Title: The risk–return tradeoff in Emerging Markets

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Abstract

This paper studies the risk-return tradeoff in some of the main emerging stock markets in the world. Although previous studies on emerging markets were not able to show a positive and significant tradeoff, favorable evidence can be obtained if a non-linear framework between return and risk is considered. Using 15 years of weekly data observations for 25 Emerging Markets MSCI index (5 Latin American, 9 Asian, 5 Eastern European, 3 Africans and 3 aggregate index for Asia, Eastern Europe and Latin America) in a Regime Switching-GARCH framework, favorable evidence is obtained for most of the emerging markets during low volatility periods, but not for periods of financial turmoil or using the traditional linear GARCH-M approach.

Key words:

JEL classification:

1.- Introduction

The relationship between return and risk has motivated lots of research in both the theoretical and the empirical field for many years. Many of the asset pricing models are based on this fundamental financial relationship and a good comprehension of the dynamics of return and risk is essential to understand these models. One of the most cited theoretical works in the financial literature analyzing the relationship between return and risk is Merton's (1973) intertemporal capital asset pricing model (ICAPM). Merton shows a linear relationship between the expected return on a wealth portfolio and its conditional variance and its conditional covariance with the investment opportunity set:

$$E_t\left(R_{M,t+1}\right)=\left[\frac{-J_{WW}W}{J_W}\right]\sigma^2_{M,t}+\left[\frac{-J_{WB}W}{J_W}\right]\sigma_{MB,t} \qquad (1)$$

where $J(\cdot)$ is the utility function (subindex represents partial derivatives), $E_t\left(R_{W,t+1}\right)$ is the expected excess market return, σ^2_M and σ_{MB} are the conditional variance and the conditional covariance with the investment opportunity set and $\left[\frac{J_{WB}W}{J_W}\right]$, $\left[\frac{J_{WW}W}{J_W}\right]$ could be viewed as the risk prices of the sources of risk.

Despite the important role of this trade-off in the financial literature, there is no clear consensus about its empirical evidence. In a theoretical framework, all the parameters (the risk prices in brackets) and the variables (the sources of risk) are allowed to be time varying. However, to make this model empirically tractable one must make several assumptions; the most common is that of constant risk prices (Goyal and Santa-Clara (2003), Bali et al. (2005)). Another common assumption made in the empirical analysis of the risk–return tradeoff is that of a set of investment opportunities constant over time, leaving the market risk as the only source of risk in the ICAPM (Baillie and De Gennaro (1990), Glosten et al. (1993)). Finally, the empirical model is established in a discrete time economy instead of the continuous time economy used in the equilibrium model of the theoretical approach. Many empirical papers studying the risk-return use one or more of the assumptions explained above.

In the studies focused in the emerging markets, the most common empirical framework is the GARCH-M approach developed by Engle et al. (1987). De Santis and Imrohoroglu (1997) find some weak evidence[1] for a positive risk–return trade-off in Latin American stock markets, but no evidence in those of Asia using weekly series from December 1988 to May 1996 in a GARCH(1,1)-M framework. Karmakar (2007) estimates an EGARCH model for Indian stock market data between July 1990 and December 2004, finding no relationship between return and risk. Chiang and Doong (2001) estimate a TAR-GARCH(1,1)-M model using data from Hong Kong, South Korea, Malaysia, the Philippines, Singapore, Taiwan, and Thailand. They find a significant positive relationship in daily data, but the impact of volatility (or risk) on market returns is weak in weekly data and insignificant in monthly data. Shin (2005) estimates both parametric and semiparametric GARCH-M models using weekly data from January 1989 to May 2003 to investigate the risk–return trade-off in emerging Latin American, Asian, and European stock markets. The results show a positive but insignificant tradeoff in most cases.

However, there are several important alternatives to the usual GARCH-M methodology in the financial literature. Ghysels et al. (2005) propose an alternative empirical methodology to counteract the disadvantages of the GARCH-M estimations, using different data frequencies to estimate the mean (with lower data frequency) and the variance (with higher data frequency) equations. Ludvigson and Ng (2007) use a factor approach to summarize a large amount of economic information in their risk–return tradeoff analysis. Bali (2008) proposes an alternative approach considering not only the time series dimension of the portfolio market but also the cross-sectional dimension that allows the consideration of the whole market. Whitelaw (1994) uses an instrumental variables specification for the conditional second moments. Harrinson and Zhang (1999) use nonparametric techniques in their study instead of the parametric approaches

[1] These authors find essentially no evidence of a relationship between expected return and country-specific volatility, which is our main point in this paper; but when they generalize the model assuming regional or global international integration, they find support for a reward–risk relationship in Latin American countries.

used above. Whitelaw (2000) and Mayfield (2004) employ methodologies whereby states of the world are essentially defined by volatility regimes.

Among the alternative methodologies to the GARCH-M framework existing in the literature, I consider the RS-GARCH[2] approach following the papers of Whitelaw (2000) and Mayfield (2004). This methodology is based on an equilibrium framework developed in the paper of Whitelaw (2000). This theoretical framework is slightly different from Merton’s approach because a complex, non-linear, and time-varying relationship between expected return and volatility is obtained.

As remarked above, the evidence of a risk–return tradeoff in emerging markets using the GARCH-M approach is poor. In a recent paper, Lundblad (2007) shows that the typically insignificant relationship between the market risk premium and its expected volatility may be because of a statistical artifact[3] of the GARCH-M framework. A large data span is required in this approach to find successfully a positive risk-return tradeoff, showing in the Monte-Carlo simulation that even 100 years of data constitute a small sample from which one is forced to make inferences, obtaining sometimes disappointing results. To avoid this limitation of analyzing the risk–return tradeoff in a shorter span, we propose an alternative methodology which let us show favorable evidence in most emerging markets. We show that for shorter span empirical analysis, the relationship between expected return and volatility follows non-linear rather than linear patterns as suggested the GARCH-M framework. The RS-GARCH approach proposed in this study lets us obtain favorable evidence for a positive and significant risk–return tradeoff.

