Inzinerine Ekonomika-Engineering Economics, 2014, 25(4), 387–394

Emerging Market Return Pricing: an Intertemporal and Interquantile Approach

Bruno Milani, Paulo Sergio Ceretta, Fernanda Maria Muller, Marcelo Brutti Righi

University of Santa Maria
Santa Maria, Rio Grande do Sul, 97105-900, Brazil
E-mail. milani_bruno@yahoo.com.br, ceretta10@gmail.com, nandamuller90@gmail.com, marcelobrutti@hotmail.com

crossref http://dx.doi.org/10.5755/j01.ee.25.4.5205

The objective of this study is to analyze the return pricing dynamics in six Latin American countries based on the ICAPM model of (Merton, 1973; Bekaert & Harvey, 1995). We analyze Argentina, Brazil, Chile, Colombia, Mexico and Peru market return and a world market proxy return as a measure of systematic risk. However, instead of traditional covariance, we used the Dynamic Conditional Correlation (DCC) model of Engle (2002) to measure the volatility correlation between each Latin market and the world market. We based the DCC model on marginal volatilities estimated by the GJR-GARCH model (Glosten et al., 1993), using a copula function. The copula-DCC-GARCH model was proposed with a financial application by (Jondeau & Rockinger, 2006). The univariate volatility and an autoregressive vector were also included as independent variables in the model, which coefficients were estimated by quantile regression. The results reveal a breakthrough because the model can capture relationships that were previously masked by the coefficients steadiness and by the lack of consideration over the differences in extreme quantiles pricing. 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, what indicates that Latin markets may present a good diversification opportunity.

Keywords: *Return Pricing, Emerging Markets, ICAPM, Copula-DCC-GARCH, Quantile Regression.*

Introduction

Market integration and capital flow between countries, due to globalization, have 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. In order to decrease the risk of investing in a single country, investors should diversify their portfolios with different assets in different countries. Markets that present opportunities for diversification usually have low correlations with other markets, however high correlations between the returns of equity markets would indicate that these markets share volatility.

In order to price the return of financial assets, Merton (1973) proposed the Intertemporal Capital Asset Pricing Model (ICAPM), which is an extension of the traditional Capital Asset Pricing Model (CAPM) developed by (Treynor, 1965; Lintner, 1965; Sharpe, 1966; Jensen, 1967) based on the relationship between risk and return delineated by Markowitz (1952). In this model, investors are not only concerned about maximizing the return, but also about the opportunities to minimize idiosyncratic risk.

Beakert & Harvey (1995) extended Merton (1973) model studying the relationship between returns of markets of different countries, using as a world market proxy the U.S market returns, namely, the New York Stock Exchange (NYSE) returns. The Market return is not only associated to the covariance between the own market return and the world market return, but it is also related to the specific risk of that market.

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 volatility correlation between Latin Markets proxies return and the world market proxy return. However, we replaced the traditional beta by the conditional correlation, using the Dynamic Conditional Correlation model (DCC) of Engle (2002). Also, the univariate volatility is estimated by the GJR-GARCH of (Glosten *et al.*, 1993). Moreover, the use of quantile regression allows the risk premium of Latin markets and world returns vary between quartiles. Furthermore, we include an autoregressive term as an independent variable. Nevertheless, the most innovative part in our methodology is the use of a copula method in the volatility estimations.

Therefore, the aim of this study is to analyze the return pricing in six Latin American countries markets, using an improved ICAPM model and estimating quantile coefficients. The paper contribution relies on the use of an innovative model, using as a measure of volatility the Copula-DCC-GARCH, bringing a new perspective about the subject. Besides, this study focuses on emerging markets, differing from the traditional literature about developed countries. 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 we obtained. Section 7 outlines the final remarks regarding these results and the study and, finally, section 8 provides the references used.

