**Eixo Temático: Estratégia e Internacionalização de Empresas**

# EMERGING MARKET RETURN PRICING: AN INTERTEMPORAL AND INTERQUANTILE APPROACH

# PRECIFICAÇÃO DE RETORNO EM MERCADOS EMERGENTES: UMA ABORDAGEM INTERTEMPORAL E INTERQUANTÍLICA

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## ABSTRACT

The objective of this study is to analyze the return pricing dynamics in six Latin American countries through the ICAPM model of Merton (1973) estimated by quantile regression approach. As a world market correlation measure, instead of traditional covariance, we used the Dynamic Conditional Correlation (DCC) model estimated by DCC copula-GARCH based on marginal volatilities estimated by the GJR-GARCH model. The univariate volatility and an autoregressive vector were also included as independent variables in the model, estimated by quantile regression. The results reveals a breakthrough because the model can capture relationships that were previously masked by the coefficients constancy and by the lack of consideration over the differences in pricing extreme quantiles. In the lower quantile, negative risk premium was found, reflecting the leverage effect. Furthermore, we found that the quantile correlation coefficients between each market return proxy and the world return proxy were not significant, i.e, only the market own risk is priced.
**Keywords**: Emerging Markets, ICAPM, Quantile Regression, Dynamic Conditional Correlation (DCC).

## RESUMO

O objetivo deste estudo consiste em analisar a dinâmica de precificação do retorno em seis países da América Latina através do modelo ICAPM de Merton (1973), estimado pelo método de regressão de quantis. Como medida de correlação com o mercado mundial, ao invés da covariância tradicional, foi utilizado o modelo de correlação condicional dinâmica (DCC), com base em volatilidades marginais estimadas pelo modelo GJR-GARCH. A volatilidade univariada e um vetor auto-regressivo também foram incluídos como variáveis independentes no modelo, estimado por regressão quantílica. Os resultados representam um avanço porque o modelo pode capturar relações que foram previamente mascaradas pela constância dos coeficientes e por desconsiderar as diferenças de precificação em quantis extremos. No quantil inferior, foi encontrado prêmio de risco negativo, reflexo da alavancagem financeira. Além disso, verificou-se que os coeficientes quantílicos de correlação entre cada proxy de de mercado eo proxy retorno mundo não foram significativos, ou seja, somente o próprio risco de mercado tem um preço.

**Palavras-chave**: Mercados Emergentes, ICAPM, Regressão de Quantis, correlação condicional dinâmica (DCC).

## 1. Introduction

The process of market integration and capital flow between countries, due to globalization, increased the possibility of transferring resources between markets, especially from developed to emerging countries. Still, emerging countries have yet to arouse interest from foreign investors. On the other hand, investors analyze the relationship between risk incurred and the possibility of higher returns to determine the amount of investment that can be allocated in each country.

This study analyzes the relationship between risk and return in six Latin markets, Argentina, Brazil, Chile, Colombia, Mexico and Peru, through the Intertemporal Asset Pricing Financial Model (ICAPM) proposed by Merton (1973). The systematic risk in this model arises from the correlation between the return of proxies from each Latin Market and the return of proxies from the world market. However, in this article the traditional beta is replaced by the dynamic correlation, using the Dynamic Conditional Correlation model (DCC). Moreover, the use of quantile regression allows the risk premium of returns from Latin markets and from the world to vary between quartiles. The univariate volatility is estimated by a GJR-GARCH model and an autoregressive term is entered as an independent variable.

Therefore, the aim of this study is to analyze the pricing of risk in Latin American countries and distinguish the results by quantiles, using the conditional volatility and Dynamic Conditional Correlation. The contribution of article refers to the use of an innovative model, conditional and quantile, which uses as a measure of correlation the DCC-GJR-GARCH-Copula, bringing a new perspective about the subject, besides studying emerging markets, differing from the traditional literature. The paper is organized as follows: sections 2, 3 and 4 show, respectively, a brief literature review of ICAPM, DCC and GJR-GARCH and quantile regression. Section 5 presents the methodological procedures of the study, followed by section 6 which brings the results obtained. Section 7 outlines the final remarks regarding these results and the study and, finally, section 8 provides the references used.

## 2 Interporal asset pricing Model

Until the first half of the twentieth century it was believed that stock returns depended only on investors' expectations regarding future earnings. This conception was challenged by the work of Markovitz (1952), who advocated the existence of the proportional relationship between risk and return, allowing the calculation of the expected return of a portfolio based on its own risk. Later, Lintner (1965), Treynor (1965), Sharpe (1966) and Jensen (1967) developed individually, indexes and measures of performance that culminated in today's model called Financial Asset Pricing Model (CAPM), the most widely used pricing model in finance.

However, the CAPM generates static coefficients, disregarding the changes in the relationship between risk and return throughout time. Aiming to solve the problem, Merton (1973) proposed an alternative method called Intertemporal Asset Pricing Financial Model (ICAPM) which provides that the relationship between risk and return is dynamic because the sensitivity of an asset in relation to the market changes in each period, supposing a stochastic variation in the number of investment opportunities between many different countries.

Besides the conditional aspect, the ICAPM also introduces a theoretical shift in the sense that the return of an asset is priced based on the average risk of investors in relation to the market, which may or may not be because of changes in investment opportunities due to decisions of local government. For Merton (1973), the interest rate is the simplest way to observe the specific risk of these changes in government policies. Thus, the model indicates that the market risk in the global sense is different from the risk of government policies. Another important contribution is the use of covariance probation as a measure of risk rather than return.