This study examines the relationship between risk and expected return in several emerging markets, using Latin American, Asian, Eastern European and African countries. Despite the multitude of literature focused on developed markets, there has been insufficient attention on emerging markets. The main contributions of this paper are the following. Firstly, an alternative empirical methodology through a Regime Switching (RS) model is considered against most of the previous studies that use a GARCH-M framework. The weak evidence for a risk–return tradeoff in emerging markets in previous studies could be because of a misspecification of the empirical model. The main results show that a specification of a non-linear relationship between return and risk in the short-term is more appealing than the common assumption of a linear risk–return trade-off. Non-linear specifications also allow distinguishing between the patterns followed by this relationship between low and high volatility states. This point is especially interesting in the current period, when the global financial crisis that started in October 2007 still questions most of the classic theoretical models.

[2] The main reason for this choice is that this framework introduces non-linearities in the analysis of the risk–return trade-off against the linear relationship of the GARCH-M framework.

3 Small sample inference is plagued by the fact that conditional volatility has almost no explanatory power for realized return.

Furthermore, differences in risk aversion levels and significance during high and low volatility periods are also detected in these emerging markets. Using this methodology, a positive and significant risk–return tradeoff for the most recent data in most of the emerging markets is obtained. Secondly, the study also shows that for shorter time span strong linear assumption in the risk-return relationship may lead to misleading results. Thirdly, the risk-free rate for each country is considered in contrast to previous studies (De Santis and Imrohoroglu (1997), Shin (2005)). Finally, we show that the risk-return trade-off is essentially observed in low volatility periods where stock markets behave according the economic intuition; however, in high volatility periods this basic relationship between return and risk is not observed.

The paper is organized as follows. Section 2 provides the data. Section 3 develops the empirical framework used in the paper. Section 4 shows the empirical results. Section 5 provides a battery of robustness tests and section 6 concludes.

2.- Data description

This empirical study uses weekly observations for five of the main stock markets in Latin America: Argentina, Brazil, Chile, Mexico, and Peru, nine Asian markets such as China, Indonesia, Malaysia, Thailand, India, Korea, Philippines and Taiwan, five Easter European Countries as Czech Republic, Hungary, Poland, Russian and Turkey and finally three African emerging markets: Morocco, Egypt and South Africa . I also use an aggregate index for Asia, Eastern Europe and Latin America emerging markets[4]. The proxy used for the market portfolio is the Emerging Markets (EM) Morgan Stanly Capital International (MSCI) index computed in US dollars for each country considered. This market portfolio presents two main advantages: first, all the risk due to exchange rate in a specific market is removed; second, allows the comparison between countries because all markets are considered in the same currency.

For each country, it is considered weekly data from January 1995 to December 2010 for a total of 835 observations. The frequency and length of the time series allow the comparison of my conclusions with previous studies analyzing the risk–return trade-off in emerging markets such as De Santis and Imrohoroglu (1997) and Shin (2005). Against the works cited above, the risk-free rate is also considered to compute the excess market returns. I use the monthly money market rate in each country suitably compounded at a weekly frequency[5] as a proxy for the risk-free rate. Thomson Datastream is used to obtain the data about the MSCI indexes and International Financial Statistics for the data corresponding to the risk-free rate. After having computed logarithmic returns[6] for both the market portfolio and the risk-free rate

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[4] The EM MSCI aggregate index for African countries only contains data since 2003, so I decided not to include it to avoid misleading results due to the difference in the length of the sample.

[5] This approach is used in Leon et al. (2007) to avoid the limitations in the availability of the risk-free rate at higher frequencies than monthly.

[6] To facilitate the convergence of the models I consider the logarithmic returns multiplied by 100.

proxies, the excess market returns in each market is obtained as the difference between the two of them.

[INSERT TABLE 1]

Table 1 contains summary statistics for the excess market returns in each country. All excess market return series exhibit non-normal distributions with strong evidence for skewness and kurtosis. This result suggests fat tails in the unconditional distributions. Moreover, the series also show conditional heteroskedasticity problems (autocorrelation in squared market excess returns). GARCH models fit properly to the data with these patterns (fat tails and conditional heteroskedasticity). There is also a common high value of the skewness statistic for all markets.

3.- Empirical specifications

In this section, we present and discuss the empirical models proposed in this study to analyze the risk–return trade-off. Assuming GARCH dynamics for the conditional second moments, we built two models considering linear and non-linear relationships between expected return and conditional variance.

3.1.- GARCH-M framework

The empirical analysis relating to expected return and conditional volatility is traditionally validated using a GARCH-M methodology. Considering the theoretical framework shown above and the assumptions usually established in the previous literature[7] this leads to the following model:

$$r_t = c + \lambda h_t + \varepsilon_t \qquad \varepsilon_t \sim N(0, h_t) \qquad (2) \qquad \text{for i=1,2.....j}$$

$$\varepsilon_t = h_t z_t \qquad z_t \sim N(0,1) \qquad (3)$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \qquad (4) \quad \text{where } \hat{\alpha} + \hat{\beta} < 1 \text{ guarantees the stationarity of the process.}$$

In this model, r_t is the excess market return, h_t is the conditional variance, and ε_t represents the innovations, which are assumed to follow a normal distribution. We estimate this first model using the Quasi Maximum-Likelihood (QML) function of Bollerslev–Wooldridge (1992), which allows us to obtain robust estimates of standard errors.

$$L(\theta) = \sum_{t=1}^{T} \ln\left[f\left(r_t, \Omega_t; \theta\right)\right] \qquad where \qquad f\left(r_t, \Omega_t; \theta\right) = \left(2\pi h_t\right)^{-\frac{1}{2}} e^{-\frac{(\varepsilon_t)^2}{2h_t}} \qquad (5)$$

In this model, the variance appears in the mean equation as a regressor and its parameter can be viewed as the market risk price or the risk aversion coefficient of a representative

[7] These assumptions often include (De Santis and Imrohoroglu (1997), Shin (2005), Karkamar (2007)) constant risk prices, time-varying risk and a constant set of investment opportunities.

investor. Therefore, this parameter reflects the presence or lack of a risk–return trade-off and the sign of this relationship.

In this empirical model, the relationship between market risk premium and conditional variance is linear as suggested by Merton's model. However, several previous studies using this methodology fail to obtain favorable empirical evidence (French et. al (1987), Baillie and De Gennaro (1990)). We show in the next subsection an alternative empirical specification to avoid some of the limitations of the GARCH-M methodology.