Intertemporal Asset Pricing Model

Until the first half of the past century, investors believed that stock returns depended only on expectations regarding future earnings. This conception was challenged by Markovitz (1952), who explained the existence of a proportional relationship between risk and return, allowing the measurement of the expected return of a portfolio based on its own risk. (Later & Lintner, 1965; Treynor, 1965; Sharpe, 1966; Jensen, 1967) developed individually, performance indexes and measures that culminated in what we call today the Capital Asset Pricing Model (CAPM), the most widely used pricing model in finance.

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

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 market risk perceived by investors, which may or may not be caused by changes in investment opportunities due to decisions of local governments. 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 global market risk 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 & Harvey (1995) used the Merton's ICAPM model to analyze the relationship between risk and return in several markets. In their estimation, the excess return of each analyzed market is priced by the covariance with a proxy that represents the world market, which in this case is an U.S market index. Also, the excess market return is also priced by the own market risk, which in this case it is variance of the specific country market return. In their model, the measure of risk associated with changes in government policies proposed by Merton (1973) was replaced by the specific market variance. As the risk associated with changes in investment conditions specific to each market is represented by their variance, the overall market is represented by an US market index. The model proposed by (Bekaert & Harvey, 1995) can be represented by Equation (1):

$$R_m - R_f = \alpha \quad + \beta_1 Cov_{R_m - R_f, R_{us} - R_f} + \beta_2 Var_{R_m - R_f} + \mu_t \quad (1)$$

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 β_1 is its pricing; $Var_{R_m - R_f}$ is the variance of the excess return of market *m* and β_2 are its pricing; μ_t is the error generated by regression in period *t*.

Similarly, this definition of the ICAPM model shows that the return pricing of an asset is due to systematic risk and to its own specific risk. The fact that this pricing includes the risk of individual assets brings back the initial idea of Markowitz (1952). The model of (Bekaert & Harvey, 1995) became known as the International CAPM.

Dynamic Conditional Correlation

The correlation is perhaps the most traditional measure of 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 correlation steadiness over time, what 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) model, previously studied by (Engle & Sheppard, 2001; Tse & Tsui, 2002) as a way to estimate the conditional correlation between two variables, based on their univariate volatility. 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.

Univariate conditional volatility modeling began with ARCH models (Engle, 1982), which later were supplemented by Bollerslev (1986). The GARCH model of Bollerslev (1986) is a generalization of ARCH, which is a stochastic conditional process on information at *t-1*. Thus, the estimation of univariate volatility can be understood by Equations (2), (3) and (4):

$$r_{i,t} = A_i + \sum B_{i,m} r_{i,t-m} + \sum C_{i,n} \varepsilon_{i,t-n} + \varepsilon_{i,t} \quad (2)$$

$$\varepsilon_{i,t} = h_{i,t} z_{i,t} \quad (3)$$

$$h_{i,t} = D_i + \sum E_{i,p} \varepsilon_{i,t-p}^2 + \sum F_{i,q} h_{i,t-q} \quad (4)$$

Where $r_{i,t}$ is the log-return of asset *i* in period *t*; $h_{i,t}$ is the conditional variance of an asset *i* in period *t*. A_i, B_i, C, D, E_i and F_i are parameters; $\varepsilon_{i,t}$ is the conditional average innovation of the asset *i* in period *t*; $z_{i,t}$ represents a white noise. Several alternatives and additions have been proposed to the original GARCH model of (Engle, 1982; Bollerslev, 1986). Among them, the GJR-GARCH is one of the most known, having been proposed by (Glosten *et al.*, 1993) as a way to model the asymmetry in conditional volatility, as shown in Equation (5).

$$h_{i,t} = G_i + \sum K_{i,m} \varepsilon_{i,t-m} + \sum L_{i,n} h_{i,t-n} + M_{i,m} \varepsilon_{t-m} I(\varepsilon_{t-m} > 0) \quad (5)$$

Where $I(\varepsilon_{t-1} < 0)$ is a dummy that assumes value 1 when ε_{t-1} is negative, and null when ε_{t-1} is greater than or equal to zero; G_i, K_i, L_i and M_i are parameters.