Bekaert and Harvey (1995) applies the ICAPM model to analyze the relationship between risk and return in several markets around the world. Thus, the excess return of each market is priced by the volatility of its relationship with a proxy that represents the world market, which in this case is an U.S market index, and it is also priced by the risk associated with the market itself, which in this case it is variance. In this model, International ICAPM, the measure of risk associated with changes in government policies proposed by Merton (1973) was replaced by the variance of the market itself. The global market is represented by the U.S. market index and the risk associated with changes in investment conditions specific to each of the other markets is represented by its variance. The model proposed by Bekaert and Harvey (1995) can be explained by Equation (1):

$$R_i\text{-}R_f = \alpha \quad + \beta_1 Cov_{R_i\text{-}R_f,R_m\text{-}R_f} + \beta_2 Cov_{R_i\text{-}R_f,x} + \mu_t \qquad (1)$$

Where $R_m$ refers to market return $m$; $R_f$ is the return of the risk-free asset; $Cov_{R_m-R_f,R_{us}-R_f}$ is the covariance of the excess return of market $m$ with the excess return of the proxy of the world market *us* and $\beta_1$ is its pricing; $Var_{R_m-R_f}$ is the variance of the excess return of market $m$ and $\beta_2$ are its pricing; $\mu_t$ is the error generated by regression in period $t$.

Similarly, this definition of the ICAPM model shows that the pricing of the return of an asset is related to the market risk to which it is subjected and to its own risk. The fact that this price includes the risk of individual assets brings back the initial idea of Markowitz (1952). The model of Bekaert and Harvey (1995) became known as the international CAPM.

**3 Dynamic Conditional Correlations**

The correlation is perhaps the most traditional way of measuring the association between two variables, and it is of great importance for the assembly of hedging strategies and portfolio management. However, Engle (2002) draws attention to the problems generated by the unsteadiness of the correlation over time, which makes it necessary to recalculate the correlation of each period and adjust these strategies to embed recent information. This understanding also raises the need for predictive models for correlation.

Thus, Engle (2002) proposes the use of Dynamic Conditional Correlation (DCC), advocated by Engle and Sheppard (2001), Tse and Tsui (2002) as a way to estimate the conditional correlation between two variables. The univariate volatility, which can be estimated, for example, by an ARCH (Engle, 1982), GARCH (Bollerslev, 1986) or a GJR-GARCH (Glosten et al., 1993) is then used as the first step in calculating the DCC, i.e. the correlation in each period, replacing the traditional static index. The DCC model can be represented by Equation (2).

$$H_t = J_t R_t J_t \qquad (2)$$

Where $H_t$ is the matrix of correlation between variables; $R_t$ satisfies $R_t = (1 - \theta_1 - \theta_2)\bar{R} + \theta_1 \varepsilon_{t-1}\acute{\varepsilon}_{t-1} + \theta_2 R_{t-1}$; $J_t$ is the matrix $J_t = diag\left(h_{11,t}^{-1/2} \ldots h_{NN,t}^{-1/2}\right)$, which serves as a normalization to ensure that $H$ is the matrix of correlation; $h_{ii,t}$ is the conditional variance of asset $i$ in period $t$; $\varepsilon_t$ is the vector of standardized innovation in period $t$; $\bar{R}$ is the unconditional covariance matrix of $\varepsilon_t$; $\theta_1$ and $\theta_2$ are nonnegative scalar parameters, that satisfy $0 < \theta_1 + \theta_2 < 1$.

Francq and Zakoian (2010) emphasizes that Equation (8) is reminiscent of a GARCH model (1,1), in which $\theta_1$ is similar to parameter $E_i$ and $\theta_2$ is similar to parameter $F_i$. Bidarkota and Todorov (2012) argues that the conditional correlation between two variables is summarized as the conditional covariance between standardized disturbances($\varepsilon$).

However, the DCC model is estimated under the assumption of multivariate normality (maximum likelyhood) or a mixture of elliptical distributions (almost maximum likelyhood). The use of a copula function considers the marginal distributions and the dependence structure both separately and simultaneously (HSU, TSENG and WANG, 2008). Thus, it is possible to model the combined distribution of the innovations of each asset in the model based on a proper copula, rather than assuming multivariate normality. Therefore, a combined distribution of asset returns can be specified with complete flexibility, being more realistic. The model was proposed by Jondeau and Rockinger (2006) for financial applications.

## 4 Quantile regression model

The quantile regression model proposed by Koenker and Bassett (1978) is an extension of the classical linear regression model. The Ordinary Least Squares method focuses only on the measure of a central tendency, while Quantile Regression allows the analysis of the entire conditional distribution of the response variable, so it is not subjected to the influence of extreme values of the dependent variable (Koenker, 2005).

Koenker and Bassett (1978) introduced the technique by setting the quantile function, given the probability distribution $F$ of the random variable *x*, which can be represented by Equation (3).

$$F\ (x) = \ P\ (X\ \leq x) \tag{3}$$

Where, in the range of 0 to 1, the quantile function appears, using the inverse function of the distribution.

$$F^{-1}\,(\tau) = \ Q(\tau) = \inf\{\, y\colon F(y) \geq \tau \tag{4}$$

In equation 5, $F^{-1}$ represents the median and $\tau$ represents the $\tau$–nth quantile of *x*. The quantile parameters are found by minimization of the expected error. Error is defined by the following linear function:

$$\rho_\tau(u) = u\big(\tau - I(u < 0)\big) \tag{5}$$

The $\tau$-nth conditional quantile function can be represented by equation (6).

$$Q_y(\,\tau \mid x\,) = x'\beta(\tau) \tag{6}$$

And the vector of parameters $\beta\ (\tau)$can be obtained by solving a minimization problem represented by Equation (7).

$$min_\beta \sum_{i=1}^{n} \rho_\tau\ \ (y_i - x_i'\beta) \tag{7}$$

Where $x_i'$ is the $\tau$-nth line of $X$ of the random values unknown of *x*. Through the minimization problem disposed, the problem of outliers not captured by classical regression can be identified (KOENKER e BASSETT, 1978).

