply a specific policy in ordet to adjust the permanent and extraordinary shock.

We could give a more extreme example where a country (A) presents a volatility lower than the other country's (B), but since A suffered a structural shock its volatility seems to be much higher with the standard measurements, when actually, correctly measured, (A) would be the least volatile. If we take the policy recommendations for country B and apply them to A, we will increase A's volatility instead of lowering it.

The traditional way of measuring volatility is particularly wrong in panel or cross-section studies (of the Barro equation kind) where dozens of countries for long time series are put together without taking into account the n possible extraordinary shocks (negative or positive) that may have hit any one of them. This leads us to ask how robust these studies are to changes in the estimation of the volatility.

Regular volatility is a permanent and intrinsic phenomenon in the distribution of the probabilities of the series while a structural break is an extraordinary phenomenon with great dimensions. Extraordinary shocks require structural policies for its treatment, while volatility is related to the application of counter-cyclical policies or macroeconomic stabilization.

For this reason, the second risk factor that could be analyzed from a univariate process is related to the distribution function of extraordinary shocks in the deterministic component (number, type and magnitude of the structural breaks).

4 Structural breaks

The capacity for econometric forecasting is an important instrument (but not the only one) to determinate the risk associated to an economy (economic variable) under study. As we have seen, the volatility of a variable is generally used as an important piece of information to determine risk.

However, that recent econometric developments have stressed the effect of other factors such as structural breaks and persistence also affect the capacity to forecast of an econometric model[iii]. The existence of these phenomena with a particular probabilistic distribution deteriorates the usual relationship between volatility, forecasting and risk.

Hendry and Clements (1998) present a taxonomy of the possible sources of error of forecasting for time series:

1. change in the slope
2. change in the equilibrium mean value
3. specification error in the slope
4. specification error in the equilibrium mean value
5. estimation of the slope
6. estimation on the equilibrium mean value
7. uncertainty in the source of the forecast
8. accumulation of errors

The main conclusion of Hendry and Clements (1999) is that the existence of structural breaks constitutes the main determinant of the forecasting errors. Structural breaks highlight a weakness in the models that could be exploited with an adequate modeling strategy.

When the structural break is not exogenous to the system under study, but endogenously generated, the best solution consists in trying to model the break as an integral part of the data generating process. If the researcher has variables that associate with the occurrence of the break, then he could use them to predict their appearance (McCulloch y Tsay, 1893; Maddala y Kim, 1998).

The inclusion of structural breaks in the analysis of risk (in as much as this is understood as precision in the forecasting) should not be restricted to its use as an instrumental variable (that allows to calculate in a precise manner the long run deterministic component) but should also be evaluated as an autonomous risk factor since their distribution function could be used to evaluate the probability of occurrence of future structural breaks in the series under analysis.

From the macroeconomic point of view, the existence of structural breaks also constitutes a risk factor since it increases the possibility of institutional changes. As we stated earlier, extraordinary shocks might require structural policies, usually associated with modifications in the institutions that regulate how the market works. This greater "institutional instability" due to the existence of significant structural breaks should be included in the risk function under analyses.

5 Persistence

Hendry and Clements (1999) present a comparison between the goodness of fit and the forecasting precision in two alternative models: a random walk (RW) and a model with a deterministic linear trend (LT). The RW model shows that forecasting uncertainty, given by the interval of forecasting at 95%, is much greater than that of the LT model[iv].

Thus, the degree of persistence of the regular shocks is also a crucial variable to determine the macroeconomic risk. It affects the forecasting precision since it is an indicator of the duration of the deviation of the series with respect to the projected long run trend. The more persistent the shocks are, the longer it will take the series to return to its trend and, thus, the less precise the forecasting will be in the long run when based on the deterministic component.

To show the impact of uncertainty on the forecasting precision we could compare a simple model for an I(0) series, an I(1) series and a series which is stationary around a deterministic trend (Hendry and Clements, 1998, 1999).

Be:

$$y_t = \ _t + \ y_{t-1} + \ _t \qquad (1)$$

where y_t is a fractionally integrated process with <1 and $_t$ $IN[0, \ ^2]$[v].

The forecast for 1 period with known parameters μ and ρ conditional on the available information in T+1 is:

$$\hat{y}_{\mathrm{T+1}} = \ + \ \hat{y}_{\mathrm{T}} = \ _h + \ y_T \qquad (2)$$

It can be proved that the variance of the forecast error for a forecast of h periods taken since period T, is:

$$V[\ _{T+h}] = V[y_{T+h} | y_T] = \ ^2 \frac{(1 - \ ^{2h})}{(1 - \ )} \qquad (3)$$

in the case where the parameters are known. The variance converges to the non-conditional variance of the process when $h \rightarrow$.

When the series is I(1) in the previous example $=1$ being:

$$y_t = \ _t + \ y_{t-1} + \ _t \qquad (4)$$

with $_t$ $IN[0, \ ^2]$

The forecast for h periods, with known parameters and conditional on the available information in T is:

$$\tilde{y}_{\mathrm{T+h}} = \ + y_{\mathrm{T+h\text{-}1}} = \ _h + y_T \qquad (5)$$

For a forecast of h periods taken since period T, it can be shown that when the series is an I(1) process the variance of the forecast error is:

$$V[\hat{e}_{T+h}] = h(\ ^2 + hV[\hat{\ }]) \cong h \ (1 + \frac{h}{T}) \qquad (6)$$

If T and h tend to infinitum

$T = Ah^K$ with $K>0$, then

$$\mathrm{V}[\hat{\mathrm{e}}_{\mathrm{T+h}}] \cong \mathrm{h} \ (1 + A^{-1} h^{1-K}) = V_{ds} \qquad (7)$$

Lastly, we should compare what happens with a data generating process that it is stationary in the trend:

$y_t = \quad + \quad t + u_t$ *(8)*

$u_t \quad IN[0, \quad ^2]$

The forecast for h periods with known parameters and conditional on the available information in T is:

$$\tilde{y}_{\mathrm{T+h}} = \quad + \quad (T + h) \tag{9}$$

If T and h tend to infinitum, $T = Ah^K$ with $K>0$, then the multiperiod variance of the error is:

$$\mathrm{V}[\hat{\mathrm{e}}_{\mathrm{T+h}}] \cong \ _u^2 (1 + 4A^{-1}h^{-K} + 12A^{-2}h^{1-2K} + 12A^{-3}h^{2-3K}) = V_{ts} \tag{10}$$

To easily compare the trend-stationary model (TS) with the difference-stationary model (DS) we can calculate the ratio between both variances where we eliminate T using $T=Ah^K$ with $K>0$.

$$\frac{V_{ds}}{V_{ts}} = \frac{\mathrm{h}(A^{-1}h^{2-K})}{\ _u^2(1+4A^{-1}h^{-K}+12A^{-2}h^{1-2K}+12A^{-3}h^{2-3K})} \tag{11}$$

When $h \rightarrow \quad$, $V_{ds} / V_{ts} \rightarrow \quad$.