The univariate volatility, which can be estimated by a GARCH model or one of its variants, is then used as the first step in the DCC estimation. In this paper, we estimate the DCC based on the univariate volatility estimated by Equation (5), i.e., the GJR-GARCH. However, all of these models are estimated under the assumption of multivariate normality or based on some mixture of elliptical distributions. This assumption is unrealistic, as evidenced by numerous empirical studies, in which it has been shown that many financial asset returns are skewed, leptokurtic, and asymmetrically dependent.

These difficulties can be treated as a problem of copulas. The concept of copula was introduced by (Sklar, 1959). A copula is a function that links univariate marginals to their multivariate distribution. Since it is always possible to map any vector of random variables into a vector with uniform margins, we are able to split the margins of that vector and a digest of dependence, which is the copula. Thus, the joint distribution of the asset returns can be specified with full flexibility, which is more realistic. Thus, emerges the Copula-DCC-GARCH model, which was proposed with a financial application by Jondeau & Rockinger (2006). Some posterior studies employed the Copula-DCC-GARCH model because of its advantages. Fantazzini (2009) performed Value at Risk simulations. (Aas & Berg 2009; Ausin & Lopes, 2010; Hafner & Reznikova, 2010) investigated dependence structures between financial assets. (Righi & Ceretta, 2011a) identified structural changes in European markets volatility. (Righi & Ceretta, 2011b) estimated value at risk and optimal hedge ratio in Latin markets. (Righi & Ceretta, 2012) performed daily risk predictions for a global portfolio.

In this paper, we estimated the conditional covariance matrix with a copula-DCC- GARCH model, represented by the Equation (6), which is able to lead with the asymmetric leptokurtic behavior of financial assets returns.

$$H_t = D'_t R_t D_t \qquad (6)$$

Where H_t is the correlation matrix between variables.

$$R_t = diag(q_{11,t}^{-1/2} ... q_{NN,t}^{-1/2}) Q_t diag(q_{11,t}^{-1/2} ... q_{NN,t}^{-1/2}) \qquad (7)$$

$$Q_t = (1-\alpha-\beta)\hat{Q} + \alpha\mu_{t-1}\mu'_{t-1} + \beta Q_{t-1}, \mu_{i,t} / \sqrt{h_{i,t}} \sim skew-t_v \qquad (8)$$

$\hat{Q}$ is the NxN matrix composed by unconditional covariance of μ_t; The definitions of residuals $\mu_{i,t}$ joint distribution extends the traditional DCC (based on multivariate normality or mixture of elliptical distributions) through copulas, which allow more flexibility in describing the data once copulas are estimated with separately from marginal; D_t is the matrix $D_t = diag\left(h_{11,t}^{-1/2} ... h_{NN,t}^{-1/2}\right)$, which serves as a normalization to ensure that H_t is the matrix of correlation; $h_{ii,t}$ is the conditional variance of asset *i* in period *t*; ε_t is the vector of standardized innovation in period *t*; α and β are nonnegative autoregressive scalar parameters, that satisfy $0 < \alpha + \beta < 1$.

The use of a copula function considers the marginal distributions and the dependence structure both separately and simultaneously (Hsu, Tseng & Wang, 2008). Thus, it is possible to model the combined distribution of each asset innovations 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.

Quantile regression model

The quantile regression model proposed by (Koenker & 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 & 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 (9).

$$F\,(x) = P\,(X \leq x) \qquad (9)$$

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

$$F^{-1}(\tau) = Q(\tau) = \inf\{\,y: F(y) \geq \tau \qquad (10)$$

In Equation (10), F^{-1} represents the median and τ represents the τ–nth quantile of *x*. The quantile parameters are found by minimization of the expected error. Error is defined by the following linear function:

$$\rho_\tau(u) = u\big(\tau - I(u < 0)\big) \qquad (11)$$

The τ -nth conditional quantile function can be represented by Equation (12).

$$Q_y(\,\tau \mid x\,) = x'\beta(\tau) \qquad (12)$$

And the vector of parameters $\beta\ (\tau)$can be obtained by solving a minimization problem represented by Equation (13).