Thus, the interest is to study various quantiles of the conditional distribution of the dependent variable, which identifies the model of quantile regression (QR) $(p)$ that can be expressed by Equation (8).

$$y_t = \ \beta_0(\tau) + \ \beta_1(\tau)x_{i1} + \cdots + \beta_\rho(\tau)x_{ip} + \varphi_{i.} \tag{8}$$

In this model, $\varphi$ are random independent variables and identically distributed in a range from 0 to 1. So, the conditional function of order $\tau$ of *Y/X* can be represented by equation (9).

$$Q_\tau\ (Y \mid x) = \beta_0 + \beta_1\,(\tau)_{x_1} + \cdots \beta_\rho(\tau)x_p\ , \tag{9}$$

or in a more simplified way, with only one explanatory variable, by Equation (10).

$$Q_\tau(\,Y \mid x\,) = \alpha(\tau) + \beta(\tau)x \tag{10}$$

With equations (9) and (10) there is the model of the $\tau$-nth conditional function of the conditional quantile of $y_t$, that express the old values of $y_t$. The autoregressive quantile coefficients may vary according to the location on the quantile between the interval 0-1 and it may present dynamic asymmetry or local persistence. According to Koenker (2005) quantile regression models can incorporate a possible heteroscedasticity, detected by the variation of $\beta_{(\tau)}$ in different quantiles.

Hence, the quantile regression leads to a more complete statistical analysis of the stochastic relationship between random variables, in comparison to classical regression (Koenker, 2005). However, there is still a substantial theoretical literature of the model, including as examples Koenker and Bassett (1978), Knight (1989), Weiss (1991), Rogers (2001), Koenker and Xiao (2004), Cai and Xiao (2012).

## 5 Methodological Procedures

This study examines the pricing of risk in Latin markets, Argentina, Brazil, Chile, Colombia, Mexico and Peru, taking as proxy a representative index of the stock market of each country. To represent the world market, Morgan Stanley Capital International (MSCI) was used as proxy, which is the value-weighted index of the global market. The sample period analyzed comprises 11 July 2002 to 13 July 2011, consisting of 2612 daily observations. The data are from Morgan Stanley Financial Services. This period was chosen because it contains distinct economic times involving crisis and stable periods, which are necessary to analyze it through conditional methods.

Risk pricing will be analyzed by the ICAPM model proposed by Merton (1973), specified in Equation (1) and known as intertemporal CAPM. However, the model is also consistent with Bekaert and Harvey (1995) international CAPM. Therefore, the model used here is analogous, concomitantly, with the international and intertemporal models.

However, instead of using the market covariance in a country with the world market as a measure of dependence, the Dynamic Conditional Correlation model (DCC) was used, according to Equation (2), as Todorov and Bidarkota (2012). Differently from Engle and Sheppard (2001), Tse and Tsui (2002) and Engle (2002) that use the ordinary GARCH model by Bollerslev (1986) to calculate the univariate volatility, this article uses a derived model, known as GJR-GARCH. Thus, the GJR-GARCH model is an asymmetric variation of the GARCH model, proposed by Glosten et al. (1993), whose objective is to evaluate the difference between the positive and negative impacts of the series. Therefore, it takes into consideration that positive and negative shocks of the innovations on the conditional mean have a different impact on volatility.

Another key difference in opposite to the approach of Engle and Sheppard (2001), Tse and Tsui (2002) and Engle (2002) is that this study estimates the Dynamic Conditional Correlation by the method of copulas, i.e., a multivariate combined function for innovations (E) much more flexible. It should also be noted that the international ICAPM model predicts, as a measure of risk, besides the dependence on the world market proxy, the volatility of the local market, according to Bekaert and Harvey (1995). In this study, the conditional volatility calculated by GJR-GARCH is used as a measure of risk of each Latin market.

The ICAPM model will be estimated using the methodology of quantile regression, defined by Equation (10), rather than the traditional method of regression by OLS, commonly used, as in Bekaert and Harvey (1995) and Todorov and Bidarkota (2012). The purpose of using this form of regression is to analyze the differences that exist in pricing of risk in situations of higher and lower return.

To ease the problems caused by auto-correlation, which are common in temporal series, a vector autoregressive of first order is also entered as independent variables in the model. Therefore, the model used can be defined by Equation (11):

$$Qr_{i,t}(\tau) = N_0(\tau) + O_1(\tau)r_{i,t-1} + P_2(\tau)DCC_{iw,t} + R_3(\tau)\sigma_{i,t} + S_{i,t} \tag{11}$$

Where: $Qr_{i,t}(\tau)$ represents the return of each quantile; $N_0(\tau)$ is the linear coefficient of each quantile; $O_1(\tau)$is the coeficiente of the vector autoregressive of each quantile; $P_2$is the coefficient of the dynamic conditional correlation of the return of a country with the return of the global market, for each quantile. $R_3$ is the coefficient of univariate market volatility, calculated by the GJR-GARCH model, in each quantile. $R_3$ is the error of each quantile, in period *t*.

**6 Results and Discussions**

An estimation of the conditional covariance matrix using the DCC-GJR-GARCH-Copula model was firstly made, as the coefficients shown in Table I. In this estimation, it is found that the coefficient L is significant for all Latin American countries analyzed, indicating that the volatility in equity markets of Latin America depends on the volatility of the previous day. The coefficient K was not significant for Brazil and Mexico, indicating that in these countries, the previous day's error does not affect the present volatility, unlike Argentina, Chile, Colombia and Peru. The value of M is positive and significant, except for Peru, representing that the past negative shocks have a stronger impact on current conditional volatility than past positive shocks.

