

Cost of Equity Capital and Country Risk: An econometric analysis of the expected rate of return for four Latin American countries¹

Costo de capital y riesgo de país: Un análisis econométrico de la tasa de rendimiento esperada en cuatro países latinoamericanos

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Abstract

Expected returns and risk assessment are important issues when evaluating capital investment projects. We use VARX-MGARCH models and asset pricing theory to model the expected rate of return in Brazil, Colombia, Mexico and Peru for late 2006. The main objective of this paper is to present an econometric study of the cost of equity² capital based upon Erb, Campbell, Harvey, and Viskanta (1996) modelling in emerging markets through country risk. We use MSCI's DTR for measuring market performance and J.P. Morgan's EMBI+spread to proxy country risk and then construct conditional mean and variance models in a univariate and multivariate context.

Key words: financial econometrics, GARCH models, asset pricing, investment, cost of capital, country risk, equity returns.

Resumen

Los rendimientos esperados y la evaluación de riesgo son asuntos importantes cuando se evalúan los proyectos de inversión. Usamos los modelos VARX-MGARCH y la teoría de asignación de precios de activos para modelar la tasa esperada en Brasil, Colombia, México y Perú para finales de 2006. The principal objetivo de este artículo es el de presentar un estudio econométrico del costo del capital basado en el modelo de Erb, Campbell, Harvey y Viskana (1996) en los mercados emergentes a través del riesgo país. Usamos MSCI's DTR para medir el desempeño del Mercado y el J.P. Morgan's EMBI+spread como proxy el riesgo país y, seguidamente, construir los modelos de media condicional y de varianza en un contexto univariado y multivariado.

Palabras claves: econometría financiera, modelos GARCH, asignación de precios de activos, inversión, costo de capital, riesgo país, rendimientos.

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1. Introduction

The decision of capital investing is nothing but complex, especially in foreign markets. It is the result of a series of theoretical, technical, and empirical studies ranging from legal to financial feasibility. As a result, pecuniary convenience is just one of many variables to be taken into account when evaluating a project of this sort. One of the main tasks of financial studies consists in stating the expected rate of return or the cost of capital of the investment. This now turns to asset pricing theory which, along risk modelling, has been proven to be a difficult task when applied in an international context and especially in the case of emerging economies (Harvey, 1994). Erb, Harvey, and Viskanta (1995) propose a simple methodology by including country risk as a forecaster of future financial market performance, and from such proposition is where the idea for this research was heuristically born. The purpose of this paper is to broaden investment management decision tools by presenting a methodological approach for modelling expected asset return and risk in emerging markets economies. In order to do so, we base our methodology in the use of financial asset pricing theory and use of the VARX-GARCH methodology.

A significant quantity of papers has been written about asset return predictability and risk modelling. Most of the applied research on capital markets is concentrated on developed economies while some few on emerging countries. One of the many reasons for this is that traditional factor models, specifically the Capital Asset Pricing Model (CAPM), have been proven to be inadequate for developing markets (Harvey, 1994). The intuition behind these models is the tradeoff between the expected rate of return and the inherent risk of an investment. The relation consists basically in that risky investments should yield higher returns. The representation on graph 1 provides evidence on the Erb, Harvey, and Viskanta (1994) proposal regarding the connection between country risk and expected returns and also implies that the study of these two variables goes hand by hand. Thus, in this paper we will try to model, simultaneously, both time series.

With the objective in mind we turn to VARX-GARCH methodology as a mean to implement and evaluate the models. Regarding expected returns modelling, the study of asset return predictability is fundamental. Many researchers have taken upon the task of proving this with some amount of success. Campbell (1991) and Hodrick (1992) have used a Vector Autoregressive (VAR) model which generated significant time-varying forecasts of returns at any future. Later on Campbell, Lo, and MacKinlay (1997) have supported the idea that if the dynamics of the returns are well described by a simple time-series model then its long-horizon properties could be derived from a short-run model rather than estimated directly. Nevertheless, the debate about these assertions has not been concluded and important research is still in the making.

Concerning risk modelling, we rely upon risk management tools. Here the study of volatility plays a major role. The notion of risk is strongly related to uncertainty because volatility tells us how a random variable departs from its usual or expected value. Investment is sensible to these deviations and is one of the reasons why risk management is important when doing a project assessment. In practice, when one tries to quantify risk there are several approaches. One popular way is via Engle's (1982) well known Autoregressive Conditional Heteroskedasticity (ARCH) models and its family of representations. These of instruments have made possible important breakthroughs in applied research when modelling and forecasting the associated volatility of a time series. Therefore, in finance the relevance of such models and their extensions lie in the direct association between variance and risk (Bera and Higgins, 1993; Bollerslev, Chou, and Kroner, 1992).

With all of the above in mind and recognizing the need for modelling not only the conditional mean of an economic variable but all together with the conditional variance and covariances, is why we extend our modelling from the well known ARMA models developed by Box and Jenkins to include de ARCH-GARCH family of models from Engle (1982) and Bollerslev (1986). The analysis is carried out not only in a univariate but also in a multivariate context, given the dynamic relationship among variables due to visible capital market integration among different nations, spillover effects, shock effects, pricing efficiency,

and other different relations that can be brought up in financial markets (Baillie and Bollerslev, 1991).

This paper is divided into six sections, being this introduction the first one. Section II provides a brief background in financial asset pricing theory and financial econometrics. Section III describes the model by discussing data properties to be used and the selected specification of the conditional distribution, while section IV provides the estimation of parameters and their results. Section V presents the forecasting of expected rate of return and volatility for the four countries in the sample. Finally, section VI contains concluding remarks.

2. Background

In order to understand the relevance of the study it is important to establish a theoretical framework that should serve as the foundation for the construction of the models and as a way for grasping its intricacies. Flood, Hodrick, and Kaplan's (1986) proposition that stock returns are predictable is the starting point of this paper. These authors argue that one could not test dramatic changes in stock prices without taking into account the rational movements in stock prices that are caused by fluctuations in expected rates of return. These fluctuations are said to be originated by a vast array of phenomena that starts with fundamentals such as financial and operational reports, dividend payments, and so on, to the economic environment in influential markets, etc. In practice, it is like to start modelling equity returns by approaching the matter from two different manners³: from the view of historic average rate of return or from its forecast in a given time frame⁴.