3.2.- RS-GARCH framework

The model explained above proposes a linear relationship between return and risk. In this section, we show an empirical model that allows us to introduce non-linearities into this relationship. This specification could be viewed as the empirical validation of the theoretical equilibrium developed in Whitelaw (2000). Whitelaw (2000) concludes that empirical models imposing a strong, often linear relationship between expected returns and volatility (such as GARCH-M models) need to be employed with caution. Given the importance of regime shifts to the results, an RS-GARCH specification is proposed, based on the model originally proposed by Hamilton and Susmel (1989) and Hamilton (1994) that allows us to distinguish between different volatility states governed by a hidden state variable that follows a Markov process.

In this model, the mean equation is not exactly as shown in Equation 2 because it is state-dependent:

$$r_{t,s_t} = c_{s_t} + \lambda h_{t,s_t} + \varepsilon_{t,s_t} \qquad \varepsilon_{t,s_t} \sim N(0, h_{t,s_t}) \qquad (6) \qquad \text{for i=1,2.....j}$$

where r_{t,s_t} , h_{t,s_t} , and ε_{t,s_t} are the state-dependent returns, variances, and innovations, and s_t = 1 (low volatility state) or 2 (high volatility state).

The state-dependent innovations follow a normal distribution, with two possible variances depending on the state of the process. The state-dependent variances are modeled as in Equation 4 allowing different parameters, depending on the state[8]:

$$\varepsilon_{t,s_t} = h_{t,s_t} z_t \qquad z_t \sim N(0,1) \qquad (7)$$

$$h_{t,s_t} = \omega + \alpha_{s_t} \varepsilon_{t-1}^2 + \beta_{s_t} h_{t-1} \qquad (8)$$

The shifts from one state to another are governed by a hidden state variable following a Markov process with a probability transition matrix:

$$\hat{P} = \begin{pmatrix} \Pr\left(s_t = 1 \middle| s_{t-1} = 1\right) = p & \Pr\left(s_t = 1 \middle| s_{t-1} = 2\right) = (1-q) \\ \Pr\left(s_t = 2 \middle| s_{t-1} = 1\right) = (1-p) & \Pr\left(s_t = 2 \middle| s_{t-1} = 2\right) = q \end{pmatrix} \qquad (9)$$

[8] Following Capiello and Fearnley (2000), to facilitate convergence, the constant variance term is not allowed to switch between regimes.

Because of this state dependence, the model is econometrically intractable[9]. We must, therefore, obtain state-independent estimates of variances and innovations. We averaged out according to the *ex ante* probability[10] of being in each state (Dueker (1997)):

$$h_t = P\left(s_t = 1 \middle| \Omega_{t-1};\theta\right) h_{t,s_t=1} + P\left(s_t = 2 \middle| \Omega_{t-1};\theta\right) h_{t,s_t=2} \qquad (10)$$

$$\varepsilon_t = P\left(s_t = 1 \middle| \Omega_t;\theta\right) \varepsilon_{t,s_t=1} + P\left(s_t = 2 \middle| \Omega_t;\theta\right) \varepsilon_{t,s_t=2} \qquad (11)$$

where h_t and ε_t are the state-independent variances and disturbances and

$$P\left(s_t = 1 \middle| \Omega_{t-1};\theta\right) = p * P\left(s_{t-1} = 1 \middle| \Omega_{t-1};\theta\right) + (1-q) P\left(s_{t-1} = 2 \middle| \Omega_{t-1};\theta\right) \qquad (12)$$

and

$$P\left(s_t = 2 \middle| \Omega_{t-1};\theta\right) = 1 - P\left(s_t = 1 \middle| \Omega_{t-1};\theta\right) \qquad (13)$$

are the *ex ante* probabilities, where

$$P\left(s_t = k \middle| \Omega_t;\theta\right) = \frac{P\left(s_t = k \middle| \Omega_{t-1};\theta\right) f\left(r_t \middle| s_t = k, \Omega_t;\theta\right)}{\sum_{k=1}^{2} P\left(s_t = k \middle| \Omega_{t-1};\theta\right) f\left(r_t \middle| s_t = k, \Omega_t;\theta\right)} \qquad (14)$$

where k=1, 2 are the filtered probabilities.

We estimate this model, maximizing the QML function of Bollerslev–Wooldridge (1992), weighted by the filtered probability of being in each state:

$$L(\theta) = \sum_{t=1}^{T} \ln\left[\sum_{k=1}^{2} P\left(s_t = k \middle| \Omega_t;\theta\right) f\left(r_t, \Omega_t;\theta\right)\right] \quad where \quad f\left(r_t \middle| s_t, \Omega_t;\theta\right) = \left(2\pi h_{t,s_t}\right)^{-\frac{1}{2}} e^{-\frac{\left(\varepsilon_{t,s_t}\right)^2}{2h_{t,s_t}}} \qquad (15)$$

3.3.- Asymmetric specifications

To robustness purposes it is also considered the well-known fact that a negative shock has a greater impact in volatility than a positive shock. In all the series analyzed there is a common high value of the skewness statistic. For this reason, it is worthy proposing the consideration of the 'leverage effect' in the empirical model because let us treat in a different way the impact of positive and negative shocks. To reflect this, we use the GJR specification of Glosten et. al(1993) in the variance equation in both linear and non-linear specifications. I just estimate the same models presented above but instead of using equation (4) and (8) we replace them by the following equations:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \delta\eta_{t-1}^2 \qquad (4')$$

$$h_{t,s_t} = \omega + \alpha_{s_t}\varepsilon_{t-1}^2 + \beta_{s_t} h_{t-1} + \delta_{s_t}\eta_{t-1}^2 \qquad (8')$$

[9] See e.g. Gray (1996) or Dueker (1997).

[10] Following Hamilton (1994), the *ex ante* probability is defined as $P\left(s_t = k \middle| \Omega_{t-1};\theta\right)$ for k=1,2 i.e. the probability of being in the k[th] state, given the information up to t-1.

Where δ is a new parameter to be estimated reflecting the impact of negative shocks and $\eta_t = \min(e_t, 0)$. The rest of parameters are the same defined above and I estimate the unknown parameters again maximizing the QML functions in (5) and (15).