Table I - Parameters for model DCC-GJR-GARCH-Copula. This table presents the results for the estimation of volatility and correlation.

| **Countries** | **GJR-GARCH ($h_{i,t}$)** | | | | | | **Copula-DCC** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **G** | **K** | **L** | **M** | **Skewness** | **GL** | **$\Theta_1$** | **$\Theta_2$** | **GL** |
| **Argentina** | | | | | | | | | |
| **Coefficient** | 0,000 | 0,064 | 0,857 | 0,070 | 0,973 | 5,857 | 0,039 | 0,952 | 7,910 |
| **p-value** | 0,010 | 0,000 | 0,000 | 0,042 | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 |
| **Brazil** | | | | | | | | | |
| **Coefficient** | 0,000 | 0,015 | 0,898 | 0,110 | 0,912 | 9,230 | 0,034 | 0,959 | 7,256 |
| **p-value** | 0,092 | 0,075 | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 |
| **Chile** | | | | | | | | | |
| **Coefficient** | 0,000 | 0,032 | 0,847 | 0,139 | 0,931 | 11,305 | 0,027 | 0,960 | 13,168 |
| **p-value** | 0,001 | 0,022 | 0,000 | 0,000 | 0,000 | 0,000 | 0,031 | 0,000 | 0,000 |
| **Colombia** | | | | | | | | | |
| **Coefficient** | 0,000 | 0,103 | 0,749 | 0,139 | 0,984 | 5,815 | 0,031 | 0,959 | (mvnorm) |
| **p-value** | 0,000 | 0,000 | 0,000 | 0,001 | 0,000 | 0,000 | 0,002 | 0,000 | |
| **Mexico** | | | | | | | | | |
| **Coefficient** | 0,000 | 0,000 | 0,907 | 0,136 | 0,890 | 7,505 | 0,016 | 0,980 | 8,119 |
| **p-value** | 0,006 | 1,000 | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 |
| **Peru** | | | | | | | | | |
| **Coefficient** | 0,000 | 0,060 | 0,927 | 0,013 | 0,976 | 5,859 | 0,036 | 0,959 | 16,163 |
| **p-value** | 0,049 | 0,000 | 0,000 | 0,517 | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 |

Source: Research data

For Peruvian market, the M coefficient is not significant, indicating that the conditional volatility does not suffer the effects of asymmetric distribution. The estimation of coefficients from the GJR-GARCH model was performed for all markets using univariate analysis.

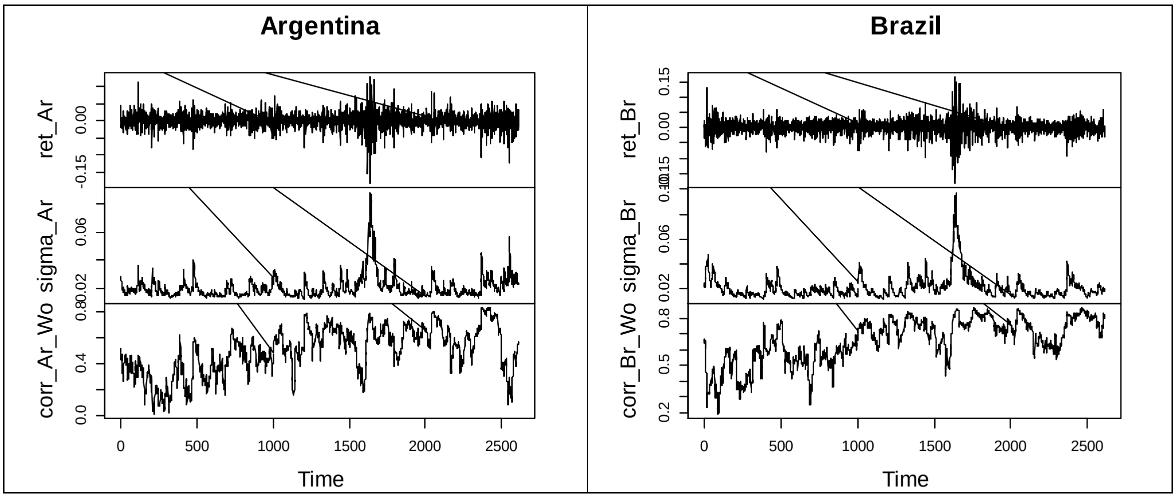
The Θ1 and Θ2 coefficients were obtained by Equation (2) and they would present sum 1 if they explained all the Dynamic Conditional Correlation between proxies of each market and the proxy of the world market, much like the K and L parameters of the GJR-GARCH model. All of them prove to be significant and their sum is close to 1 for all countries, showing the proper degree of explanation of the DCC model. The flexibility of the copula function, evidenced by Hsu, Tseng and Wang (2008), which is independent of the type of distribution, may have contributed to this.

Figure 1 shows the returns series and the estimation results of the volatility of Latin markets, as well as the correlation between returns from these markets and the world market returns. In this figure, the DCC of the proxy of each country with the world proxy was called "corr_country_world"; the univariate volatility of the proxy of each country, obtained by the GJR-GARCH was called "sigma_country"; the return of each proxy was termed "ret_country ". All markets have a volatility peak in 2008 due to the global economic crisis that erupted that year.

Argentina, Brazil and Colombia have volatility peaks higher than others, which can be checked visually by the volatility charts, reaching the level of 0.06, higher than the others. This situation confirms the analysis of the standard deviations of Argentina and Brazil, which had the highest (0.022 and 0.024, respectively).

It is observed that Argentina, Brazil and Colombia have higher volatility peaks than others, which can be checked visually by the volatility charts, that reach the level of 0.06, higher than the others. This situation confirms the analysis of the standard deviations of Argentina and Brazil that had the highest (0.022 and 0.024, respectively).

Colombia presents two moments of crisis, rather than just one, and one of them corresponds to the global crisis of 2008, in congruence with other countries. Colombia also presented a previous crisis, exclusive to itself, causing a spike in volatility, prior to the 2008 crisis, but with similar magnitude. Thus, the conditional volatility of it reached a level close to 0.06 in both cases, as shown in Figure 1, although, on average, its volatility has not been as high as the markets indexes of Argentina and Brazil, which is evidenced by a standard deviation of 0.018. Possibly this crisis was triggered by the terrorist attack suffered in 2004, and the attacks of the Revolutionary Armed Forces of Colombia (FARC), which led to heavy losses to the country.