For the first approach one would need very long samples of equity portfolio to calculate its performance as a simple historic average. The second method consists of having a series of past returns and trying to predict its future behavior by specifying a detailed function that depicts its dynamic performance, if any. Each of the approaches has its own virtues but if we recognize that financial returns and their volatility are time variant, then the last approach appeals as the most adequate,

assuming a large sample⁵. Additionally, financial markets in Latin America are relatively young and small; obtaining a historic average of the rate of return would then mean having a very small sample and therefore introducing several biases (temporality, survivorship, construction, upward or downward biases, and so on) that would affect the estimation⁶. Table 1 portrays the observed financial market returns for Brazil, Colombia, Mexico, and Peru as of the 2nd of January of 2006, relevant information in the sense that it gives reference values for the expected returns.

There is a great deal of specialized literature regarding asset pricing theory and equity returns modelling. Since the 1950's major academic efforts have been made in order to discover the intricacies of the reward an economic agent expects for assuming a certain amount of risk (Harvey, 1994). In the case of country risk and expected returns there are several methods that come to mind such as the CAPM or the Arbitrage Pricing Theory (APT). Such kind of approaches looks to explain such reward. The usual CAPM equation is a direct implication of the mean-variance efficiency of the market portfolio.

Such traditional approaches to the cost of equity capital have presented ambiguous evidence to support the proposed specifications when applied to emerging economies. Harvey's (1995) study of emerging market returns suggests that there is no correlation between expected returns and Betas measured with respect to the world market portfolio. Other distinguishing features of emerging capital markets are: average returns are much higher, correlations with developed market returns

Table 1. Emerging Markets. Annualized Historic Returns (Gross) in U.S. dollars as of Jan 2, 2006

	Term structure (years)			
	1	3	5	10
Brazil	58.598%	66.289%	21.529%	15.663%
Colombia	102.108%	98.219%	70.188%	21.29%
Mexico	50.185%	42.161%	25.467%	17.545%
Peru	35.271%	39.441%	33.089%	10.668%

Source: MSCI

are low, returns are more predictable and volatility is higher (Bekaert, Erb, Harvey, and Viskanta, 1996). These findings together with other documented results set apart the study of asset pricing in developed economies from such in emerging markets.

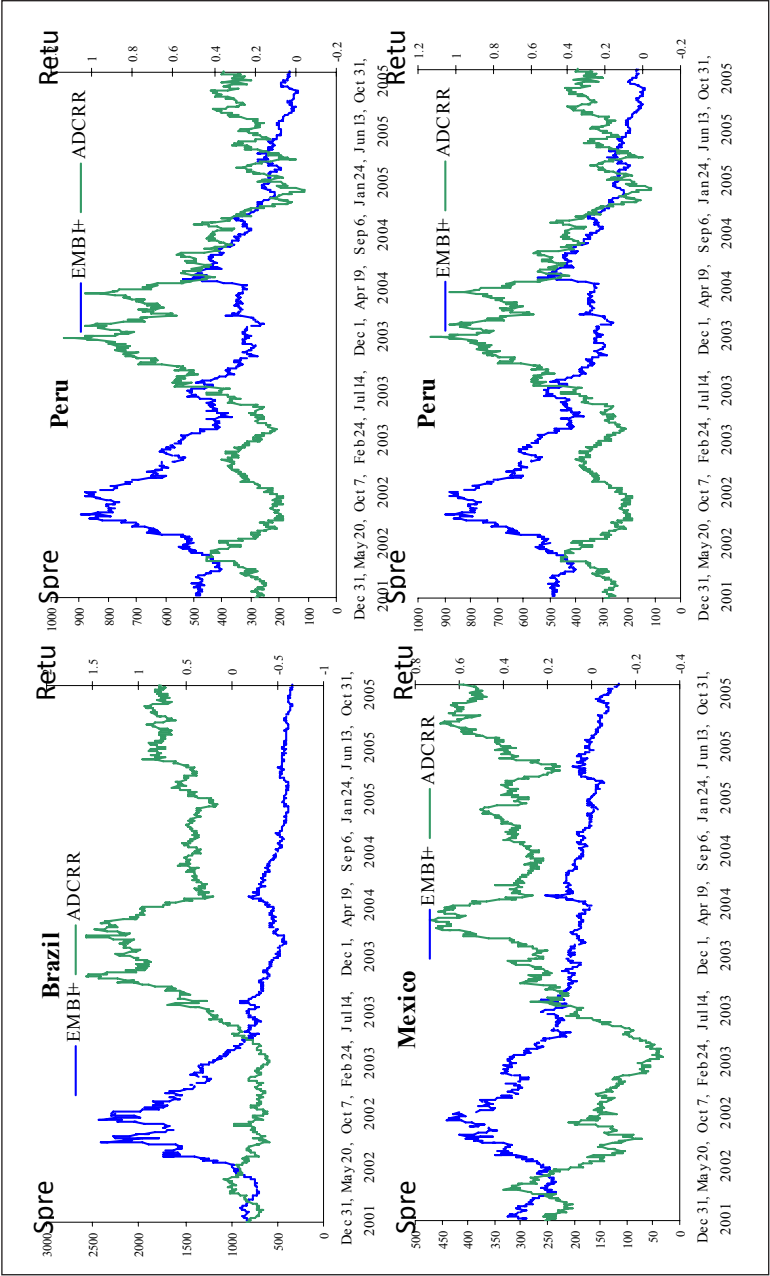
Our analysis builds on the work of Erb, Campbel, Harvey, and Viskanta (1996). The failure of the asset-pricing literature of the 1980's to nest the features commented above for measuring the cost of capital in emerging markets motivated the authors mentioned above to develop an alternative approach. The idea of their model was to fit this specification:

$$R_j = a_0 + a_1 \text{Log}(CCR_j) + \varepsilon_j \quad (1)$$

where R is the semi-annual return in U.S. dollars for country j , $\text{Log}(CCR)$ is the natural logarithm of the country credit rating⁷. Here time is measured in half years and ε is the regression residual or associated disturbances. The authors estimated a time-series cross-sectional regression by combining all the countries and credit ratings into one large model. In this sense, the coefficient associated with country risk is considered as the "reward for risk".

It is important to use the log of the credit rating since a linear model may not be appropriate. That is, as credit rating gets very low, expected returns may go up faster than what a linear model suggests. Convincing evidence is presented in Erb, Campbel, Harvey, and Viskanta (1996) about the fit of the credit rating model. They find that higher rating (i.e. lower risk) leads to lower expected returns. It should be noted that the correlation coefficient (R^2) in the 1990s is 30%. These results are significantly superior to those of the best multifactor model, even in the U.S. market (Harvey, 2001).