4.- Empirical results

This section shows the main empirical results of the risk–return analysis in the emerging markets. I focus my attention on the relationship between expected market returns and conditional volatility rather than the well-known patterns and dynamics followed by volatility in these markets[11]. It is worthwhile noting the results of this relationship because it is the inconclusive point of the previous literature; the expected returns and volatility dynamics are similar in previous studies of emerging markets (Choudry (1996), De Santis and Imrohoroglu (1997), Shin (2005)). This study is directly comparable with previous studies because the choice of data (in terms of frequency[12] and sample size) is similar. Furthermore, the data selection also includes the recent period of the global financial crisis (from October 2007), which is not treated in any previous study for emerging markets.

The left side of Table 2 shows the estimated parameters for the mean equation[13] using the GARCH-M framework for the emerging markets considered. The parameter c represents the constant term (the intercept) and the parameter λ represents the risk aversion parameter; that is the risk–return relationship.

[INSERT TABLE 2]

The main conclusion of these results is that the GARCH-M framework fails to show favorable evidence of the risk–return trade-off in emerging markets. There is no clear evidence about either the sign or significance of the relationship using this approach. Brazil is the only country where a significant trade-off is obtained but is negative. Therefore, the influence of volatility on stock markets is not enough to be significant in the linear framework drawn here. This result is inconsistent with the theoretical model that it is based on. Following Merton's ICAPM, we expect a positive and significant risk–return tradeoff. However, some previous studies also obtained similar results using this framework for both developed and emerging markets (Baillie and Di Gennaro (1990), Glosten et al. (1993), Shin (2005)).

[11] Previous papers (De Santis and Imrohoroglu (1997) and Shin (2005)) analyzing emerging (and Latin American markets) reach similar conclusions about the volatility dynamics. For almost all these countries, there is evidence of time-varying volatility, which exhibits clustering and predictability.

[12] The selection of the data frequency may be a concern. Most previous studies use weekly data in emerging markets. Even though there are slightly differences in the parameter estimations using different data frequencies, there is no particular reason that the conclusions in this study should be affected by the selection of data frequency. Some authors note this point in their studies (De Santis and Imrohoroglu (1997), Shin (2005), Lundblad (2007)).

[13] Estimations for variance equation are not presented to save space. Moreover, the results for the variance equation do not provide any relevant contribution about the risk–return trade-off. They only suggest the volatility dynamics (which is not the objective of the paper).

A potential reason for these results may be that in shorter periods the risk–return trade-off follows a non-linear relationship. The limitations imposing a linear relationship between return and risk are clearly observable in inconclusive previous studies. Whitelaw (2000) states the concerns about the importance of non-linear risk and develops a theoretical framework analyzing the relationship between return and risk in a two-regime economy, remarking the perils of linear models such as GARCH-M.

Right side of table 2 shows the estimations for the RS-GARCH model proposed. In this approach, there are two intercepts and two risk prices (aversion coefficients) corresponding to low and high volatility states. The introduction of regime switching in the empirical analysis lets us establish a non-linear relationship between expected return and conditional volatility as an alternative to the disappointing results obtained when we assume a linear relationship.

The main results for the RS-GARCH estimations show positive and significant estimations for the risk–return relationship in low volatility periods but the results turn non-significant in the high volatility state. With the sample used in this study, I am able to find favorable evidence for a positive and significant risk–return trade-off in most of the emerging markets. In some countries such as Peru, Philippines and Russia this evidence is very strong with significance even at 1% confidence level. In several countries as Argentina, Brazil, Mexico, Chile, Thailand, Egypt, Morocco, Poland, Turkey and the aggregate Asian index the trade-off is significant at 5% level. In some countries, the evidence is weaker just at 10% confidence level as China, Indonesia, India, Korea, Thailand, South Africa, Hungary and the aggregated index for Latin America. Finally in some emerging markets I cannot find evidence of a risk-return trade-off even in the low volatility periods as in the cases of Malaysia and the aggregated European index. This positive evidence is essentially observed in low volatility states where the financial markets are stable. However, the results for the high volatility state reveal a lack of a trade-off in periods of market jitters. None of the parameters in this state is significant at any confidence level (except for Turkey which is significant negative at 5%). Therefore, what this evidence suggests is that a positive and significant risk-return trade-off is only observed during periods of financial stability but this fact is not observed in times of financial turmoil in the emerging stock markets.

Moreover, some interesting results deserve some attention as well. First, the risk aversion coefficients in state 1 (corresponding to low volatility states) are higher than those corresponding to state 2 (high volatility states). This result suggests that there is less risk aversion in high volatility states. This finding is not consistent with the spirit of the theoretical models that suggest that higher volatility should be compensated with higher returns. However, some papers such as Mayfield (2004), Lettau and Ludvigson (2003), and Lundblad (2007) found the same evidence; in high volatility states, there is a decreasing level of risk aversion. One possible explanation could be the different risk aversion profiles for the investors in each state. During calm (low volatility) periods, more risk-averse investors are trading in the markets, but in high volatility periods only the less risk-averse investors remain in the market because they are the only investors interested in assuming such risk levels, decreasing the risk premium demanded during these periods. However, the specification presented here may be confounding expected returns with realized returns, particularly in the less common high volatility states (corresponding generally with recession periods) often associated with low or even negative markets returns (Lundblad, 2007).

The evidence obtained in this paper about a significant trade-off in calm periods but non-significant during high volatility situations may also be related to the findings in papers as Nyberg (2011) and Kim and Lee (2008). These authors find similar evidence in developed markets but establishing the state-dependence of the risk aversion on the business cycles instead of volatility regimes. In a certain way, they are different forms of introducing the non-linear relationship between return and risk but very similar in the sense that many periods corresponding to recessions are associated with high volatility situation states and boom cycles often coincide with low volatility periods in stock markets. In our case, we also support the procyclical risk aversion observed in the paper of Kim and Lee (2008) since in low volatility states (boom periods) the investors show are stronger risk-aversion than during high volatility (recession) periods.

Another interesting result is related with the significance of the constant term. In many countries this parameter presents a significant value. Some authors (Leon et. al(2007)) relate this significance with structural market imperfections. This interpretation is totally plausible in the markets analyzed here which are in developing process and may present some of these imperfections. Moreover, due to the significance of this parameter, its omission could lead to misleading results because the model would be misspecified. However, I explain this issue in more detail in the next section.

Finally, note that the volatility persistence estimated with linear models is usually very high (around 0.9). However, considering two regimes we get a reduction of this persistence overall in the high volatility state where there is a greater impact of the shocks and the impact of these decay more quickly (Marcucci, 2005). Considering just one volatility process could be another of the reasons of the inconclusive results obtained with linear models.