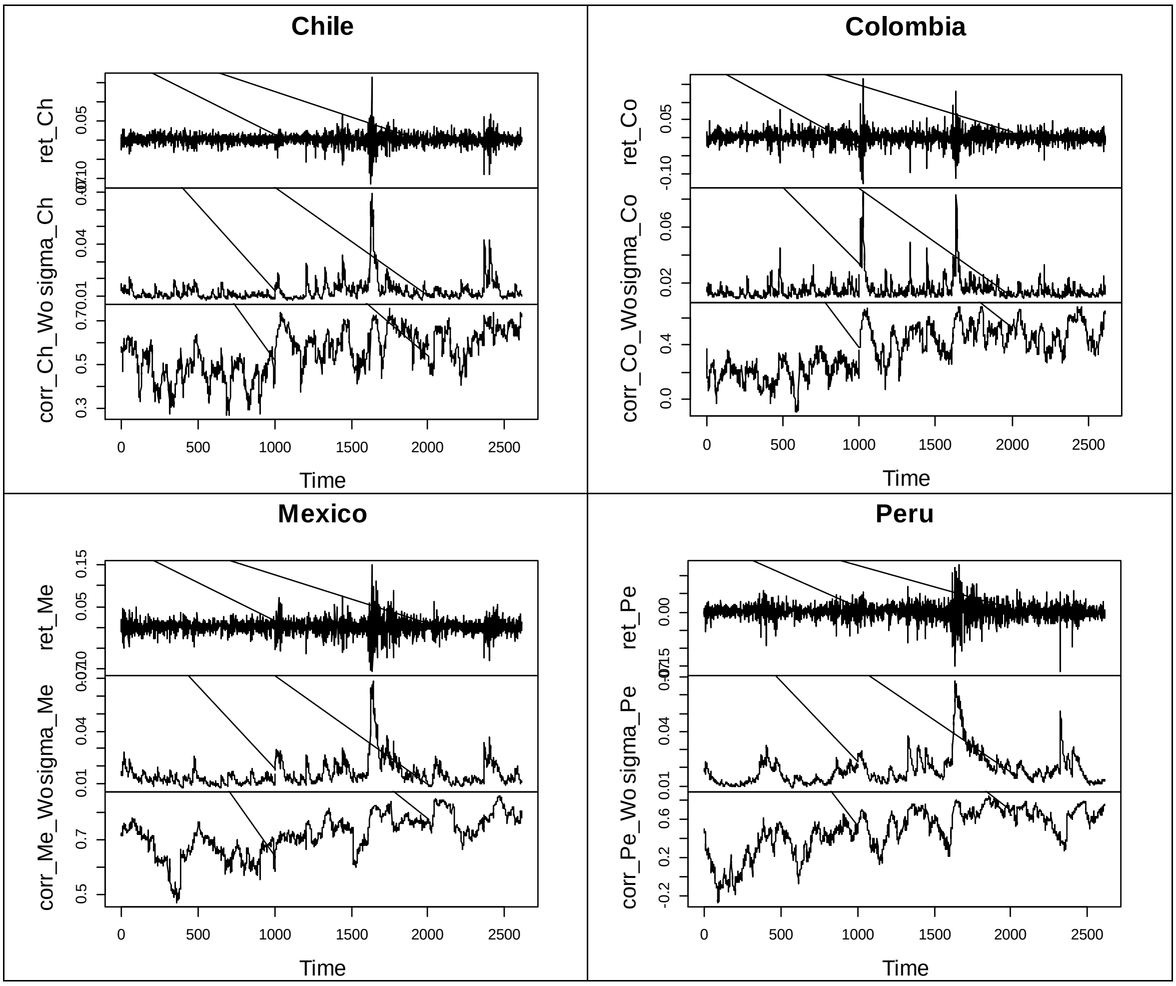



Figure 1 - log-returns, volatility and dynamic correlation for the Latin American markets. Source: Research Data

The next step was to estimate the pricing of risk by the ICAPM quantile model. Table II presents the results for quantile parameters as well as the coefficients estimated by OLS, for comparison purposes, aiming to price the risk of the six markets analyzed. The quantile regression coefficients are shown for the extreme conditional quantiles 0.1 and 0.9, in which the lower quantiles are associated to lower market returns and the upper quantiles to higher returns.

Table II - This table presents the coefficients and p-value of autoregressive vector (Country Market (*t-1*)), of the univariate risk (sigma_Market) and of the correlation of returns in each market with the proxy that represents the world (corr_Market_Wo). Estimations are presented through the use of quantile regression of the coefficients from the extreme quantile (0.1 and 0.9), as well as the estimation of the coefficients by the method of OLS for comparison purposes. The significant values for the pricing of risk in Latin markets, the degree of significance of 5%, are highlighted in bold. The significant values for the pricing of risk in Latin markets, to the degree of significance of 5%, are highlighted in bold.