There is also a linkage to the country-spread model. Erb, Campbel, Harvey and Viskanata (1998) find that there is an 81% correlation between country ratings and the sovereign yield spreads (U.S. dollar bonds issued in emerging markets minus U.S. Treasury yields). So, credit ratings pick up the "country risk" reflected in these spreads but



Graph 1. Annualized daily compounded gross rate of return and Embi+ Sovereign Spread

Source: MSCI, J.P. Morgan and author's calculations

optimally fit the model to the current data. The latter intuition can be validated when comparing annualized returns against country risk. Such information is presented in the next graph which shows how returns are affected by movements in country risk.

3. Data analysis

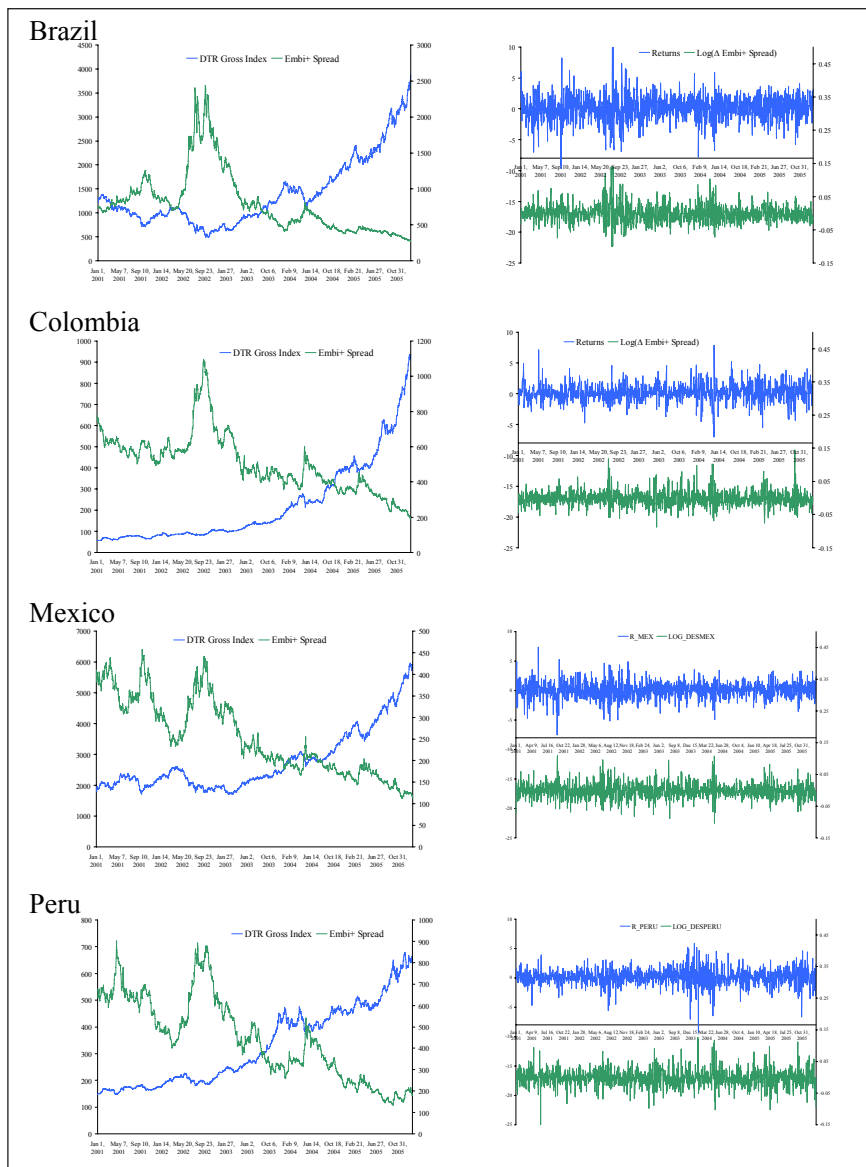
3.1. Data review

Market performance is the center of this research. The endeavor begins by analyzing the dynamic behavior of equity returns in financial markets for the selected countries. Morgan Stanley Capital International–MSCI–publishes worldwide indices that aim to value market performance. We begin with a univariate analysis because it is considered as a guiding complement for understanding the dynamics of the data and for facilitating multivariate modelling. Graph 2 and table 3 present the summary statistics for each country. The sample is composed by 1322 observations for each series, from January the 1st of 2001 to January the 24th of 2006. The return series was formed by transforming the MSCI's Gross DTR index into nominal returns (in percentages) by applying the following formula:

$$R_{it} = 100 \cdot \log(P_{it} / P_{it-1})$$

where P represents the value of the index. The information counts for commercial days only where holiday's missing values were substituted by their immediately prior commercial day. Here we focus on Daily Total Return in U.S. dollars from the 1st of January of 2001 to the 23rd of January of 2006. Additionally, the Spread of Emerging Market Bond Index Plus (Embi+ Spread) of J.P. Morgan is introduced as a state variable that, as Erb, Campbell, Harvey, and Viskanta (1995) proposed, should improve the measure of the cost of capital in emerging economies.

Graph 2 tells us that financial markets in the region have had an important increase in size since mid-2003 and at the same time country



Graph 2. Daily Total Return Gross Index, Embi+ Spread, daily equity returns and growth rates of country risk.1st of January 2001 to the 24th of January 2006.

Source: MSCI, J.P. Morgan and author's calculation

Table 2. Descriptive statistics for equity returns and country risk

	Returns				Country risk			
	Brazil	Colombia	Mexico	Peru	Brazil	Colombia	Mexico	Peru
Mean	0.0877	0.2118	0.0887	0.1131	-0.0008	-0.0010	-0.0009	-0.0010
Median	0.1461	0.1230	0.1070	0.0756	-0.0016	-0.0015	0.0000	0.0000
Maximum	13.1833	7.8635	7.3446	5.8524	0.1403	0.1450	0.1091	0.1264
Minimum	-9.7325	-6.9957	-7.5113	-9.3377	-0.0996	-0.0872	-0.1032	-0.1595
Std. Dev.	2.0420	1.3602	1.3592	1.3440	0.0257	0.0223	0.0236	0.0270
Skewness	-0.1001	0.0986	-0.1355	-0.4641	0.6379	0.7702	0.3165	0.1611
Kurtosis	5.9918	5.8804	5.2961	7.5692	5.7611	6.6720	5.0561	5.9094
Jarque-Bera	494.8799	458.8069	294.2126	1196.5700	509.2131	872.7655	254.7462	471.6286
P-value	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
Q(15)	45.6900	100.6000	11.8340	24.7590	59.549	36.473	24.3080	26.291
P-value	{0.000}	{0.000}	{0.692}	{0.053}	{0.000}	{0.002}	{0.060}	{0.035}
Q ² (15)	345.0500	159.9500	68.9990	167.15	833.61	240.7600	213.3300	68.0080
P-value	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}