$$min_\beta \sum_{i=1}^{n} \rho_\tau\ (y_i - x_i'\beta) \qquad (13)$$

Where x_i' is the τ-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 & Basset, 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 (14).

$$y_t = \beta_0(\tau) + \beta_1(\tau)x_{i1} + \cdots + \beta_\rho(\tau)x_{ip} + \varphi_i \qquad (14)$$

In this model, φ are random independent variables and identically distributed in a range from 0 to 1. So, the conditional function of order τ of *Y/X* can be represented by Equation (15).

$$Q_\tau\ (Y \mid x) = \beta_0 + \beta_1\ (\tau)_{x_1} + \cdots \beta_\rho(\tau)x_p \qquad (15)$$

Or in a more simplified way, with only one explanatory variable, by Equation (16).

$$Q_\tau(\,Y \mid x\,) = \alpha(\tau) + \beta(\tau)x \qquad (16)$$

With Equations (15) and (16) there is the model of the τ-nth conditional function of the conditional quantile of y_t, that express the previous 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). Still, there is a substantial theoretical literature of the model, including as examples (Koenker & Bassett, 1978; Knight, 1989; Weiss, 1991; Rogers, 2001; Koenker & Xiao, 2012; Cai & Xiao, 2012).

Methodological Procedures

This study examines the return pricing in six Latin markets, such as Argentina, Brazil, Chile, Colombia, Mexico and Peru, using as market proxies each country stock market index. To represent the world market, we use Morgan Stanley Capital International (MSCI), which is the value-weighted index of the global market. The analyzed sample period is from July 11th, 2002 to July 13th, 2011, consisting of 2612 daily observations. The data comes from Morgan Stanley Financial Services. This period was chosen because it comprises distinct economic moments, involving crisis and stable periods, so we can make the most of the conditional methods.

The return 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 & Harvey, 1995) international CAPM. Therefore, the model used here is analogous, concomitantly, with the international and intertemporal models.

However, instead of using the covariance between a country market return with the world market return as a measure of dependence, the Dynamic Conditional Correlation model (DCC) was used, according to Equation (2), Todorov & Bidarkota (2012). Differently from (Engle & Sheppard, 2001; Tse & Tsui, 2002; Engle, 2002) that use the ordinary GARCH model by (Bollerslev, 1986) to calculate the univariate volatility, we used 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 was to evaluate the difference between the positive and negative impacts of the volatility series. Therefore, it takes into consideration that positive and negative shocks of conditional mean innovations have a different impact on volatility.

Another key difference in relation of (Engle & Sheppard, 2001; Tse & Tsui, 2002; 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 ICAPM model uses as a measure of risk, besides the dependence on the world market proxy, the volatility of the local market proxy, according to (Bekaert & Harvey, 1995). In this study, we used the conditional volatility calculated by GJR-GARCH as a measure of risk of each Latin market.

The ICAPM model will be estimated by quantile regression, defined by Equations (15) and (16), rather than the traditional OLS regression, commonly used, as in (Bekaert & Harvey, 1995; Todorov & Bidarkota, 2012). The purpose of using this form of regression is to analyze the pricing differences in situations of higher and lower return. To ease the common problems caused by auto-correlation, a vector autoregressive of first order is also entered as independent variable in the model. Therefore, the model we used can be defined by Equation (17):

$$Qr_{i,t}(\tau) = N_0(\tau) + O_1(\tau)r_{i,t-1} + P_2(\tau)DCC_{iw,t} + R_3(\tau)\sigma_{i,t} + S_{i,t} \qquad (17)$$

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 vector autoregressive coefficient of each quantile; P_2 is the coefficient of the dynamic conditional correlation between the specific country market return with the global market return, for each quantile. R_3 is the univariate market volatility coefficient, calculated by the GJR-GARCH model, in each quantile. R_3 is the error of each quantile, in period *t*.