When we allow T and h to grow it does not matter at what rate they do so as long as $K \quad 0$, $V_{ds} / V_{ts} \rightarrow \quad$.

In this way we may see that the greater the persistence in the shocks the lesser the confidence of the forecast. Of corse, the longer the forecasting period is the lesser the confidence is.

From the macroeconomic perspective it is usually stated that the persistence of the shocks that hit an economy increase the probability of hysteresis in a group of variables that have incidence in the capacity for long run growth. Under this line of thinking, it is usually stated that persistent shocks can severely affect the accumulation of physical and human capital, deteriorating the basic conditions for sustained growth.

When taking together the econometric and macroeconomic analysis we find the need to include in the risk analysis some indicators of persistence of the regular shocks to identify the true data generating process and to obtain a more precise measurement of the forecast confidence for each series.

6 Methodological aspects for the determination of macroeconomic risk associated with a variable or indicator

There are multiple methods for calculating the macroeconomic risk of a country. As an example we may take Erb, Harvey and Viskanta (2000) who takes five complementary risk indicators (International Country Risk Guide's political risk, Financial risk, Economic risk, Composite risk indices and Institutional Investor's country ratings) to classify a sample of more than a 130 countries. The authors find that the different measures are highly correlated and that financial risk contains the greatest amount of information on the behavior of future returns.

However, each indicator used in the work of Erb *et al (2000)* is in principle multivariate since it includes a group of explanatory variables which, after being weighted, are used to build an index.

For univariate processes, the most usual index of macroeconomic risk in the real volatility of the GDP[vi] or another relevant variable of the real or financial sectors. The econometrics of time series has recently generated several instruments which are useful to make inferences on risk based on the volatility by using the ARCH methodology.

Within this methodology, the GARCH type (Bollerslev, 1986) takes into account the order of integration (persistence) of the series, but not the structural breaks and thus it has the same problems as those of the traditional unit root tests[vii]. The SWARCH (Hamilton y Susmel, 1992) does capture the breaks but it does not take it as an input, so its predictive performance is not good when evaluating the global (total) risk of a series.

In these models, information efficiency on the "true" variance is appropriate. But they do not include the structural breaks (number, type and magnitude) for the evaluation of the global risk of the variable.

This risk could be calculated with a multidimensional univariate macroeconomic risk indicator. Such an indicator is much more ambitious since it includes and exceeds the objective of calculating in an improved fashion the volatility of a variable. This is an index useful for the comparison between countries since we could take the mean of the sample as well as the central country in the financial markets as a comparative reference point.

If we wish to calculate this indicator we must first know what the best approximation is of the long run trend of the economy with the objective of optimizing the forecast of the series.

To do so, it is important to separate the breaks in trend or constant, which imply a spurious alteration of the volatility as well as those that reflect a miss-specification of the long run behavior of the trend. Knowing where the structural breaks are will also allow us to correctly determine the level of integration of the data generating process including the possibility of fractional integration.

To sum up, a multidimensional univariate indicator of macroeconomic risk should give the policy maker or the investor information on:

1) the distribution of shocks in the expected growth rate (shocks in trend),
2) the distribution of abrupt shocks in the level of the series (changes in the constant),
3) the parameter of persistence of regular shocks, and
4) the cyclical volatility of the series after the effect of the structural breaks is taken into account.

Our procedure consists in a sequence of complementary tools designed to obtain the best determination of the behavior of the variable associated with a country's macroeconomic risk. The steps to be taken are the following:

6.1 Identification and estimation of the risk factors of each series

Consists in:

1) Seasonally adjusting the series, using the X-11 ARIMA procedure and taking the natural logarithm of the series.
2) Determining the structural breaks endogenously using the methodology proposed by Bai and Perron (1998,a,b), and using the procedure Break.src for GAUSS developed by Perron. We will take into account both breaks in the constant and breaks in the trend separately since they imply forecasting errors of different kind.
3) Calculating the degree of persistence of the series with a study of fractional integration using the ARFIMA methodology, taking the series without the structural breaks. The fractional integration tests used have been developed by Sowell (1992a) who applies the maximum likelihood method for the estimation of the parameters of interest[viii].
4) Calculating the "normal" volatility and the volatility corrected by structural breaks. Taking into account the trend that best represents the long run behavior of the series, we can obtain the cycle and from it calculate the "pure" volatility of the series.

6.2 Classification of the countries according to the different indicators of univariate macroeconomic risk and comparison of alternative clustering methodologies.

Consists on:

1) Ranking the countries according to their structural stability in mean.
2) Ranking the countries according to their structural stability in trend.
3) Ranking countries according to the persistence of the shocks.
4) Ranking countries according to the ordinary cyclical volatility (to simulate the results of the traditional methodologies).
5) Ranking the countries according to the cyclical volatility corrected by structural breaks.
6) Constructing an univariate multidimensional index of macroeconomic risk[ix].
7) Clustering the countries according to the ordinary cyclical volatility (to see the results that would be obtained from the traditional methodology).

8) Clustering the countries according to the structural stability in mean and trend, persistence (corrected) of the shocks and corrected cyclical volatility.

9) Clustering the countries according to the multidimensional univariate index of macroeconomic risk.

10) Comparing the results of the traditional methodology with those that of the multidimensional univariate index of macroeconomic risk.