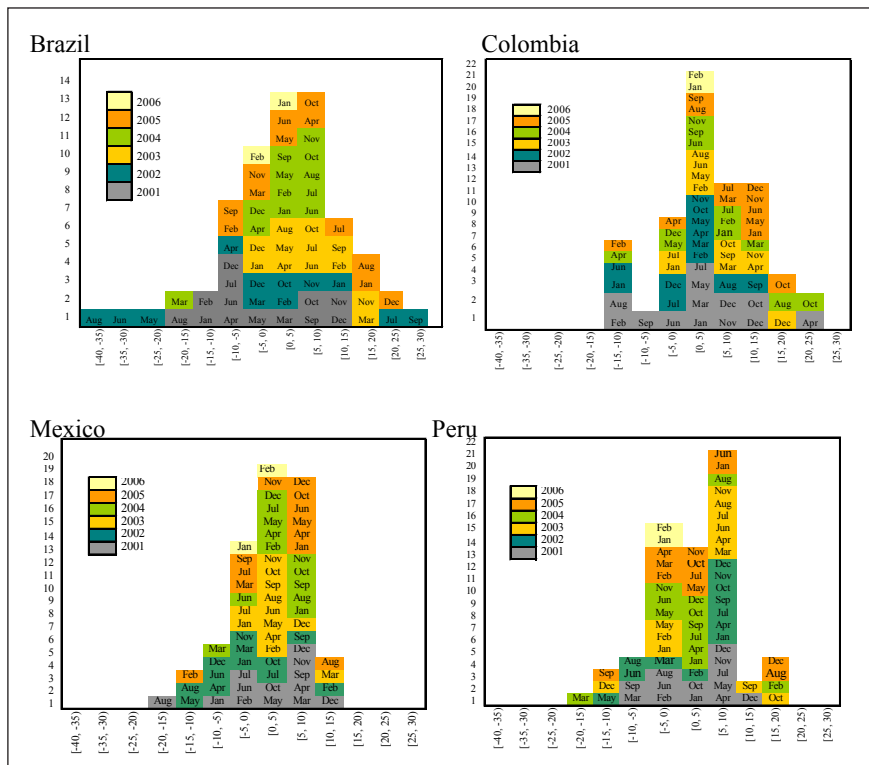
Source: MSCI, J.P. Morgan and author's calculation

risk has diminished. Regarding returns and the growth rate of the Embi+Spread several issues come to mind. For instance, it appears that the series are stationary, as the Dickey-Fuller, Phillips-Perron, and KPSS unit root test confirmed. There is no empirical evidence of deterministic trends or seasonal changes. And finally, there are indications of volatility clustering for low (high) volatility periods having positive or negative values followed by other low (high) changes in prices.

It is important to emphasize that one essential characteristic of these variables is that their dynamic behavior reflects not only the struggle between supply and demand in financial markets, but also reflects the “healthiness” of an economy. Participating agents rely on expectations, on their assessment of national *status quo*, and the uncertainty surrounding capital markets makes it vulnerable to disturbing situations that ultimately imply risk. Political, economic, and social environments determine the value and level of financial markets. The principle

behind the EMBI+ Spread as a measure of country risk falls on the ability of the market to establish the necessary conditions for assuming such uncertainty via differential interest rates among countries. Safe, healthy, and non-volatile markets have the attribute of counting with lower interest rates as a result of reducing future uncertainty. Therefore, information is the key, as the hypothesis of market efficiency basically states, and claims that the available information in a market at a given point in time, whether public or private, is accounted for in prices (interest rates are prices).

MSCI's gross returns include reinvested gross income as well as capital gains. This equity index measures capital gains and includes



Graph 3. Monthly returns histograms

Source: MSCI and authors calculations

dividends, and therefore avoids a serious downward bias. Graph 3 below displays the frequency and date for a range of values that returns have presented overtime. As can be seen, each country exhibits a different performance and Colombia's seems to outstand. An important result shown in the graph is that the market shows better results and volatility decreases as times passes. It is also interesting to observe the lack of symmetry and the extent that the tails of the graph reach.

3.2. Specification

Investors optimizing behavior is evaluated through the performance of their investments in terms of the expected preferred portfolio gains and risk. These results are represented by means of the first two conditional moments of the returns, e.g. mean and variance. Both statistics can be estimated using the ARMA and ARCH models. The first type of models successfully captures the movements of conditional means while the second ones are commonly used to address the issue of the conditional heteroskedasticity proper to financial series. By estimating these models we study the dynamics of the series as well as their volatility. Nevertheless, more complex techniques are being developed by researchers in order to account for other stylized facts such as time-variant volatility, leptokurtic distributions, volatility clustering, leverage effects, persistence, and asymmetric volatility among many others⁸.

4. Estimated results

4.1. Univariate conditional mean and variance models results

From table 2 it is possible to derive several interpretations. First, the Peruvian financial market appears to have the most skewness and kurtosis excess, implying a non-Gaussian behavior. This result is corroborated by the Jarque-Bera normality test, which not only was rejected for Peru, but also for the entire sample. Another interesting finding is that Colombia

and Brazil show the highest average daily returns but the Brazilian market exhibits almost twice the volatility of any of the other markets. Regarding modelling clues, the Ljung-Box Q statistic for Mexico and Peru's returns show evidence on the lack of serial correlation of the series as the univariate modelling confirmed.