Results and Discussions

We first estimate the conditional covariance matrix using the model described in Section 5, which we will call therefore simply Copula-DCC-GARCH. Table 1 presents the estimated coefficients. In this estimation, we 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 1

Estimated coefficients of copula-DCC-GARCH model. This table presents the results for the estimation of volatility and correlation

Countries	GJR-GARCH (Equation (5))						Copula-DCC (Equation (6))		
	G	K	L	M	Skewness	GL	α	β	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

Countries	GJR-GARCH (Equation (5))						Copula-DCC (Equation (6))		
	G	K	L	M	Skewness	GL	α	β	GL
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

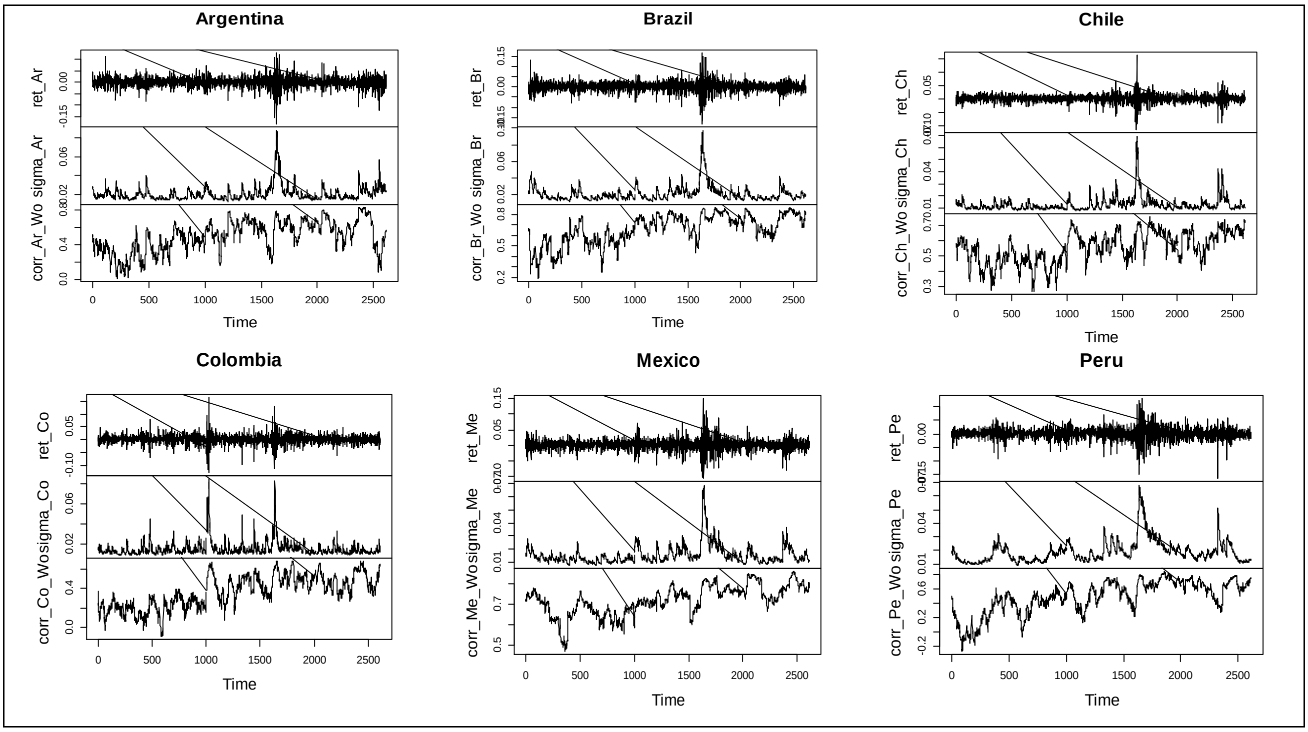

Figure 1. Log-Returns, volatility and dynamic correlation for the Latin American markets
Source: Research Data

The next step was to estimate the return pricing by quantile regression. Table 2 presents the estimated coefficients for extreme quantiles, as well as the OLS estimated coefficients, for comparison purposes, aiming to price the return 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 returns and the upper quantiles to higher returns. Only the Colombian market presents a significant linear coefficient, considering 5% significance level. The autoregressive vector is significant in all markets on the lower quantile and in none of the top quantiles, showing that persistence is higher in periods of extreme fall (turbulence). By the OLS method, the autoregressive vector is significant for Brazil, Chile, Colombia and Mexico markets.The quantile coefficients of univariate volatility of Latin markets are significant for 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., proportional relation between risk and return. However, these coefficients are negative in the lower quantile, possibly because they are related with turbulence periods, featuring what is known as leverage effect.