[INSERT FIGURE 1]

Figure 1 presents the smooth probability of being in a low volatility state in each of the emerging markets analyzed. It is not possible to extract a common pattern among all these countries because each country follows its own idiosyncratic volatility process. However, it is worthy to note that in most cases low volatility states governs the volatility process and high volatility states are just present during the crisis periods in each specific country.

4.1.- Diagnosis tests

In this subsection, I perform some specification tests on the standardized residuals from our estimations. The objective is to detect potential misspecifications in our empirical model that could lead to wrong or spurious results. Table 3 shows the diagnosis tests using the standardized residuals for the aggregated Asian, European and Latin American countries case as a representation of all emerging markets[14].

[INSERT TABLE 3]

The first rows in Table 4 show summary statistics for the standardized residuals ($\in_{i,t} = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$), in levels and squares for both GARCH-M and RS-GARCH. The mean values for residuals in levels are around 0 and variance values are around 1. The degree of skewness and kurtosis is also reduced compared with the original series. This reduction is even higher in the RS-GARCH approach, suggesting a better fit for the fat tails in the unconditional distribution. Table 6 also shows the Ljung-Box autocorrelation test; the results show that there is no evidence for autocorrelation in standardized residuals for levels or squares. Finally, at the bottom of the table, there are two order moment tests (developed by Bollerslev and Wooldridge (1992)) to validate the consistency of the QML estimations for deviations from normality. These authors demonstrate that the estimations obtained for the QML estimations are consistent even in the case of deviations from normality if: $E_{t-1}\left(\hat{\in}_{i,t}\right) = 0$, $E_{t-1}\left(\hat{\in}_{i,t}^2\right) = 1$. The results support consistency in our estimation results despite the non-normality patterns of the original series. All the analysis performed for the standardized residuals show that the models proposed reflect the dynamics of both the market risk premium and the conditional second moments. We cannot find any sign or evidence of a potential model misspecification.

5.- Robustness test

The results in the previous section show a significant relationship between expected returns and risk in almost all the emerging markets analyzed. In this section we repeat the empirical analysis both from a linear and non-linear point of view using different specification proposed in the literature to model the mean and the variance equation[15]. More specifically, in the variance equation I consider the asymmetric response of volatility against shock of different sign (the ‘leverage effect’) and I propose a model omitting the constant term in the mean equation (Lanne and Saikkonen (2006), Guo and Neely (2008)).

[INSERT TABLE 4]

Table 4 shows the estimations for the original model with an asymmetric GJR specification in the variance equation[16]. In this case we observe a significant risk-return trade-off of at least at 90% confidence level in 19 of our 24 index analyzed during the

[14] The choice for these markets is purely arbitrary and is done in order to save space. The results for other markets are similar and are available upon request.

[15] All the estimations have been replicated assuming a t-student distribution for the innovation term and the results are very similar to those reported in the paper.

[16] The results are very similar to the symmetric case. For the sake of brevity I just describe bravely the main implications on the risk-return trade-off observed.

low volatility periods. The results for high volatility periods and for the GARCH-M framework are similar than the symmetric case. If anything, these results support the findings obtained above.

[INSERT TABLES 5 AND 6]

Table 5 and Table 6 represent the risk aversion coefficient in the case we omit the constant term in the mean equation for the symmetric and asymmetric variance specification respectively. Lanne and Saikkonen (2006) have pointed out that in many empirical studies analyzing the risk-return trade-off the intercept is included in the model for the conditional mean in the GARCH-M model although, based on the ICAPM, it is not theoretically justified. They failed to find a positive risk-return tradeoff in the U.S stock returns when the intercept is included in the model. However, a positive and statistically significant GARCH-M estimate (using the notation employed in this paper) is obtained when the intercept is excluded. The results of Tables 5 and 6 do not support this evidence for emerging markets. Among the 24 indexes markets analyzed, using the linear framework without constant in only 5 (4 in the asymmetric case) of them we can find a positive and significant tradeoff between return and risk and in some cases this relationship is negative. The results for the non-linear cases show that a significant tradeoff is obtained in 21 (only 13 in the asymmetric case) for low volatility periods and essentially a negative and non-significant relationship is obtained during high volatility periods. But the evidence omitting the constant term in the mean equation are generally weaker than including it. So, in a linear framework one is more likely by imposing the restriction of no constant term in the return equation to find a positive risk-return relation but in the non-linear framework this fact is not observed and the omission of the constant could lead to weaker results. Anyway, as we do not know the true data generating process one could be estimating misspecified models is preferably including the constant term (Guo and Neely (2008)).

Suming up, the main result here is that I can obtain favorable evidence of a positive and significant risk–return tradeoff with a time ‘span’ of approximately 15 years for almost all the emerging countries considered, as it is suggested by the theoretical intuition. However, only in the case of (i) a proper relationship between return and risk (that is, non-linear rather than linear); and (ii) periods identified as low volatility states, I can obtain the empirical evidence supporting the theoretical models. The results shown in this study demonstrate the importance of non-linear risk and RS in the patterns followed by the dynamics and the trade-off between return and risk in emerging markets. Strong linear assumptions about the risk–return tradeoff in shorter ‘spans’ could be the reason for the weak evidence documented in the previous literature.

6.- Conclusions

This study provides a risk–return analysis for almost all of the main stock markets known as Emerging Markets. We analyze different countries in several worldwide regions as Asia, Latin America, Eastern Europe and Africa. Using the standard GARCH-M framework (similar to previous studies in emerging markets), we do not find favorable evidence about a significant risk–return trade-off. However, using a RS-GARCH approach to explore this trade-off I obtain a significant estimation for the risk aversion parameter with a relatively short time span (15 years of data). The results suggest that the RS-GARCH framework can identify a non-linear relationship between expected return and risk for 'shorter' time spans in contrast to the disappointing results of the GARCH-M framework. So, strong linear assumptions analyzing the risk–return relationship in emerging markets must be taken with caution.