Knowing all of the above, an ARMA-GARCH with exogenous variables was estimated for the mean and variance of conditional returns.

$$\begin{aligned}
 y_{it} &= v_t + \delta D_t + \sum_{j=1}^{m_i} \phi_{ij} y_{i,t-j} + \sum_{j=1}^{n_i} \theta_{ij} \varepsilon_{i,t-j} + \sum_{j=0}^{k_i} \varphi_{ij} x_{i,t-j} \\
 \varepsilon_{it} | \mathfrak{T}_{t-1} &\sim N(0, h_{it}) \\
 h_{it} &= c_i + \delta D_t + \sum_{j=1}^{q_i} \alpha_{ij} \varepsilon_{i,t-j}^2 + \sum_{j=1}^{p_i} \beta_{ij} h_{i,t-j} + \sum_{j=0}^{k_i} \varphi'_{ij} x_{i,t-j}
 \end{aligned} \tag{2}$$

where D_t represents a dummy variable for the last day of the week in order to capture extra weekend volatility, $x_{i,t-j}$ represents an exogenous lagged variable which in this case was EMBI+ for each country and y_{it} stands for the annualized returns of each country. The inadequate assumption of normality of the disturbances is confronted by correcting the coefficient covariances through the Bollerslev-Wooldridge robust estimation method. Additionally to the quasi-maximum likelihood – QML– corrected parameters, the Bernt, Hall, Hall, and Hausman (1974) optimization algorithm was applied. The results of these procedures are reported in table 3.

For the definitive specifications of each model, the Box and Jenkins identification method and the Akaike –AIC– and Schwarz – SIC– information criteria were employed along with other diagnostic tests. Many other different specifications were tested without finding evidence that supported some stylized facts like asymmetric responses. One enthusiastic result was the one from the Engle's Lagrange Multiplier ARCH (LM) test indicating the presence of more ARCH effects than what was accounted for. On the other hand, the Ljung-Box serial correlation test showed that the standardized disturbances and their

squares behave as white-noise processes. Normality is also rejected since there are still problems with excess skewness and excess kurtosis. Finally, another important feature of the estimated GARCH is that they satisfied the necessary conditions for a stationary process.

Table 3. ARMA-GARCH with exogenous variables models estimation results

	Brazil's Returns	Colombia's Returns	Mexico's Returns	Peru's Returns
<i>Conditional Mean</i>				
ϕ_1	0.05685 (2.05495)	0.264904 (8.584362)	-	-
ϕ_2	-0.07183 (-2.370347)	-	-	-
θ_1	-	-	-	0.05985 2.168576
φ_1	-10.84279 (-4.532467)	-	-4.54945 (-2.669368)	-
φ_2	-	-6.620488 (-4.367295)	-	-5.198798 -3.733115
δ	-	0.19566 (2.746905)	-	-
ν	0.20251 (4.061411)	0.133572 (3.182557)	0.13989 (3.977451)	0.119934 (3.559263)
<i>Conditional variance</i>				
C	0.213928 (3.119161)	0.11808 (3.034179)	0.033065 (2.01134)	0.033972 (2.5349)
α_1	0.054388 (2.663647)	0.262866 (3.774062)	0.023224 (2.645105)	0.044563 (3.816543)
α_2	-	-0.141356 (-1.998691)	-	-
β_1	0.889707 (11.53141)	0.815184 (17.24117)	0.958691 (62.66667)	0.937915 (59.26556)
φ_1'	11.53141 (2.29319)	2.446913 (1.837326)	3.606842 (2.11371)	2.491865 (2.427335)
δ'	-	-	-	-
Log likelihood	-2687.455	-2132.652	-2132.652	-2141.779
Skewness	-0.029229	0.28825	-0.068746	-0.098375
Kurtosis	4.042849	4.220326	4.802936	4.40263
Jarque-Bera	59.957 {0.000}	100.109 {0.000}	179.958 {0.000}	110.334 {0.000}
Q(15)	8.7259 {0.793}	13.769 {0.467}	7.9228 {0.927}	14.841 {0.389}
Q ² (15)	14.972 {0.309}	11.338 {0.659}	8.8953 {0.883}	9.968 {0.764}
$\alpha_i + \beta_i$	0.944095	0.936694	0.981915	0.982478

The t-statistics are in parenthesis while p -values are in curly brackets {}.

Concerning the estimated parameters, there are also some issues to take notice of. For instance the *non-trading day* dummy was only significant in the case of the Colombian market and only in the conditional mean model. The low magnitudes of the autoregressive coefficients compared to those associated with the random disturbances also tells us something important about the predictability of asset returns: there is little or few impact of past observations on the actual value of returns. This supports the hypothesis of Martingale stochastic processes⁹.

4.2. Multivariate conditional mean and variance model

Jointly analyzing and modelling the series enables us to understand the dynamic relationships among the series over time and to improve the accuracy of forecasts for individual series by utilizing the additional information available from the related series and their forecasts (Gourieroux and Jasiak, 2001).

Multivariate conditional mean and volatility models are widely used in finance to capture both volatility clustering and contemporaneous correlation of asset return vectors among other stylized facts. Here we focus on the multivariate VARMAX-GARCH models.

It is assumed that the covariance of the error distribution follows a time dependent process conditional on information generated by the history of the process. A VARMAX process includes the possibility that the series might be not only contemporaneously correlated to each other but also correlated to each other's past values and allows modelling both the dynamic relationship between the dependent variables and the dynamic relationship between the dependent and independent variables. These models are defined in terms of the orders of the autoregressive or moving average process (or both). The form of the model can be written as

$$\mathbf{y}_t = \boldsymbol{\delta} + \sum_{i=1}^m \boldsymbol{\Phi}_i \mathbf{y}_{t-i} + \sum_{k=0}^s \boldsymbol{\Theta}_k^* \mathbf{X}_{t-k} + \sum_{j=0}^n \boldsymbol{\Theta}_j \boldsymbol{\varepsilon}_{t-j} \quad (3)$$

The above representations rely on the assumption that the conditional distribution of the disturbances is $\boldsymbol{\varepsilon}_t | \mathfrak{F}_{t-1} \sim N(\mathbf{0}, \mathbf{H}_t)$ where \mathbf{H}_t is a

symmetric and positive definite conditional covariance matrix. The second moment modelling procedures consist in specifying a functional form for \mathbf{H}_t .

There are a number of representations for the conditional covariance matrix, \mathbf{H}_t^{10} , and each comes with challenges. One mayor difficulty is the computational limitations when performing a multivariate analysis, specifically with respect to simultaneous estimation of both expected returns and volatility which can be surpassed by estimating the VARMAX specifications for the conditional mean and obtaining the associated GARCH residuals. Subsequently, these residuals are used for the multivariate GARCH process. Unfortunately this generates difficulties in the forecasting process because the data has to be introduced simultaneously and reduces parameter estimation efficiency.