| **Countries** | | **Quantile 0,1** | | **OLS** | | **Quantile 0,9** | |
|---|---|---|---|---|---|---|---|
| | | **Coefficient** | **p-value** | **Coefficient** | **p-value** | **Coefficient** | **p-value** |
| **Argentina** | **(Intercept)** | 0,006 | 0,093 | 0,003 | 0,061 | 0,006 | 0,112 |
| | **Ar(*t-1*)** | 0,111 | **0,007** | 0,020 | 0,319 | -0,034 | 0,463 |
| | **sigma_Ar** | -1,619 | **0,000** | -0,163 | **0,004** | 0,765 | **0,000** |
| | **corr_Ar_Wo** | 0,005 | 0,247 | 0,002 | 0,499 | 0,005 | 0,218 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Brazil** | **(Intercept)** | 0,003 | 0,502 | 0,003 | 0,240 | 0,006 | 0,066 |
| | **Br(*t-1*)** | 0,189 | **0,000** | 0,077 | **0,000** | -0,013 | 0,695 |
| | **sigma_Br** | -1,441 | **0,000** | -0,022 | 0,673 | 1,213 | **0,000** |
| | **corr_Br_Wo** | 0,001 | 0,865 | -0,002 | 0,472 | -0,008 | 0,054 |
| **Chile** | **(Intercept)** | 0,000 | 0,872 | 0,000 | 0,958 | 0,003 | 0,227 |
| | **Ch(*t-1*)** | 0,263 | **0,000** | 0,108 | **0,000** | 0,033 | 0,419 |
| | **sigma_Ch** | -1,465 | **0,000** | 0,002 | 0,962 | 1,091 | **0,000** |
| | **corr_Ch_Wo** | 0,005 | 0,217 | 0,001 | 0,779 | -0,002 | 0,517 |
| **Colombia** | **(Intercept)** | -0,010 | 0,022 | 0,000 | 0,857 | 0,012 | **0,001** |
| | **Co(*t-1*)** | 0,237 | **0,000** | 0,105 | **0,000** | 0,048 | 0,206 |
| | **sigma_Co** | -1,050 | **0,000** | -0,120 | 0,052 | 0,815 | **0,000** |
| | **corr_Co_Wo** | 0,009 | 0,171 | 0,004 | 0,271 | -0,006 | 0,351 |
| **Mexico** | **(Intercept)** | -0,001 | 0,846 | 0,002 | 0,513 | -0,001 | 0,851 |
| | **Me(*t-1*)** | 0,104 | **0,006** | 0,085 | **0,000** | -0,001 | 0,987 |
| | **sigma_Me** | -1,255 | **0,000** | 0,009 | 0,850 | 1,246 | **0,000** |
| | **corr_Me_Wo** | 0,002 | 0,772 | -0,003 | 0,601 | 0,001 | 0,910 |
| **Peru** | **(Intercept)** | 0,001 | 0,636 | 0,001 | 0,245 | 0,003 | 0,172 |
| | **Pe(*t-1*)** | 0,161 | **0,001** | 0,038 | 0,052 | 0,011 | 0,817 |
| | **sigma_Pe** | -1,140 | **0,000** | -0,049 | 0,368 | 0,965 | **0,000** |
| | **corr_Pe_Wo** | -0,004 | 0,243 | 0,001 | 0,627 | 0,004 | 0,235 |

Source: Research Data

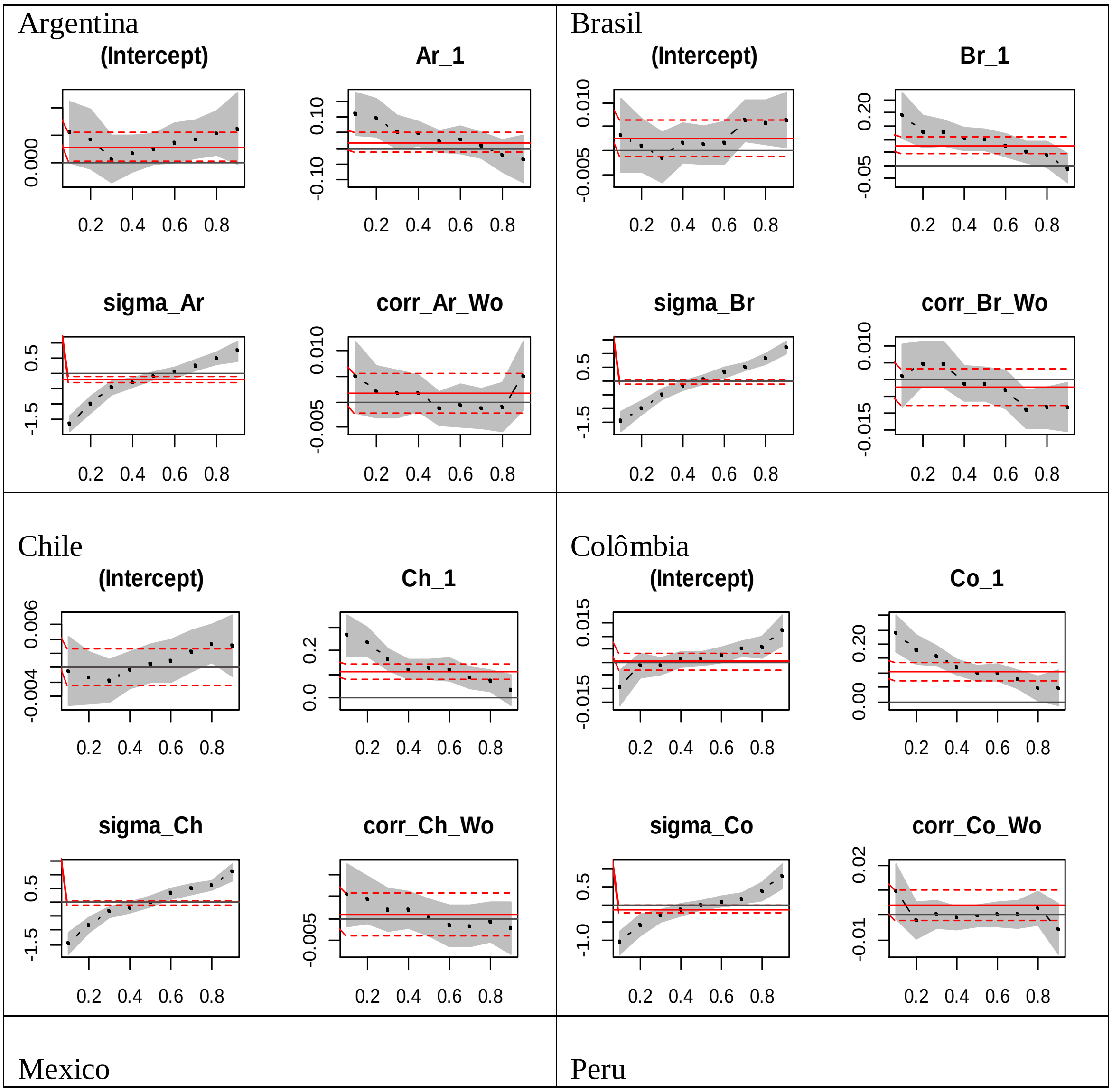
Only the Colombian market presents a significant intercept, to a significance level of 5%. As for the autoregressive vector, it is significant in all markets in the lower quantile and in none of the top quantile, showing that persistence is higher in periods of extreme drop (turbulence). By the OLS method, the autoregressive vector is significant for the markets of Brazil, Chile, Colombia and Mexico.