The results also provide a relationship between volatility regimes and risk aversion level. The risk aversion level in emerging markets is higher in low volatility states and lower in high volatility states. This suggests that a lower risk premium is demanded during recession when the realized returns are often lower (even negative) than during calm periods. The investor profile in each context may also have an influence on this lower risk aversion coefficient during high volatility periods. Generally, high volatility regimes correspond to periods of recession or low expansion in the country's economy, whereas low volatility regimes correspond with periods of economic expansion and let us link our findings with some papers focused in developed markets that obtain this result as well (Kim and Lee, 2008). Therefore, our study also support the procyclical risk aversion of investors documented for developed markets

References

Baillie, R.T., and De Gennaro R.P., 1990. "Stock returns and volatility." *Journal of Financial and Quantitative Analysis* 25, no. 2, pp. 203–214.

Bali, T.G., Cakici, N., Yan, X., and Zhang, Z., 2005. "Does idiosyncratic risk really matter?" *Journal of Finance* 60, no. 2, pp. 905–929.

Bali, T.G., 2008."The intertemporal relation between expected returns and risk." *Journal of Financial Economics* 87, no. 1, pp. 101–131.

Bollerslev, T., and Wooldridge, J., 1992. "Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances." *Econometric Reviews* 11, no. 2 pp. 143–172.

Capiello, L., and Fearnley, T.A., 2000. "International CAPM with Regime-Switching Parameters." FAME Research Paper Series, rp17, International Center for Financial Asset Management and Engineering

Chiang, T.C., and Doong, S.S., 2001. "Empirical analysis of stock returns and volatility: Evidence from seven Asian stock markets based on a TAR-GARCH model." *Review of Quantitative Finance and Accounting* 17, no. 3, pp. 301–318.

Choudry, T., 1996. "Stock Market Volatility and the Crash of 1987. Evidence for Six Emerging Markets." *Journal of International Money and Finance* 15, no. 6, pp. 969–981.

De Santis, G., and Imrohoroglu, S., 1997. "Stock market and volatility in emerging markets." *Journal of International Money and Finance* 15, no. 6, pp. 561–579.

Dueker, M.J., 1997 "Markov switching in GARCH Processes and Mean-Reverting Stock-Market Volatility." *Journal of Business and Economic Statistics* 15, no. 1, pp. 26–34.

Engle, R.F., Lilien, D.M, and Robins, R.P., 1987. "Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model." *Econometrica* 55, no. 2, pp. 391–407.

French, K.R., Schwert, G.W., and Stambaugh, R.F., 1987. "Expected stock returns and variance." *Journal of Financial Economics* 19, no. 1, pp. 3–29

Ghysels, E., Santa-Clara, P., and Valkanov, R., 2005. "There is a risk–return trade-off after all." *Journal of Financial Economics* 76, no. 3, pp. 509–548.

Glosten, L.R., Jagannathan, R., and Runkle D.E., 1993. "On the relation between the expected value and the variance of the nominal excess return on stocks." *Journal of Finance* 48, no. 5, pp. 1779–1801.

Goyal, A., and Santa-Clara, P., 2003. "Idiosyncratic risk matters!" *Journal of Finance* 58, no. 3, pp. 975–1008.

Gray, S.F., 1996. "Modelling the conditional distribution of interest rates as a regime-switching process." *Journal of Financial Economics* 42, no. 1, pp. 27–62.

Guo, H., and Neely, C. J., 2008. "Investigating the intertemporal risk-return relation in international stock markets with the component GARCH model," *Economics Letters*, vol. 99, no.2, pp. 371-374

Hamilton, J.D., 1989. "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle." *Econometrica* 57, no. 2, pp. 357–384.

Hamilton, J.D., 1994. *Time Series Analysis*, Princeton University Press.

Harrinson, P., and Zhang, H., 1999. "An investigation of the risk and return relation at long horizons." *Review of Economics and Statistics* 81, pp. 1–10.

Karmakar, M., 2007. "Asymmetric volatility and Risk-Return Relationship in the Indian stock market." *South Asia Economic Journal* 8, no. 1, pp. 99–116.

Kim, S. W., and B. S. Lee. (2008). "Stock Returns, Asymmetric Volatility,Risk Aversion, and Business Cycle: Some New Evidence". *Economic Inquiry*, no.46, pp. 131-148.

Lanne, M., and Shaikkonen, P., (2006). "Why is so difficult to Uncover the Risk-Return Tradeoff in Stock Returns?" *Economics Letters*, no. 92, pp. 118-125.

León, A., Nave, J., and Rubio, G., 2007. "The relationship between risk and expected return in Europe." *Journal of Banking and Finance* 31, pp. 495–512.

Lettau, M., and Ludvigson, S., 2003. *Measuring and modelling variation in the risk return trade-off*. Working paper, New York University.

Ludvigson, S.C., and Ng, S., 2007. "The empirical risk-return relation: a factor analysis approach." *Journal of Financial Economics* 83, no. 1, pp. 171–222.

Lundblad, C., 2007. "The risk-return trade-off in the long run: 1836–2003." *Journal of Financial Economics* 85, no. 1, pp. 123–150.

Mayfield, S., 2004. "Estimating the market risk premium." *Journal of Financial Economics* 73, pp. 867–887.

Merton, R.C., 1973. "An intertemporal asset pricing model." *Econometrica* 41, no. 5, pp. 867–888.

Nyberg, H. (2011). \Risk-Return Tradeo in U.S. Stock Returns Over the Business Cycle". Forthcoming in the Journal of Financial and Quantitative Analysis. Available at http://blogs.helsinki./hknyberg/2010/02/10/qr-garch-m.

Shin, J., 2005. "Stock returns and volatility in emerging stock markets." *International Journal of Business and Economics* 4, no. 1, pp. 31–43.

Whitelaw, R., 1994 “Time variations and covariations in the expectations and volatility of stock market returns. *Journal of Finance* 49, pp. 515–541.

Whitelaw, R., 2000. "Stock market risk and return: an equilibrium approach." *Review of Financial Studies* 13, pp. 521–547.