The most important methodology innovations consist in the implementation of a multiple structural break test and the estimation of the fractional integration parameters to evaluate the persistence of the shocks that affect the series. In both cases, the innovation allows us to identify with greater precision the true data generating process (through the most appropriate estimation of the deterministic component and the "memory" of the regular stochastic shocks). As a whole, this alternative methodology allows us to evaluate in a more appropriately manner what is the intrinsic forecasting potential in each series and thus give a better approximation of the estimated risk from a univariate process.

Next we present a brief description of the methodological innovations as a way to facilitate the understanding of the results from the empirical application.

6.3 Endogenous determination of the multiple structural breaks.

The procedure developed by Bai and Perron (1998) is used to determine the number of structural breaks in a series, identifying the date of the breaks and estimating the magnitude of each break in the constant and trend.

The methodology we implement has a wide range of applications since it can be used for models with pure or partial structural breaks. Pure models are those which include only regressors whose coefficients are time changing, while partial models admit the existence of at least one regressor whose coefficient is constant.

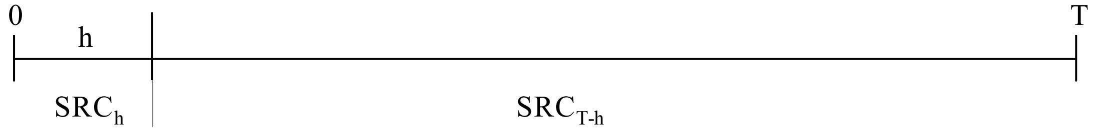
The mechanism for detecting the dates of breaks in a series is based on an algorithm whose function is to find the points T_i^* which minimize the sum of squared residuals that have previously been calculated from the sample data.

Before proceeding to the explanation of how the algorithm works we must specify certain parameters which characterize the procedure, which include "*h*", the minimum number of observations that are admitted in each segment in which the sample is divided. It is also important to determine the degree of robustness of the procedure which is related to the existence or not of heterocedasticity and autocorrelation between the residuals in each segment.

In particular, it could be allowed for the distribution of the residuals to be different in different regimes or we could impose the restriction of a common structure on them in the complete series.

We begin by evaluating the optimal partition of the series but allowing only one break. This is performed for every possible partition in the sample, but taking into account the limitation that each segment should have a minimum extension of *h* observations. In such a manner we will have partitions ranging from *h* to *T*-*mh* observations with *m* being the number of predetermined structural breaks. In this first stage *m*=1. Then we calculate the sum of squared residuals (SSR) for each of the segments generated from the partition, which taken together determine the residual total sum (RTS) of this partition. Thus, this first step determines a group of *T*-*(m+1)h+1* partitions with only one break with its respective STR.

An illustration serves to understand better this first step:



$$SRT = SRC_h + SRC_{T-mh}$$

The procedure continues by allowing for two breaks in the series. This second specification divides the sample into three segments and for each one we calculate the SSR to be able to calculate the STR associated with this partition. The result is a group of T-(m+1)h+1 partitions each one with two breaks and an associated STR. The final moment

This method works sequentially until we obtain a set of *T-(m+1)h+1* optimal partitions with (*m-1*) breaks and its associated STR which were calculated from the *m* regimes from each partition. We follow by analyzing which of the partitions with (*m-1*) breaks has the lowest RTS when it is combined with an additional segment. The method can be seen as the a sequential calculation of *T-(m+1)h+1* segments with optimal partitions of *1,2,…,(m-1)* breaks. The last step consists in simply creating the optimal partition with *m* breaks.

After estimating the optimal number of structural breaks we must use a methodology that allows for the identification of the appropriate break dates.

There is a wide variety of test for such a task, including the Bayesian F tests[x] and other F tests of the same class such as the UDmáx F_t and the WDmáx F_t (weighted versions of other similar tests, developed by Bai and Perron, 1998a).

In our case we use a sequential test designed by Bai and Perron (1998a) due to its ease of use and easy comprehension. The test can be used to confront the null hypothesis H_0 that a series contains " " breaks with the alternative H_A that the parameter of the model is " +1".

The statistic used to determine the rejection or not of H_0 is based on the comparison of the sum of squared residuals under both models.

The test rejects H_0 in in favor of the model with (+1) breaks if the value of the sum of squared residuals for the all the segments which include an additional break is significantly smaller than the sum of squared residuals of the model with   structural changes.

This procedure calculates sequentially the SupF(+1/) statistic assuming that the series has no structural breaks. The test ends when it is no longer possible to reject the null H_0 of the model with breaks.

This test has two important virtues as regards its application: i) it does not require that the break dates used in the computation of the F values be globally minimized, and ii) the test can be used even when the trimming period[xi] in both models (with   and (+1) breaks) is not the same.

7 Persistence and fractional integration. An analysis of the memory of the shocks from ARFIMA models.

During the last decade there has been a growing interest in the research on the degree of integration of macroeconomic time series, as well as in the measurement of the persistence of shocks. Much of the work has been developed with ARIMA class models (see, for example, almost all of the literature on unit roots).

However, in recent years several econometrists have argued that ARIMA models are far too restrictive. For example, Sowell (1992b) states that ARIMA models tend to adjust basically to the short run properties of the data and thus could provide erroneous estimation of the long run properties.

ARFIMA models (Autoregressive Fractionally Integrated Moving Average) provide an alternative to ARIMA models. They allow a series to present an ARMA behavior after being differentiated in a fractional manner. Granger and Joyeux (1980) and Hosking (1981) proposed the use of ARFIMA models to model “long memory” processes. Some of the theoretical properties of these stochastic processes can be found in Beran (1994), Brockwell and Davis (1991) and Odaki (1993). In the context of applied econometrics, Sowell (1992b) describe how the ARMA component can recover the short run behavior while the fractionally differentiated component recovers the long run behavior.

An ARMA (p;q) process (stationary and invertible) is formally a special case of an ARFIMA (p; d; q) process (also stationary and invertible) with a value d=0 for the parameter of fractional integration.

The autocorrelation function of an ARFIMA process can be shown to decay at a hyperbolic rate for values of d different from zero. This is a much slower rate than the geometric rate associated to stationary ARMA processes.