The second, and in our concept the most restricting limitation, is that such estimation requires algorithms that are computationally very intensive and are in need of further perfection. Estimation generally requires several attempts before arriving to a good model and, in multivariate analysis, the real difficult part is determining the adequate initial values in order to facilitate convergence of the non-linear optimization algorithm. Such data is important in the sense that such values are fundamental for obtaining good estimations. A High dimension of the return vector is also an important issue when defining the correct estimation process for \mathbf{H}_t .

Engle's (2002) Dynamic Conditional Correlation MGARCH model was chosen for its desired properties which deals with overparameterization issues and hence reduces the computational requirements in the estimation algorithm. These models have the flexibility of basing their estimations on the results of the univariate analysis, facilitating the estimation of conditional covariances matrices with increased dimensions.

Before presenting the estimation results it is necessary to point out several important issues. The first and most restrictive is the level of computational difficulties. When modelling multivariate models, most packages lack a complete set of algorithms that allow different types of specifications. For instance, a very well known software program

for econometrics has the capacity of modelling mean and variance conditional returns in a univariate contexts, even including exogenous variables, but when it comes to modelling simultaneous equations there is little space for applied research. The greatest setback was the incapacity of obtaining a satisfactory model when estimating simultaneously a VARX-GARCH model. In addition, forecasting such models entails even bigger problems from a theoretical and computational point of view. The biggest problem consists in joining both models in one which was not achieved and each specification was set to forecast nearly ten months ahead. This projection of values is considered merely as an exercise due to the well known randomness of financial markets.

Given this situation we estimated the multivariate models in to steps. First we constructed a satisfactory VARX model, ran a series of tests and obtained the associated disturbances. Next, the MGARCH was estimated and confronted with more tests in order to analyze its goodness of fit. Results are shown in table 4.

For the autoregressive matrix, an important feature is the importance of the Brazilian market in the region. This can be seen through the statistical significance of the Brazilian returns and where its leader status is verified for the lags of the other countries do not seem to significantly explain Brazil's performance. Colombia and Mexico seem to have mutual interdependency and the Peruvian AR(1) estimates were not significant. Another relevant characteristic of the estimates were their relatively low values implying that random disturbances seem to prevail in the financial markets pricing mechanisms, corroborating the Martingale property and Fama's (1965) market efficiency hypothesis. The most important estimation for the multivariate model is the $\hat{\mathbf{E}}_1^*$ matrix for the reason that with those values it is possible to test the validity of the hypothesis of country risk as a valid forecaster of equity returns. At this stage, the results are not definite. Brazil and Colombia seem to respond to country risk but Mexico and Peru.

The evaluation of the specification for the multivariate conditional mean model requires several tests. Jarque-Bera's normality test is rejected for the presence of skewness but kurtosis. The Ljung-Box statistics for ε_t at lag 15 is not rejected (except in the case of Brazil), but for the

Table 4. VAR with exogenous variables estimation results

Parameters	Equations			
	Brazil's Returns	Colombia's Returns	Mexico's Returns	Peru's Returns
Φ_1	0.167915 (5.46788)	0.04224 (2.08336)	0.056605 (2.72351)	0.037868 (1.83877)
	-0.016195 (-0.39790)	0.222563 (8.28237)	0.047847 (1.73695)	0.040909 (1.49878)
	-0.064397 (-1.41238)	0.062469 (2.07522)	0.002115 (0.06855)	0.08281 (2.70827)
	-0.005122 (-0.12125)	-0.006508 (-0.23334)	-0.045622 (-1.59567)	0.004292 (0.15149)
	-7.83328 (-2.67872)	2.377886 (1.23164)	0.484879 (0.245)	-1.732859 (-0.88362)
	-10.75391 (-3.13783)	-3.842183 (-1.69805)	-5.177499 (-2.23218)	-0.295457 (-0.12855)
	5.321985 (1.65535)	2.332609 (1.09892)	-1.552694 (-0.71359)	-0.919767 (-0.42659)
Θ_1^*	-3.921382 (-1.45872)	-0.465929 (-0.26252)	-2.516418 (-1.38312)	-1.680173 (-0.93198)
	0.025633 (0.41386)	0.091229 (2.23093)	0.077852 (1.8572)	0.059042 (1.42143)
δ	0.203205 (1.48418)	0.322816 (3.5712)	-0.031264 (-0.33740)	0.146222 (1.59251)
Skewness	0.004415 {0.9478}	0.204233 {0.0025}	-0.138971 {0.0393}	-0.299195 {0}
Kurtosis	5.710162 {0.000}	6.177647 {0.000}	6.268713 {0.000}	6.324723 {0.000}
Jarque-Bera	403.9779 {0.000}	564.5356 {0.000}	591.8954 {0.000}	627.6518 {0.000}
Q(15)	34.656 {0.003}	15.485 {0.417}	14.998 {0.452}	22.895 {0.086}
Q ² (15)	401.42 {0.000}	158.18 {0.000}	77.91 {0.000}	167.08 {0.000}
Portmanteau (15)	260.004 {0.0496}	LM (12)	17.078 {0.3806}	

The t-statistics are in parenthesis while p-values are in curly brackets {}.

square of the residuals autocorrelation is a problem. This also entails the obligation for modelling the conditional variance. Different estimation methods should improve these results and further research needs to be done.

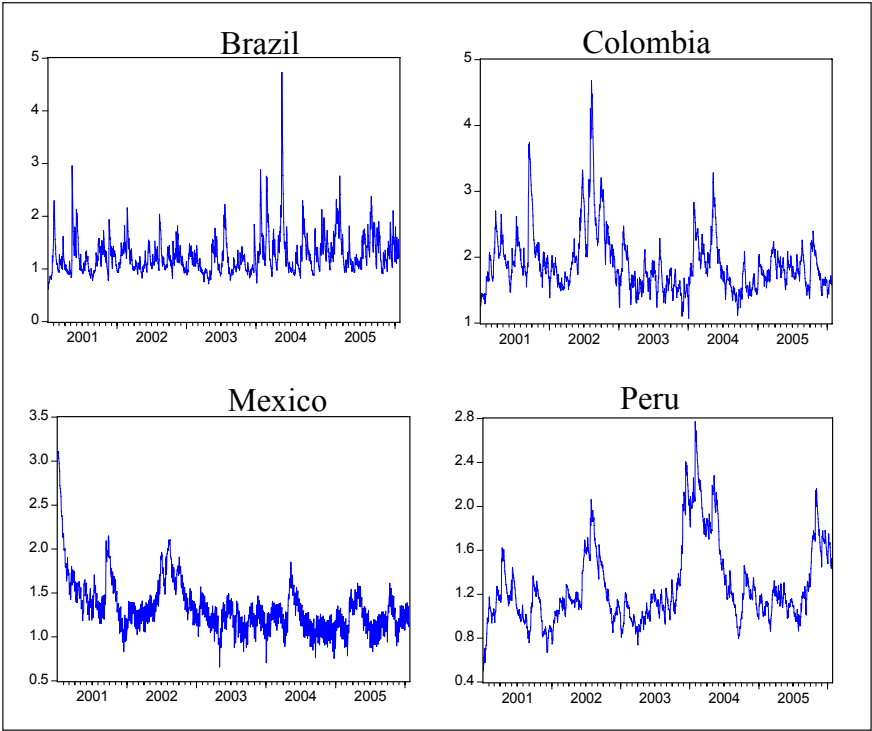
Concerning the multivariate conditional variance model, the DCC-CCC specification was selected for its computational simplification. The results of the estimation are presented in the following table¹¹. Several different specifications were conducted but the best fit was presented by the DCC(1,1). Furthermore, the model