Table 1.- Summary statistics for weekly excess market returns

	Summary statistics for weekly excess market returns						
	Mean	*Variance*	*Skewness*	*Kurtosis*	*JB test*	*LB6*	*LB(6) squares*
Argentina	-0.0540	28.634	-0.7764	8.9830	1493.26***	28.755*	351.818***
Brazil	-0.6793	37.848	-0.8169	6.1116	482.73***	125.61***	529.395***
Peru	0.1962	18.566	-0.1714	7.4347	773.23***	16.309	430.190***
Mexico	-0.0125	20.939	-0.8160	9.7620	1891.19***	41.583***	219.274***
Chile	0.0370	11.634	-1.3262	16.4009	7293.65***	34.061**	186.583***
China	-0.0791	23.981	-0.2772	5.5502	236.97***	18.039	173.181***
Indonesia	-0.1887	49.361	-0.9430	18.2803	8247.16***	80.460***	448.258***
Malasia	-0.0414	19.159	-1.0231	25.2975	17443.3***	97.788***	333.309***
Thailand	-0.1412	29.283	-0.0942	6.7539	491.50***	51.946***	582.739***
India	0.1616	16.743	-0.4341	5.3038	210.88***	40.135***	191.021***
Korea	-0.0223	33.480	-0.9590	14.4785	4711.96***	49.281***	224.261***
Phillipines	-0.0664	18.211	-0.6377	7.7093	828.18***	28.445*	167.802***
Taiwan	-0.0053	15.345	-0.0327	4.8785	122.91***	19.068	86.061***
Egypt	0.1047	15.759	-0.5329	6.7209	521.20***	74.570***	266.139***
Morocco	0.1831	6.206	-0.4811	5.9916	343.59***	34.912**	235.534***
South Africa	-0.0667	16.434	-0.2080	7.6092	745.18***	22.392	519.180***
Hungary	0.0299	28.698	-1.1089	11.4632	2663.13***	46.434***	123.216***
Poland	-0.0882	24.959	-0.4728	5.9675	337.48***	27.847	216.849***
Turkey	-0.5001	55.551	-1.1520	16.6894	6704.63***	28.463*	92.242***
Czech Republic	0.1323	16.434	-0.6497	8.8403	1245.44***	31.395*	329.386***
Russia	0.0161	57.533	-0.1659	7.5360	719.68***	36.294**	455.892***
MSCI Asia	-0.0674	12.245	-0.5714	5.8076	319.70***	35.425***	309.663***
MSCI Europe	-0.0941	20.590	-0.4939	11.3763	2475.02***	52.336***	561.192***
MSCI Latin America	-0.0023	19.154	-0.8682	9.6571	1646.79***	47.227***	513.575***

This table shows the statistics for the sample used in the study. Panel A presents the statistics for excess market returns (multiplied by 100) in each country. Panel B presents the statistics for the risk-free rate returns in each market. J-B test is the Jarque-Bera test for normality. L-B (6) is the Ljung-Box autocorrelation test including six lags for the series in levels. L-B (6) squares is the Ljung-Box autocorrelation test including six lags for the series in squares.***, **, and * represent significance at 1%, 5%, and 10% levels.

*Table. 2- Estimations for the MSCI index using the GARCH-M and RS-GARCH-methodology. (T-stats in parenthesis). ***,**,* represents significance at 1%, 5% and 10%.*

This table shows the estimations for the intercept, the risk aversion parameter and the shock persistence in the emerging markets considered using the symmetric variance specification. T-stats in parenthesis. ***,