The estimated OLS coefficients for Argentina, Brazil, Chile, Colombia, Mexico and Peru, showed pricing difficulties, because only Argentina market presented a significant univariate volatility coefficient, in which negative risk premium was found. By the OLS regression, we did not find significant coefficients for DCC or univariate volatility in the analysis of other country markets. The OLS method estimates the average coefficients without discrimination by quantile. The upper quantiles coefficients compensate the lower quantiles, what may explain the absence of significant coefficients for most markets, masking the fact that there are significant relations, i.e., we would find significant coefficients for lower and higher returns if quantile regression was used.

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

Table 2

This table presents the coefficients and p-value of autoregressive vector (country Market(*t-1*)), of the univariate volatility (sigma_Market) and of the dynamic conditional correlation of each market volatility with world market volatility (corr_Market_Wo). We present the quantile regression estimated coefficients for the extreme quantile (0,1 and 0,9), as well as the OLS estimated coefficients, for comparison purposes. The significant values for the return pricing of Latin markets, considering 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

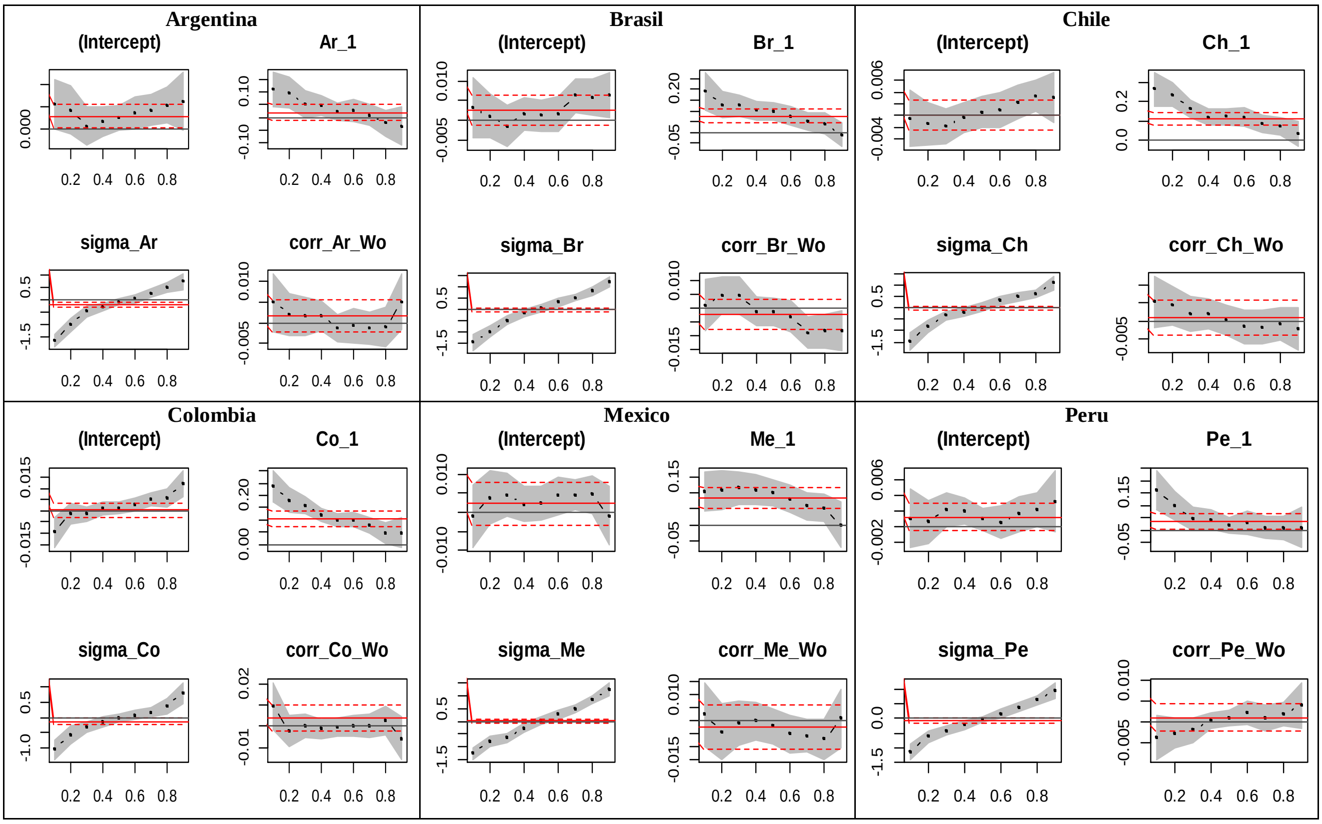

Figure 2. This figure shows the vector autogressive (Market (*t-1*)), the univariate risk (sigma_Market) and dynamic conditional correlation between market and word returns (corr_Market_Wo) for quantiles of 0,1 to 0,9, besides the OLS confidence interval for comparison. The solid line represents the estimated OLS coefficients, while the dashed line delineates their confidence intervals (5 %). The dotted line refers to quantile parameters, while the dark area represents the confidence interval

Figure 2 shows clear similarities in the dynamics of each country market. In every market analyzed, the specific market volatility (sigma) exceeds the OLS confidence interval both in lower and in upper quantiles, generating significant coefficients. It also appears that this variable behavior differs depending on the analyzed quantile, showing an increasing trend as it moves from lower to higher quantiles. The quantile coefficients estimated for the autoregressive vector of each country market exceed the OLS confidence interval only in the lower quantiles, as we can see where the shaded area overcomes the dotted line only on the left side of the graph, confirming the results shown in Table 2. The downward trend in the shaded area causes it to be inserted within the OLS confidence interval in the upper quantiles. The intercept is significant only in the upper quantile of the Colombian market, what can be confirmed by Figure 2, 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 DCC of each country market with 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 %.