The quantile coefficients of univariate volatility of Latin markets are significant in all markets in both the lower and in the upper quantile. On the top quantile, the coefficients are positive, showing that the relationship between risk and return follows the traditional expectations, i.e., the higher the risk, higher the return. However, these coefficients are negative in the lower quantile, possibly because they are related to moments of turbulence, forming what is known as leverage effect.

When analyzing the results for the coefficients estimated by OLS for Argentina, Brazil, Chile, Colombia, Mexico and Peru, it was realized the difficulty of pricing, because only the market of Argentina showed a significant coefficient, in which negative risk premium was found. Through the OLS method, it was not possible to identify the relationship between pricing of the risk of other Latin markets and returns worldwide. It is possible to conclude that the OLS method estimates the average of the coefficients without discrimination by quantile, the coefficients of the upper quantiles cancel the lower quantiles, which explains the absence of significant coefficients for most of the markets estimated by this method, masking the fact that it is possible to find significant coefficients if it is taken into account results of quantiles that represent situations of higher and lower returns.

The dynamic conditional correlation coefficient of the proxy of each market and the proxy of the world market were significant in neither case, demonstrating that this dependence is not priced. Figure 2 helps to understand the quantile parameters.

The graphs in Figure 2 show clear similarities in the behavior of the variables of each market. In every markets analyzed, the risk of the market itself (sigma) exceeds the confidence interval OLS both in lower and in the upper quantiles, generating significant coefficients for the pricing of the return. It also appears that the behavior of this variable differs between the quantiles analyzed, showing an increasing trend as it moves from lower to higher quantiles.



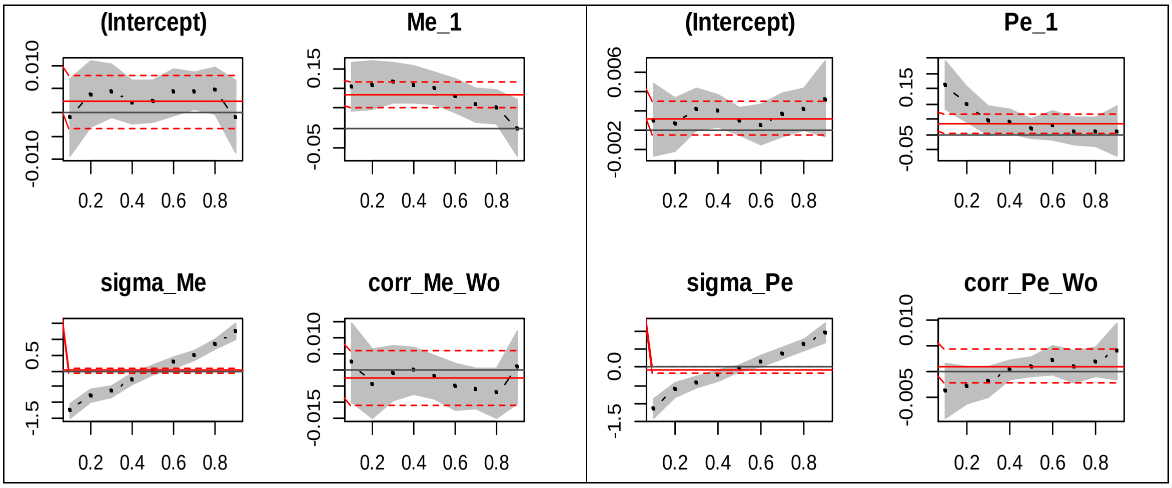



Figure 2: Complementing Table 3, this figure shows the vector autogressive (Market (*t-1*)), the univariate risk (sigma_Market) and the correlation of the returns of each market with the proxy that represents the world (corr_Market_Wo) for quantiles of 0.1 to 0.9, and the confidence interval of the Least Squares Method for comparison. The solid line represents the coefficients obtained by the OLS method, while the dashed line delineates their confidence intervals (5%). The dotted line refers to quantile parameters, while the dark area represents the confidence interval.

The quantile coefficients estimated for the autoregressive vector of each market exceeds the confidence interval OLS only in the lower quantiles, because the shaded area overcomes the dotted line only on the left side of the graph, confirming the results shown in Table 3. The downward trend in the shaded area causes it to be inserted within the confidence interval of the OLS in the upper quantiles. The intercept is significant only in the upper quantile of the Colombian market, which can be confirmed by observation of Figure 02, as the shaded area exceeds the OLS interval on its right side. In the other markets, this has not been verified. It also has been noticed that the correlation of each market with the world market does not exceed the confidence interval OLS in any case, since the shaded area did not exceed significantly the dashed line, to the degree of significance of 5%.

The graph confirms the observation that the risk premium presented different behavior over the conditional quantiles, whereas in the lower quantiles it is negative and in the upper quantiles, positive. The quantile regression estimators are different from those obtained by OLS, although they were not significant for some variables. Coefficients that would be considered constants can thereby be distinguished over the different quantiles, manifesting peculiarities relevant to the pricing of risk. Coefficients that would be considered constants can thereby be distinguished over the different quantiles, manifesting peculiarities relevant to the pricing of risk.