was tested for constant conditional correlation against the hypothesis of dynamic conditional correlation (Engle and Sheppard, 2001) where the evidence was definitive in supporting such specification. The validity of the model was verified through the Ljung-Box statistics and no evidence of autocorrelation was found at lag 15 for the standardized residuals or its squares. Table 5 and graph 4 present the estimated cross correlation matrix and the estimated conditional standard deviations for each country. Table 6 shows the basic instrument in order to include time variant volatilities in the multivariate representation. One important conclusion of the estimated matrix is the direction of the correlations. Brazil's parameters have greater magnitude and statistical significance supporting the previous conception of this country's leadership in the region.

Table 5. DCC – CCC conditional variance results

	Constant Conditional Correlation Model (CCC)				Dynamic Conditional Correlation Model (DCC)			
	Brazil's Returns	Colombia's Returns	Mexico's Returns	Peru's Returns	Brazil's Returns	Colombia's Returns	Mexico's Returns	Peru's Returns
C	0.3705 (124.740)	0.22217 (69.841)	0.19167 (149.988)	0.019612 (305.478)	0.3705 (122.816)	0.2222 (70.299)	0.1917 (153.188)	0.0196 (320.707)
α_1	0.10623 (296.923)	0.19381 (133.616)	0.10362 (187.388)	0.050662 (764.975)	0.1062 (302.237)	0.1938 (134.415)	0.1036 (187.586)	0.0507 (783.048)
β_1	0.79363 (10043.025)	0.68383 (403.654)	0.79034 (9478.658)	0.93938 (4868767.493)	0.7936 (9964.591)	0.6838 (404.927)	0.7903 (9432.476)	0.9394 (4880760.638)
α_l	-	-	-	-	0.0069 (810.658)			
β_s	-	-	-	-	0.9876 (15451.772)			
	Log likelihood				Log L. [DCC]			
	Skewness				-8990.5			
	Kurtosis				-0.068746			
	Jarque-Bera				4.802936			
	Q(15)				4.40263			
	Q ² (15)				59.957 {0.000}			
	$\alpha + \beta$				179.958 {0.000}			
	Portmanteau (15)				7.9228 {0.927}			
					14.841 {0.389}			
					8.8953 {0.883}			
					9.968 {0.764}			
					0.89396			
					0.990042			
					LM (12)			
					11.322 {0.789}			

The t-statistics are in parenthesis while p -values are in curly brackets {}.



Graph 4. Estimated conditional standard deviation

Table 6. Estimated cross correlation matrix from a CCC model*

Variable	Returns			
	Brazil	Colombia	Mexico	Peru
Brazil	1			
Colombia	0.10567 (133.973)	1		
Mexico	0.47251 (748.863)	0.066609 (92.079)	1	
Peru	0.19103 (210.91)	0.10548 (138.48)	0.16628 (196.085)	1

The t-statistics are in parenthesis.