The alternative of a fractionally integrated process puts the debate between stationarity (d=0) and unit root (d=1) in another perspective. At the same time, this alternative eliminates the need to choose from one of those special cases, corresponding to different degrees of integer integration in the context of ARIMA models. As long as $d \in (0, 0.5)$, y_t (the dependent variable) will be stationary around a deterministic trend (with long memory). In this case, the limit value of the impulse response functions is 0, implying that shocks do not have permanent effects. On the contrary, for $d \in (0.5, 1.5)$ the differentiated series, Δy_t, will be stationary, with an intermediate memory for *d* < 1 and a long memory for *d* > 1. In this case, past shocks have permanent effects on the series but the diffentiated series is stationary with a covariance function of long memory.

The use of ARFIMA models has increased amongst empirical researchers (see, amongst others, Baillie, Chung and Tieslau (1992), Diebold and Rudebusch (1989, 1991), Cheung (1993), Cheung and Lai (1993)). Virtually all of these papers have used non-Bayesian statistical techniques[xii]. The most commonly used techniques can be divided into three categories:

(i) Maximum likelihood (Sowell, 1992a);

(ii) Approximate maximum likelihood (Baillie and Chung (1992), Li and McLeod (1986), Fox and Taqqu (1986)); and

(iii) Two step procedures (Geweke and Porter-Hudak (1983), Janacek (1982)).

In this paper we test the degree of integration of the series with the maximum likelihood methodology (Sowell, 1992a). We begin with the following equation which is a MA(∞) representation:

$$y_t = (1-L)^{-d} \quad (L) \quad _t \tag{12}$$

Multiplying both sides of the equation by $1-L$ (which is equivalent to applying the first difference operator to y_t) we have:

$$\Delta y_t = (1-L) y_t = (1-L)(1-L)^{-d} \quad (L) \quad _t \tag{13}$$

which can be transformed into:

$$(1-L)^{d-1} \Delta y_t = \quad (L) \quad _t \tag{14}$$

In conclusion, to determine the degree of integration of a series y_t we test (through the maximum likelihood method proposed by Sowel, 1992a) the null hypothesis of d=1 which implies that the series is integrated of order 1 (stationary in first differences) against the alternative hypothesis of d≠1.

8 Empirical application

The methodological proposal presented in this paper was applied to a group of countries with the aim of calculating and comparing the cross-country macroeconomic risk. In the sample we included 18 countries, 9 developed and 9 underdeveloped (Argentina, Australia, Brazil, Canada, Chile, South Korea, Spain, Philippines, France, Indonesia, Italy, Japan, Malaysia, Mexico, United Kingdom, Sweden, Thailand and the U.S.). We used quarterly GDP data. The sample includes 80 quarterly observations for each country for the period 1980:1-1999:4.

The main results will be discussed first for each individual indicator and later comparing the different risk indexes and countries.

9 Structural breaks

In table 1 we present the results of the sequential test for multiple structural breaks designed by Bai and Perron (1998). By allowing for the endogenous selection of more than one structural break we find that 8 countries (4 developed and 4 underdeveloped) have had multiple deterministic breaks. This result confirms the importance of testing for multiple endogenous structural breaks in macroeconomic time series, as Bai and Perron (1999) stress. The result also verifies that there is no unique relationship between development and the probability of occurrence of structural breaks.

Of the other 10 countries, only 4 do not present significant structural breaks: the U.S., Italy, Australia and Brazil. The other 6 had only one break.

Most of the structural breaks occurred in the period 1986-1991 (11 out of 22). The geographic distribution of the breaks shows that it is Asia the region that concentrates the greatest number of trend or intercept changes (10 out of 22). These countries are also the ones with the biggest breaks, especially in the intercept.

The highest shock was the 23% fall in the potential GDP of Indonesia. It is also interesting to note that Chile had the greatest break in trend in 1984.

Table 1. Structural breaks in the deterministic component of the series.

Optimal number of breaks, break dates and magnitude of the changes

Country	Break number	Value F(l+i/l)	Critical F	Optimal number of breaks	Break date	Confidence interval at 90%	% Change in the intercept	% change in trend
Argentina	1	67,2	11,47	2	ii 91 //Obs.46	45-47	7,6%	1,7%
	2	35,5	11,47		i 95 //Obs.61	60-62	-8,9%	-0,4%
Australia	1	3,2	11,47	0				
Brazil	1	3,8	11,47	0				
Canada	1	16,4	11,47	1	iii 90 //Obs.43	41-44	-8,4%	-0,1%
	2	10,5	11,47					
Chile	1	3402,5	11,47	1	iv 84 //Obs.20	18-21	-0,8%	2,3%
	2	10,4	11,47					
South Korea	1	53,6	11,47	1	ii 95 //Obs.62	60-63	1,0%	-1,5%
	2	6,7	11,47					
Spain	1	1397,8	11,47	2	ii 84 //Obs.18	16-19	-0,7%	0,6%
	2	332,6	11,47		ii 87 //Obs.30	29-30	5,3%	-0,3%
Philippines	1	601,8	11,47	1	iv 84 //Obs.20	18-21	-14,4%	0,3%
	2	3,2	11,47					
France	1	31,6	11,47	2	iv 84 //Obs.20	18-21	-0,2%	0,4%
	2	15,0	11,47		iv 87 //Obs.32	31-33	3,9%	-0,2%
Indonesia	1	108,4	12,25	2	ii 88 //Obs.34	32-35	-0,4%	0,5%
	2	180,5	12,25		iv 97 //Obs.72	71-72	-22,6%	-1,6%
Italy	1	7,0	11,47	0				
Japan	1	33,1	11,47	2	i 87 //Obs.29	27-30	0,3%	0,4%
	2	19,5	11,47		i 90 //Obs.41	39-42	3,2%	-1,0%
Malaysia	1	14,8	12,25	2	ii 90 //Obs.42	41-43	5,2%	0,8%
	2	273,1	12,25		iv 97 //Obs.72	70-73	-13,2%	-0,9%
Mexico	1	44,6	11,47	1	ii 86 //Obs.26	23-29	-4,6%	0,5%
	2	9,0	11,47					
United Kingdom	1	15,5	11,47	2	iv 82 //Obs.12	10-13	1,6%	0,8%
	2	18,1	11,47		iv 90 //Obs.44	42-45	-8,3%	-0,2%
Sweden	1	19,1	11,47	1	i 92 //Obs.49	48-49	-9,6%	0,05%
	2	6,6	11,47					
Thailand	1	81,6	12,25	2	i 88 //Obs.34	32-35	10,0%	0,7%
	2	18,0	12,25		ii 97 //Obs.70	68-71	-18,9%	-2,2%
United States	1	5,2	11,47	0				

10 Persistence

The results for the persistence of macroeconomic shocks have been constructed from the fractional integration test applying the maximum likelihood method described by Sowell (1992) discussed before. The following table groups these results.