Analyzing these results, it is clear that the estimated model fits better the estimation of the risk pricing, because it reduces error and obtains results that are not possible through the traditional CAPM model. However, the non-significance of the dynamic correlation raises questions about the validity of the ICAPM model by showing that the relationship with the global volatility is not priced, as expected theoretically. It is possible that the presence of the autoregressive vector contributed for that.

## 6 Final Considerations

This study aimed to analyze the pricing of risk in Latin American countries and distinguish the results by quantiles, using the conditional volatility and dynamic conditional correlation. After a brief literature review on the development of models and methods used, the section of Methodological Procedures outlined how and what methods were used effectively.

The Results section presented the coefficients obtained and showed that the proposed modifications to ICAPM improve the adjustment. It also raised interesting points, especially the non-significance of the dynamic correlation of each market proxy with the proxy of the world market and the differences in each quartile, in the sense that in the lower quantile there is a negative risk premium and in the upper quantile, positive.

The methodological changes applied to the traditional model of Merton (1973), exemplified by Equation (1) do not support the model in its original form, because the correlation of the proxy of each country with the world market proxy was not considered significant even by the OLS method. This may have happened mainly by the insertion of the autoregressive vector or because the MSCI index, which represents the world market, is not very influenced by Latin markets. That is, within the construction of the index, the Latin markets have a smaller importance. The result of this is that great part of its variation is due to the movements of the more mature markets, reducing the correlation with the Latin markets. The non-significance of the market correlation of a country with the world market also opposes Bali and Wu (2010), Bali and Engle (2010), Miralles-marcelo et al. (2012), that also found a positive risk premium. In this study, that segregated the analysis into quartiles, the risk premium was negative in the lower quantiles, demonstrating the leverage effect and supporting Baur, Dimplf and Jung (2012) and Ceretta et al. (2012).

From the perspective of international investors, it is noticed that the Latin markets are a good alternative for diversification, because of the low correlation with global markets, since it explores quantiles that present positive risk premium.

**7 References**

BEKAERT, G.; HARVEY, C. Time-varying world market integration. **The Journal of Finance**, v. 50(2), p. 403–444, 1995.

BOLLERLSLEV, T. Generalized autoregressive conditional heterosdasticity. **Journal of Econometrics**, v. 31, p. 307–327, 1986.

CAI, Z.; XIAO, Z. Semi parametric quantile regression estimation in dynamic models with partially varying coefficients. **Journal of Econometrics**, v.167, n. 2, p. 413-425, 2012.

ENGLE, R.F. Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. **Journal of Business and Economic Statistics**, v. 20, p. 339–350, 2002.

ENGLE, R.F. Autoregressive conditional Heteroskedacity with the estimates of variance of the United Kingdon inflation. **Econometrica**, v. 50, n. 4, p. 987-1008, 1982.

ENGLE, R.; SHEPPARD, K. Theoretical and Empirical properties of Dynamic Conditional Correlation Multivariate GARCH", **NBER Working Paper**, n. 8554, 2001.

FRANCQ, Christian; ZAKOIAN, Jean-Michel. Inconsistency of the MLE and inference based on weighted LS for LARCH models. **Journal of Econometrics**, v. 159, i. 1, p. 151-165, 2010.

GLOSTEN, L.; JAGANNATHAN, R; RUNKLE, D. On the relation between the expected value and volatility of the nominal excess return on stocks. **Journal of Finance**, v. 48, p. 1779—1801, 1993.

HSU, C. C.; TSENG, C. P.; WANG, Y. H. Dynamic hedging with Futures: a copula-based GARCH model. **The Journal of Futures Markets**, 28, 1095–1116, 2008.

JENSEN, M. C. The performance of mutual funds in the period of 1945-1964. **Journal of Finance**, v. 23, n. 2, p. 389-416, 1967.

KNIGHT, K. Limit theory for autoregressive-parameter estimates in an infinite-variance random walk. **Canadian Journal of Statistics**, v. 7, n. 3, p. 261–278, 1989.

KOENKER, R.; BASSETT, G. Regression quantiles. **Econometrica**, n. 46, p. 33–50, 1978.

KOENKER, R. Quantile regression. New York: Cambridge University Press, 2005. (Econometric Society Monographs n. 38)

KOENKER, R.; XIAO, Z. Quantile autoregression. Texto para discussão, 2004. Disponível em: Disponível em: <http://www.econ.uiuc.edu/~roger/research/qar/qar9.pdf>. Acesso em: 30 mai. 2012.

LINTNER, John. Security Prices, Risk and Maximal Gains from Diversification". **Journal of Finance**, v. 20, p. 587, 616, 1965.

MARKOWITZ, H. M. Portfólio selection. **Journal of Finance**, Oxford, v. 7, n. 1, p. 77-91, Mar. 1952.

MERTON, R. C. An Intertemporal capital asset pricing model**. Econometrica**, n. 41, v. 5, p. 867-887, 1973.

ROGERS, A. Least absolute deviations regression under nonstandard conditions. **Econometric Theory**, v. 17, n.4, p. 820–852, 2001.

SHARPE, W. F. Capital asset prices: a theory of market equilibrium under conditions of risk. **The Journal of Finance**, Oxford, v. 19, n. 3, p. 425-442, set. 1964.

SHARPE, W. F. Mutual Fund Performance. **The Journal of business**, v. 39, n. 1, p.119-138, 1966.

TODOROV, Galin; BIDARKOTA, Prasad V. Time-Varying Risk and Risk Premiums in Frontier Markets. *SSRN*. Available at: http://ssrn.com/abstract=1947412, 2011.

TREYNOR, J. "How to Rate Management of Investment Funds". **Harvard Business Review**, v. 43, p. 63-75, 1965.

TSE, Y. K.; TSUI, A. K. C. A multivariate GARCH model with time-varying correlations. **Journal of Business and Economic Statistics**, 20, 351-362, 2002.

WEISS, A. Estimating nonlinear dynamic models using least absolute error estimation. **Econometric Theory**, v. 7, p. 46–68, 1991.