Figure 2 confirms that the risk premium present different behaviors over the conditional quantiles, whereas in the lower quantiles it is negative and in the upper quantiles, positive. The quantile regression coefficients 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, showing relevant peculiarities to the return pricing.

It is clear that the estimated model represents an advance in the Latin markets return pricing, because we have obtained more precise results that would not be possible if we have used the traditional CAPM model, estimated by OLS. However, the non-significance of the dynamic correlation pricing raises questions about the validity of the 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.

Final Considerations

This study aimed to analyze the Latin American markets return pricing using the ICAPM model and quantile regression, estimating the univariate volatility and dynamic conditional correlation. After a brief literature review on models and methods developments, the section of Methodological Procedures outlined how and which methods were used.

The Results section presented the estimated coefficients and showed that the proposed modified ICAPM provided a good model fit. It also raised interesting points, especially the non-significance of each market and world market DCC pricing 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. Our results do not support (Merton 1973; Bekaert & Harvey, 1995) models, since the correlation of each country market with the world market was not 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 country market and the world market DCC also opposes (Bali & Wu, 2010; Bali & Engle 2010; Miralles Marcelo *et al.*, 2012), that 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 *et al.*, 2012; Ceretta *et al.*, 2012).

From the perspective of international investors, the low correlation with global markets may shows that the Latin markets are a good alternative for investment diversification. However, the fact that the return is not well priced by our model does not mean that it would not be priced by other variables, so we cannot exclude the possibility that our model is not the most appropriate.

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The article has been reviewed.

Received in September, 2013; accepted in October, 2014.