Table 2. Persistence in macroeconomic shocks

	Fractional integration test				**Fractional integration test (corrected for the presence of structural breaks)**			
Country	AR	MA	Prob. d=1	d	AR	MA	Prob. d=1	d
Argentina	3	2	0,34	1,00	3	3	0,02	0,18
Australia	3	2	0,21	1,00	3	2	0,21	1,00
Brazil	3	2	0,00	0,07	3	2	0,00	0,07
Canada	3	2	0,12	1,00	3	2	0,12	1,00
Chile	3	3	0,74	1,00	3	3	0,50	1,00
South Korea	0	0	0,63	1,00	3	2	0,96	1,00
Spain	3	2	0,61	1,00	1	0	0,71	1,00
Philippines	3	2	0,88	1,00	2	0	0,57	1,00
France	0	0	0,02	1,23	3	3	0,09	1,00
Indonesia	2	2	0,62	1,00	3	3	0,79	1,00
Italy	3	2	0,00	0,32	3	2	0,00	0,32
Japan	2	2	0,00	1,26	3	2	0,00	0,23
Malaysia	2	2	0,78	1,00	0	3	0,76	1,00
Mexico	1	2	0,21	1,00	1	0	0,00	0,28
United Kingdom	3	2	0,01	0,62	3	3	0,00	0,30
Sweden	2	0	0,05	1,27	1	0	0,13	1,00
Thailand	3	3	0,01	0,46	3	3	0,01	0,42
United States	3	3	0,43	1,00	3	3	0,43	1,00

We find that when we include the structural breaks the persistence of shocks is reduced in all of the series that present deterministic shifts, with Japan showing the most impressive change. The parameter of persistence for this country changes from 1.26 (which implies a long memory even for the series in the first differences) to 0.23 (which represents stationarity with a long memory for the series in level).

Without taking into account the structural break, and at 5% significance, the tests of fractional integration do not allow the rejection of the null hypothesis of d=1 for most of the series (11 out of 18). Of the other 7 countries, 3 of them have long memory in the growth rate and the rest have long memory in the level of the series.

When we include the structural breaks the main result is that no country has long lasting shocks in the growth rate of the GDP (for no country d>1).

Together with Japan, the countries whose persistence changes the most when breaks are included are: Sweden, France, Mexico and Argentina. The latter country and Brazil have the least persistence shocks in the whole sample of countries under study.

11 Volatility

The indicator of volatility used is the standard deviation of the business cycle, which was calculated in the traditional way (as the difference between the seasonally adjusted series and its linear trend), correcting it for the presence of structural breaks.

As with the case of persistence, the most appropriate modelization of the structural breaks reduces any indicator of volatility. This implies that the range of variation of the different indicators of volatility for the different observations in the sample would also fall.

Table 3. Volatility of the macroeconomic cycle.

Country	Linear trend	Linear trend with structural break
	Standard deviation of the cycle	Standard deviation of the cycle
Argentina	8,30%	3,20%
Australia	2,20%	2,20%
Brazil	4,40%	4,40%
Canada	3,09%	1,99%
Chile	9,50%	4,39%
South Korea	5,68%	2,82%
Spain	2,62%	1,05%
Philippines	5,53%	2,55%
France	1,83%	1,18%
Indonesia	7,07%	1,49%
Italy	1,96%	1,96%
Japan	4,31%	1,12%
Malaysia	5,53%	2,09%
Mexico	4,21%	2,81%
United Kingdom	2,60%	1,16%
Sweden	3,04%	1,72%
Thailand	8,84%	2,52%
United States	2,16%	2,16%

Note: The countries in which the Bai and Perron (1998) test did not detect any structural breaks have the same volatility in both columns due to the fact that we assume that the same trend is implicit in the data generating process.

In the comparative analysis of the standard deviation of the series, obtained with a linear trend with or without structural breaks in intercept and/or slope, we found that the countries that reduced their volatility the most are those in the Asian continent.

The countries with the greatest cyclical volatility (calculated with the standard technique) are: Chile, Thailand and Argentina. When we include the structural breaks, the three countries with the greatest volatility are Chile, Brazil and Argentina.

In the other extreme, we find that France, Italy and the United States have the lowest volatility (with the standard estimation technique). After correcting for structural breaks, the less volatile countries are Spain, Japan and the United Kingdom.

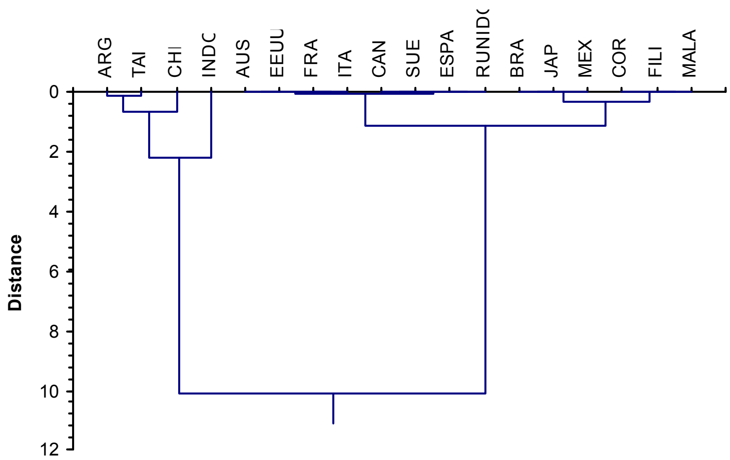
12 Multivariate risk index and cluster analysis

Based on the results of the indicators compared in the previous sections, we built a multidimensional univariate macroeconomic risk index. We will use it to group the countries in four clusters from a measure of their similarity based on the equally weighted Euclidean distance of the different factors of risk[xiii].