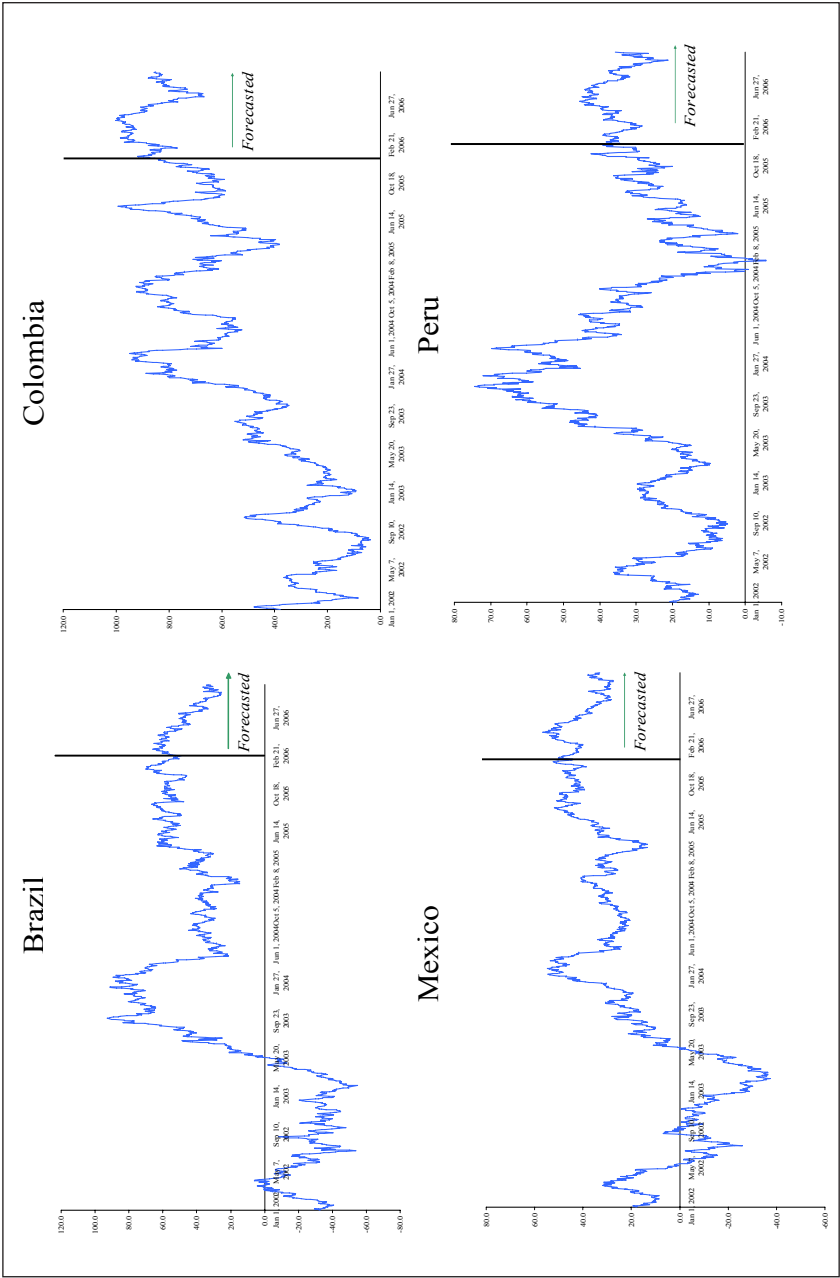
V. Forecasting

One of the principal uses of VAR systems is the production of forecast, especially short-term forecasts. Even though this approach is generally *atheoretical* in the sense that there has been no use of economic theory to specify explicit structural equations among the set of variables, we took heuristically from Erb, Campbell, Harvey, and Viskanta (1996) research the proposed relationship between cost of capital and country risk. In this way, when modelling multivariate models we make use of the proposition that economic variables tend to move together, *i.e.* exhibit autocorrelation among variables.

The most surprising characteristics of the results is the ability of the model to continue a trajectory for the projected values that does not differ much of how variables have behaved in the past. This is an interesting result given the stationary property of the series implying that the values should converge as times passes; and that is what would happen if we do not include the future values of the exogenous values. We assumed that those variables followed an AR(1)-GARCH(1,1) process with no exogenous variables. Such specification was obtained by evaluating the data with different lag information criteria (AIC, SIC, FPE and HQ).

In all of the countries a pattern seems to appear for a clear growing tendency of the general performance of the financial markets after mid 2002's. This could be explained by the global financial downfall at the end of last century on regional markets. In other words, for the case of Colombia, if an investor would have decided to invest in this country in early 2000, he or she would find out that his or her portfolio would have nearly nine folded by the beginning of 2006.

Table 7 below summarizes all of the above analysis. It portrays the monthly average forecasted rate of return for the out-of-sample following semester and the estimated cost of equity capital for Brazil, Colombia, Mexico, and Peru. The most noticeable conclusion is that Colombia's financial market performance implies that on average capital investment in this country yields a return almost three times higher than in the other three countries. These results seem prohibitive compared



Graph 5. Annualized Continuously Compounded Returns

to those of developed economies; however, the Colombian financial market has presented in the last five years incredible capital gains and the Latin American region has recovered quite successfully from the previous financial crises of late 1990s.

Table 7. Annualized continuously compounded return by monthly average in percentage

	Brazil's returns	Colombia's returns	Mexico's returns	Peru's returns
May	56.2	97.9	44.7	43.2
June	47.7	89.8	37.6	42.3
July	42.6	78.3	31.8	37.4
August	37.7	73.9	32.0	35.0
September	29.2	82.6	29.8	27.1
October	32.6	84.0	35.5	30.4
CoEqCap	27%	72%	27%	27%
R_f	4.7%	4.7%	4.7%	4.7%

6. Conclusions

In this research, the econometric study of the cost of equity capital for Brazil, Colombia, Mexico, and Peru measured through MSCI's Gross Daily Total Returns presented several findings. The first result was that the hypothesis of using a country's risk as a forecaster of expected returns for emerging markets could not be accepted nor rejected. The statistical significance of the associated parameters was not conclusive for the four countries in the multivariate specification. Another interesting conclusion was the evidence of Brazil's leadership in the region. The rejection of Wald's coefficient restriction tests explains equity returns in Colombia, Mexico, and Peru, implying the direction of the spillovers effects. Furthermore, in general evidence neither of asymmetry nor of extra non-trading day's volatility was found among the markets.

The low magnitude of the autoregressive parameters implied that random disturbances effects seem to influence in financial markets pricing mechanisms corroborating the Martingale property and Fama's

(1965) market efficiency hypothesis. Regarding forecasts, the model suggests that in mid-2006 the markets in the region should decrease to levels similar to those at the beginning of the year. However, this situation is reversed at the start of September, particularly in the case of Colombia's market whose performance showed an increasing trend.

The most important finding, but not unexpected, was the outstanding performance of the Colombian financial market. Empirical results showed a cost of equity almost three times higher than the ones reported for the other countries. This can be explained by the capital gains this market has yield during the last five years. However, research needs to be conducted before obtaining more accurate values. A world market factor, industry-wise expected returns, and risks should be included since these tend to vary across industries. Finally, the use of structural analysis and regime switching models would help see how forward looking the series are, and also how to diversify portfolios among the countries.

7. Notes

- 1 Undergraduate research paper for the Program of Economics, Universidad de Antioquia, Colombia. We are grateful for the assistance of Santiago Gallón and to Hernán Alzate for helpful comments. Nevertheless, errors and/or omissions are exclusive responsibility of the author.
- 2 In this study, either one the cost of capital or the cost of equity capital means the same.
- 3 Ivo Welch (2001) conducted a survey as an alternative approach to finding out what the expected rate of return was through the opinion of experts.
- 4 This debate can also be contemplated as the discrepancy between fundamental and technical analysis.
- 5 Low samples for the second method would bring about statistical problems that could render uninteresting the methodology. That is why a researcher should be armed with good data.

- 6 For an historical approach for measuring the expected rate of return along with an explication of how several biases could be performed see Dimson, Marsh, and Staunton. (2002).
- 7 Institutional Investor publishes each semester a survey in which near a 100 bank specialist from around the world grade the perception of default of over 180 countries. The range goes from 0 to a 100, in which a 100 means no risk of default.
- 8 Check Bollerslev, et al. (1994), Ghysels, et al. (1996), y Engle y Patton (2001) for a complete reference of the stylized facts.
- 9 A Martingale Process basically states that there is no relevance of past information for modelling a conditional distributions, i.e. $E[R_t | \mathfrak{I}_{t-1}] = 0$
- 10 See Bauwens, 2005
- 11 Estimated through the use of Kevin Sheppard's macro in Matlab's Toolbox available at http://www.kevin-sheppard.com/research/ucsd_garch/ucsd_garch.aspx.

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