If we make a traditional analysis of risk centered on the cyclical volatility of production, the results of the clustering procedure presented in table 4. Every developed country, with the exception of Japan, fall into the category of lowest risk. The emerging countries are divided into the other three categories of risk with Chile, Thailand and Argentina being grouped in the category of the biggest risk.

Table 4. Clustering of the countries according to the different types of risk

Type of risk	Very low	Low	Moderate	High
Ordinary Cyclical volatility	Australia, Canada, United States, Spain, France, Italy, United Kingdom y Sweden.	Brazil, South Korea, Philippines, Japan, Mexico y Malaysia	Indonesia	Argentina, Chile y Thailand



DENDOGRAMA POR VOLATILIDAD

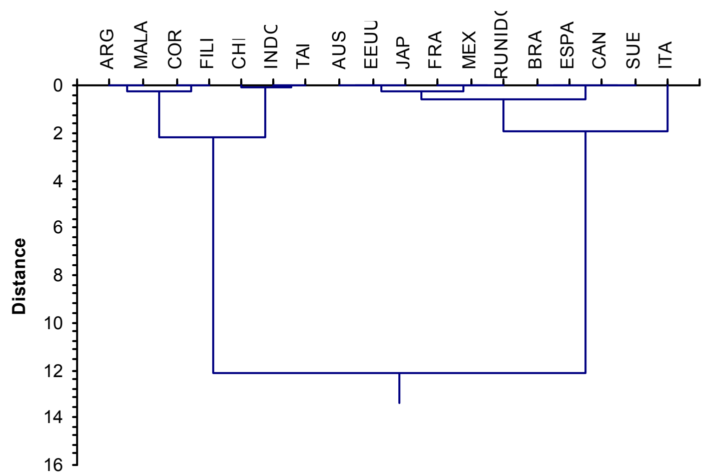
When we include the four factors to obtain a multidimensional univariate risk index, the results show important changes.

With this new methodology the only country that can be included in the very low risk is Italy. In the second group, from the lowest to moderate risk, we have the rest of the developed countries plus Mexico and Brazil.

The cluster including the countries with the highest risk presents results that are similar to the traditional analysis (which uses only the cyclical volatility as a factor of risk) although Argentina reduces its relative risk and Indonesia increases it.

Table 5. Clustering of countries according to the different types of risk (persistence indicators and volatility corrected for the presence of structural breaks)

Type of risk	Very low	Low	Moderate	High
Risk due to persistence	Argentina, Brazil and Japan	Italy, Mexico and United Kingdom	Thailand	Australia, Canada, Chile, South Korea, United States, Spain, Philippines, France, Indonesia, Malaysia and Sweden
Risk due to volatility	Australia, Canada, United States, Spain, France, Indonesia, Italy, Japan, Malaysia, United States and Sweden.	South Korea, Philippines, Mexico and Thailand	Argentina	Brazil and Chile
Structural risk 1 (change in intercept)	Australia, Brazil, Chile, South Korea, United States, Spain, France, Italy, Japan and Mexico.	Canada, United Kingdom and Sweden	Argentina, Philippines and Malaysia	Indonesia and Thailand
Structural risk 2 (change in trend)	Australia, Brazil, Canada, United States, Philippines, France, Italy, Mexico and Sweden.	Spain, Japan and United Kingdom	Argentina, South Korea, Indonesia and Malaysia	Chile and Thailand
Multidimensional risk	Italy	Australia, Brazil, Canada, United States, Spain, France, Japan, Mexico, United Kingdom and Sweden.	Argentina, South Korea, Philippines and Malaysia	Chile, Indonesia and Thailand.



DENDOGRAMA MULTIDIMENSIONAL

We design a transition matrix to study the changes between clusters in the different methodologies. The selection of the index of risk has important effects on the classification of the countries. The principal diagonal of the matrix in table 6 (which includes those countries that do not change from risk group when the index of risk changes) includes only 34% of the cases under analysis. In other words, using the multidimensional univariate risk index changes the relative ranking of more than 60% of the countries.

Table 6. Transition matrix of the groups in the clusters obtained from the multidimensional risk index (common and corrected for the presence of structural breaks).

		Clusters from the multidimensional univariate risk index				
		Very low	**Low**	**Moderate**	**High**	***Cases in the row***
Clusters from the cyclical volatility not corrected by structural breaks	**Very low**	6%	39%	0%	0%	*8*
	Low	0%	17%	17%	0%	*6*
	Moderate	0%	0%	0%	6%	*1*
	High	0%	0%	6%	11%	*3*
	Cases in column	*1*	*10*	*4*	*3*	*18*

Note: The different elements in the matrix indicate the proportion of countries (with respect to the whole sample) which had been grouped in cluster i with the ordinary multidimensional risk index that move to cluster j (with the possibility that j equals i) when we use the multivariate risk index corrected by structural breaks.

We also verify an important modification in the inter-cluster distribution of the different countries. If we use as an indicator of risk the ordinary cyclical volatility almost 50% of the countries can be classified in the very low risk cluster and 78% can be defined as low or very low risk countries. These proportions go down to 5% and 61%, respectively, when we use the multidimensional univariate risk index.

13 Conclusions

This paper presents a methodological proposal for the analysis of the multidimensional univariate risk that could be applied to macroeconomic and financial studies. We perform an empirical application of this methodology to measure the real macroeconomic risk in a sample of 18 countries (9 developed and 9 underdeveloped) with quarterly data for the period 1980:1-1999:4.

If we relate uncertainty to a number of factors that affect the forecasting ability we may optimize the evaluation of risk by taking into account all the available information, which is an improvement on the use of the traditional volatility as a proxy for the country risk.

Our methodology gives the policy maker or the investor a new tool of analysis which takes into account the information on the risk associated with any univariate process. The four factors included are:

11) the distribution of shocks in the expected growth rate (changes in the deterministic trend),

12) the distribution of shocks in the level of the series (changes in intercept),

13) the persistence of regular shocks, and

14) the cyclical volatility of the series after considering the effect of structural breaks.

This information can be used to establish a risk ranking based on each of the individual factors or by taking them together to build a multidimensional univariate risk index (or forecasting confidence indicator).

From the application of this methodology to our case study we find that it improves the estimation of risk implicit in the series due to the fact that:

1) 14 countries present at least one structural break and 8 have multiple breaks.

2) After taking into account the existence of these breaks, the persistence of the regular shocks is drastically reduced.

3) The same happens with the cyclical volatility indicator in every country that has suffered a deterministic shift in trend or intercept.

4) 7 of the countries have fractional integration on the series of the GDP something that would not have been detected by the traditional unit root tests.

5) The multidimensional univariate risk index we have built substantially alters the clustering of countries in different risk categories in more than 60% of the cases.

The results of the empirical application show that the 18 countries under analysis can be grouped in great sub-divisions. On the one hand, we find the low or very low risk countries which include all the developed nations plus Mexico and Brazil. Amongst them, Italy is the lowest risk country when the four risk factors are taken into account.

The other 7 countries are emerging and show a very significant real macroeconomic risk. Amongst them we can, however, also distinguish two groups. The greatest real risk group includes Thailand, Chile and Indonesia. The common element between them is the presence of important structural breaks in the deterministic component.

14 References.

Agenor, R. and Aizenman, J. (1997). Contagion and volatility with imperfect credits markets. IMF.

Aizenman, J. and Marion, N. (1996). Volatility and the investment response. NBER. WP 5841.

Aizenman, J. and Powell, A. (1997). Volatility and financial intermediation. NBER. WP 6320.

and finance. Vol. 1 n. 3.

Bai, J and Perron, P. (1998b). Estimating and testing linear models with multiple structural changes, Econometrica 66,47-78.

Bai, J. and Perron, P. (1998a), Computation and analysis of multiple structural-change models, manuscript, Boston University.

Baillie, R. and Chung, C. (1992). Estimation of fractionally integrated processes with ARCH innovations, manuscrito.

Baillie, R., Chung, C. and Tieslau, M. (1992). The long memory and variability of inflation: A reappraisal of the Friedman hypothesis, CentER Discussion Paper 9246, Tilburg University.

Banerjee, A, Lazarova, S. and Urga, G.. (1999). Bootstrapping Sequential Test for Multiple Structural Breaks.

Beran, J. (1994). *Statistics for Long-Memory Processes*, New York, Chapman and Hall.

Black, F. (1972). Capital markets equilibrium with restricted borrowing. Journal of Business 45, pp 444-455..

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31. pp307-327.

Brockwell, P. J. and Davis, R. A. (1991). *Time Series: Theory and Methods*, New York Springer-Verlag.

Cantor, R. and Packer, F. (1995). Sovering credit ratings. Current issues in economics Carlin, J. y Dempster, A. (1989). Sensitivity analysis of seasonal adjustments:

Carrera, J. Féliz, M. and Panigo, D. (1999). Unit roots and cycles in the main macroeconomic variables for Argentina. Anales de la AAEP 1999. Rosario.

Cati, R.C. (1998). Stochastic and segmented trends in Brazilian GDP from 1900 to 1993, Anales, Sociedad Brasileña de Econometría.

Cheung, Y.-W. (1993). Long memory in foreign-exchange rates, Journal of Business and Economic Statistics, 11, 93-102.

Cheung, Y.-W. and Lai, K.(1993). A fractional cointegration analisis of purchasing power parity, Journal of Business and Economic Statistics, 11, 103-112.

Cribari Neto, F. (1996). On time series econometrics, The Quarterly Review of Economics and Finance, 36, Special Issue, 37-60,.

Cuttler, D. Poterba, J. and Sum, L.. (1989). What moves stock prices?. Journal of portfolio management, vol 15, n. 53, pp4-12.

Diebold, F. X. and Rudebusch, G. D. (1989). Long memory and persistence in agrégate output, Journal of Monetary Economics, 24, 189-209.

Diebold, F. X. and Rudebusch, G. D. (1991). Is consumption too smooth? Long memory and the Deaton paradox, Review of Economics and Statistics, 73, 1-9.

Doornik, J. A. and Ooms, M. (1999). A package for estimating, forecasting and simulating ARFIMA models: ARFIMA package 1.0 for Ox, Nuffield College, Oxford, Erasmus University, Rotterdam.

Easterly, W. Roumeen, I. and Stiglitz, J. (2000). Shaken and stirred: explaining growth volatility. The World Bank.

Erb, C. Harvey, C. and Viskanta, T. (2000a). Expected returns and volatility in 135 countries. www.duke.edu.

Erb, C. Harvey, C. and Viskanta, T. (2000b). Political risk, economic risk and financial risk. www.duke.edu.

Ferson, W. and Harvey, C. (1994). An explanatory investigation of the fundamental determinants of national equity market returns, in Frankel, J. (ed) The internationalization of equity markets. UC Press.

Fox, R. and Taqqu, M. (1986). Large-sample properties of parameter estimates for strongly dependent stationary Gaussian time series, Annals of Statistics, 14, 517-532.

Geweke, J. and Porter-Hudak, S. (1983). The estimation and application of long memory time series models, Journal of Time Series Analysis, 4, 221-238.

Goldfajn, I. and Valdez, R. (1997). Balance of payment crises and capital flows: the rol of liquidity, mimeo. MIT.

Granger, C. W. J. and Joyeux, R. (1980). An introduction to long-memory time series models and fractional differencing, Journal of Time Series Analysis, 1, 15-39.

Hamilton, J. D. and Susmel, R. (1992). Autoregressive conditional heteroskedasticity and changes in regime. University of California at San Diego. Mimeo.

Harvey, C. (1991). The World price of covariance risk, Journal of Finance, 40 pp 111-157.

Harvey, C. (1995). Portfolio enhancement with emerging markets and conditional information, in Classens, S. y Gooptu, S. (eds) Portfolio investment in developing countries. The World Bank.

Hausmann, R. and Gavin, M. (1995). Overcoming volatility, special report in economic and social progress in Latin America. IDB.

Hendry, D. and Clements, M.(1998) Forecasting non-stationary economic time series. MIT Press.

Hendry, D. and Clements, M.(1999). Economic forecasting in the face of structural breaks. In Holly, S. y Weale, M. (eds.), Econometric Modeling: Techniques and applications. CU Press.

Hosking, J. R. M. (1981). Fractional differencing, Biometrika, 68, 165-176.

Inter-American Development Bank-IDB (1995). Overcoming volatility in Latin America in Overcoming volatility, special report in economic and social progress in Latin America. Part II. IDB.

Janacek, G. (1982). Determining the degree of differencing for time series via the long spectrum, Journal of Time Series Analysis, 3, 177-183.

Li, W. K. and McLeod, A. I. (1986). Fractional time series modelling, Biométrica, 73, 217-221.

Liljeblom, E. and Stenius, M. (1995). Macroeconomic volatility and stock market volatility; empirical evidence on Swedish data. Swedish School of Economics and Business Administration.

Liljeblom, E. and Stenius, M. (1997). Macroeconomic volatility and stock market volatility; empirical evidence on finish data. Applied financial economics, 7 pp 419-426.

Maddala, G.S. and Kim, I.,(1998). Unit Roots, co-integration and structural change, Cambridge University Press.

McCulloch, R. and Tsay, R. (1893). Bayesian inference and prediction for mean and variance shits in autoregressive time series, Journal of American Statistical Association. 88, pp 968-978.

Odaki, M. (1993). On the invertibility of fractionally differenced ARIMA processes, Biometrika, 80, 703-709.

Perron, P. (1989). The great crash, the oil price shock, and the unit root hypothesis, Econometrica, 57, 1361-1401.

Pindyck, R. and Solimano, A. (1993). Economic instability and aggregate investment, NBER, Macroeconomic annual report.

Ramey, G. and Ramey, V. (1995). Cross country evidence on the links between volatility and growth. AER, December, p 1138-1151.

Schwert, W.(1989). Why does stock market volatility change over time?. Journal of Finance, vol. 44, n. 5, pp 1115-1153.

Shape, W. (1964). Capital assets price: A theory of market equilibrium under conditions of risk, Journal of Finance, 19, pp 425-442.

Solnik, B. (1974). An equilibrium model of international capital market, Journal of Economic theory, 8, pp 500-524.

Solnik, B. (1977). Testing international asset pricing: some pessimistic views, Journal of Finance 32. pp 503-511.

Sowell, F. (1992a). Maximum likelihood estimation of stationary univariate fractionally integrated models, Journal of Econometrics, 53, 165-188.

Sowell, F. (1992b). Modelling long-run behavior with the fractional ARIMA model, Journal of Monetary Economics, 29, 277-302.

Uribe, M. (1996). The tequila effect: Theory and evidence from Argentina, International Finance Discussion Paper n. 552. Board of Governors of the Federal Reserve System.

Volgelsang, T.J. and Perron, P. (1994). Additional tests for a unit root allowing for a break in the trend function at an unknown time, CRDE, Université de Montréal, Cahier de Recherche, No 2694,.

Wang, J and Zivot, E. (1999) A Time Series Model of Multiples Structural Changes in Level, Trend and Variance.

---

[i] The traditional focus on systemic risk are the beta (Shape, 1964) and the CAMP models (Black, 1972). Used initially in the United States, the model was presented in an international context in Solnik (1974, 1977). Harvey (1991) present evidence against the CAMP model for the world when risk and expected returns change over time. Harvey (1995) and Ferson and Harvey (1994) discuss the relationship between risk and returns in developing countries. They consider that systemic risk can be measured in the same way in developed and underdeveloped countries. In Harvey (1995) it is shown that there is no relationship between expected returns and betas measured against a world portfolio.

[ii] Weak legal systems, high costs of information and risk neutral agents.

[iii] Perron (1989), Volgensan and Perron (1994), Crivari Netto (1996), Cati (1998).

[iv] The authors report the same example in first differences and verify that the ranking of forecasting precision is not reversed. Even though first differences are much lower, the RW model presents a greatest bias in the estimation of the change rate in comparison with the LT model.

[v] The process is strictly stationary if the error term is IID without the normality assumption, but doing so facilitates the calculation of the forecasting confidence intervals.

[vi] Even though some authors, such as Cuttler, Poterba and Summers (1989), have pointed out the weak relationship between the macroeconomic fundamental and the movements in the market index (something which could be interpreted as a weak relationship between macro fundamentals and investors perceived risk), other authors, such as Liljeblom and Stenius (1995, 1997), analyze this relationship for Sweden and Findland, respectively, and find that macroeconomic volatility presents positive and significative correlation with the equity markets' volatility.

[vii] An example of the empirical problems with ARCH/GARCH models can be verified in the work of Liljeblom and Stenius (1995, 1997) who estimate the conditional volatility as the weighted moving averages (or "predicted absolute errors") and also with GARCH models. The problem here is the actual measurement of the volatility since the different alternatives give different results. Additionally, they do not take into account the

possible changes in regime that could imply the existence of structural breaks (something very probable in a 100 year long period), something that could over-state real volatility.

[viii] The results of the fractional integration tests were calculated with the "Arfima 1.0 for OX" package developed by Doornik and Ooms (1999).

[ix] The multidimensional univariate index is defined as the sum of the square of the different factors of risk (to penalize for excessive deviations). The factors of risk are normalized to avoid the scale effect that could distort the equal weighting used in the summation.

[x] Wangy Zivot (1999). Banerjee, Lazarova and Urga (1998).

[xi] Trimming refers to the proportion of the observations that is included in each segment in which the sample is divided.

[xii] Exceptions to this rule are the works of Koop (1991) and Carlin and Dempster (1989). However, the first paper uses a very simple model while the second one performs a conditional Bayesian analysis (that is, the analysis is performed conditional on the value of the adjusted parameters).

[xiii] The algorithm used here to group the countries in cluster uses the "complete" method (also known as the "farthest neighbor" method) that requires that the distance between two groups be equal to the distance between the farthest members within both groups.