	GARCH-M			***RS-GARCH-M***					
Parameter				***State k=1***			***State k=2***		
(t-stat)	c	λ_1	Persist.	c	λ_1	Persist.	c	λ_1	Persist.
Argentina	**0.0033*** *(1.6648)*	**-0.0077** *(-1.4123)*	**0.9984**	**-0.6094** *(-0.5204)*	**0.0939**** *(2.0765)*	**0.9674**	**-0.8429** *(-0.4925)*	**-0.0058** *(-0.1990)*	**0.1631**
Brazil	**-0.0003** *(-0.1192)*	**-0.0160**** *(-2.2417)*	**0.9986**	**-3.8899*** *(-1.8796)*	**0.3283**** *(2.1170)*	**0.9718**	**-0.3735** *(-0.4452)*	**-0.0356** *(-1.1974)*	**0.2460**
Peru	**0.0034** *(1.0102)*	**-0.0134** *(-0.4942)*	**0.9394**	**-2.082***** *-(3.0990)*	**0.0930***** *(2.6489)*	**0.9920**	**1.2366***** *(4.2526)*	**-0.0287** *(-1.4156)*	**0.8906**
Mexico	**0.0048**** *(2.0823)*	**-0.0092** *(-0.6837)*	**0.9539**	**-1.332***** *(-2.9639)*	**0.0278**** *(2.0743)*	**0.9581**	**0.7536***** *(3.2841)*	**-0.0055** *(-0.2179)*	**0.8653**
Chile	**-0.0025** *(-1.1054)*	**0.0278** *(1.1145)*	**0.9582**	**-1.9582** *(-1.6070)*	**0.3749**** *(2.0506)*	**0.9574**	**-1.6822***** *(-2.9749)*	**0.0245** *(1.6416)*	**0.1275**
China	**0.0017** *(0.7048)*	**-0.3891** *(-0.3468)*	**0.9879**	**-1.1206** *(1.5205)*	**0.7943*** *(1.6949)*	**0.9834**	**-1.0071*** *(-1.8155)*	**0.0061** *(0.7329)*	**0.0595**
Indonesia	**0.0019** *(1.0531)*	**0.2078** *(0.3460)*	**0.9885**	**-1.6542** *(-1.5241)*	**0.9417*** *(1.6534)*	**0.9858**	**-1.0883*** *(-1.8517)*	**0.0069** *(0.8024)*	**0.0509**
Malaysia	**0.0013** *(1.2275*	**0.4308** *(0.4836)*	**0.9988**	**-0.2799** *(-1.3606)*	**0.0069** *(0.2958)*	**0.9806**	**0.6476** *(2.5412)*	**0.0043** *(0.4530)*	**0.9725**
Thailand	**0.0020** *(0.8707)*	**-0.3323** *(-0.3157)*	**0.9982**	**-2.2689**** *(-2.0499)*	**0.1119**** *(2.2787)*	**0.9865**	**-0.4497** *(-0.7871)*	**0.0535** *(1.4824)*	**0.8403**
India	**0.0022** *(0.9382)*	**0.3082** *(0.1999)*	**0.9737**	**0.2172** *(0.1700)*	**0.1188*** *(1.8061)*	**0.9281**	**-1.8606**** *(-2.4293)*	**0.0586** *(0.6636)*	**0.1971**
Korea	**0.0006** *(0.3642)*	**0.6988** *(0.9322)*	**0.9837**	**-0.8231**** *(-2.1287)*	**0.0244*** *(1.9266)*	**0.9789**	**0.7654***** *(2.9612)*	**0.0012** *(0.1305)*	**0.9492**
Philippines	**0.0004** *(0.1378)*	**0.6996** *(0.4227)*	**0.9665**	**-0.4497** *-(0.7871)*	**0.1119***** *(2.2787)*	**0.9723**	**-2.2689**** *(-2.0499)*	**0.0535** *(1.4824)*	**0.7873**
Taiwan	**0.0015** *(0.7407)*	**0.2053** *(0.1443)*	**0.9709**	**-1.5389**** *(-2.0643)*	**0.0508*** *(1.6628)*	**0.9629**	**0.5468** *(1.5661)*	**0.0370** *(0.6903)*	**0.3070**
Egypt	**-0.0013** *(-1.2003)*	**1.0308** *(1.2702)*	**0.9868**	**1.7453***** *(3.3960)*	**0.0519**** *(2.0974)*	**0.9759**	**-0.7881***** *(-4.6347)*	**0.0112** *(0.9432)*	**0.7383**
Morocco	**0.0010** *(0.7648)*	**1.3871** *(0.5496)*	**0.9370**	**-0.826***** *(-3.8264)*	**0.0998**** *(2.0660)*	**0.9385**	**0.8595***** *(2.9842)*	**-0.0470** *(-0.8947)*	**0.9206**
South Africa	**-0.0012** *(-0.5483)*	**1.5616** *(0.9941)*	**0.9630**	**-1.4903*** *(-1.9311)*	**0.0672*** *(1.8277)*	**0.9649**	**0.4619** *(1.6020)*	**0.0165** *(0.6672)*	**0.6798**
Hungary	**0.0022** *(0.7426)*	**0.1386** *(0.1255)*	**0.9481**	**-0.7771** *(-0.4731)*	**0.1231*** *(1.7172)*	**0.9818**	**-2.3796***** *-(2.7573)*	*0.0306* *(0.8941)*	**0.0360**
Poland	**0.0004** *(0.1365)*	**0.1476** *(0.1576)*	**0.9601**	**-2.850***** *(-2.6421)*	**0.0952**** *(2.0089)*	**0.9962**	**0.9420**** *(2.3069)*	**-0.0244** *(-1.1923)*	**0.8815**
Turkey	**0.0041** *(0.9713)*	**-1.3477** *(-1.5430)*	**0.9750**	**-12.154**** *(-2.4855)*	**0.5203**** *(2.3014)*	**0.9184**	**1.1348** *(1.4090)*	**-0.0267**** *(-2.4106)*	**0.2182**
Czech Republic	**0.0039*** *(1.7196*	**-0.7682** *(-0.4747)*	**0.9306**	**0.1893** *(0.3387)*	**0.0795*** *(1.7160)*	**0.9540**	**-1.4449*** *(-1.6520)*	**0.0245** *(0.9446)*	**0.1839**
Russia	**0.0045*** *(1.6775)*	**-0.3516** *(-0.5465)*	**0.9898**	**-8.714***** *(-11.014)*	**0.1307***** *(6.7283)*	**0.9585**	**0.7273**** *(2.0076)*	**0.0109** *(1.3975)*	**0.9023**
MSCI Asia	**0.0009** *(0.7896)*	**0.6225** *(0.5238)*	**0.9874**	**-1.3243** *(-1.6044)*	**0.5028**** *(2.0055)*	**0.9877**	**-0.1258** *(-0.1643)*	**-0.0195** *(-0.4128)*	**0.1757**
MSCI Europe	**0.0001** *(-0.0188)*	**-0.1216** *(-0.1098)*	**0.9728**	**-1.1167** *(-1.9689)*	**0.0428** *(1.2895)*	**0.9713**	**0.6415** *(2.3894)*	**-0.0198** *(-1.3140)*	**0.9326**
MSCI Latin America	**-0.0002** *(-0.0713)*	**0.5455** *(0.3832)*	**0.9480**	**-6.9891** *(-1.2647)*	**0.7638*** *(1.7149)*	**0.9274**	**-1.5876**** *(-2.0133)*	**0.0189** *(0.7707)*	**0.0626**

**, and * represent significance at 1%, 5%, and 10% levels. Persist. means the persistence of an unexpected shock in the market volatility and is computed as the sum of the parameters ($\alpha+\beta$) in the variance equation.

Table 3.- Summary statistics for standardized residuals

Index	Model	Stand. resid	Mean	Variance	J-B test	L-B (6)	t-stat for H0:	t-stat for H1:
MSCI ASIA	GARCH	$\hat{\epsilon}_{m,t}$	-0.0052	0.9987	104.6^{***}	53.17^{***}	0.1072	-
		$\hat{\epsilon}^2_{m,t}$	0.9991	3.2501	63235^{***}	17.991	-	0.9899
	RS-GARCH	$\hat{\epsilon}_{m,t}$	-0.0055	1.0328	76.487^{***}	23.164	0.8704	-
		$\hat{\epsilon}^2_{m,t}$	1.0325	2.3578	14148^{***}	6.5294	-	0.8031
MSCI EUROPE	GARCH	$\hat{\epsilon}_{m,t}$	-0.0021	1.0003	208.9^{***}	37.35**	0.9483	-
		$\hat{\epsilon}^2_{m,t}$	0.9996	3.9287	85573^{***}	13.8586	-	0.9959
	RS-GARCH	$\hat{\epsilon}_{m,t}$	-0.0086	1.0548	31.189^{***}	23.911	0.6701	-
		$\hat{\epsilon}^2_{m,t}$	1.0566	3.1097	30146^{***}	0.1861	-	0.5839
MSCI LATIN AMERICA	GARCH	$\hat{\epsilon}_{m,t}$	-0.0418	0.99375	231.4^{***}	30.683^{*}	0.2001	-
		$\hat{\epsilon}^2_{m,t}$	0.9994	3.9964	112873^{***}	12.9796	-	0.9931
	RS-GARCH	$\hat{\epsilon}_{m,t}$	-0.0098	1.0895	35.26^{***}	22.056	0.7829	-
		$\hat{\epsilon}^2_{m,t}$	1.0899	3.5056	8635.2^{***}	2.7955	-	0.4322

This table shows the statistics for the standardized residuals ($\in_{i,t} = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$) for both models used: GARCH-M and RS-GARCH. J-B test is the Jarque-Bera test for normality. L-B (6) is the Ljung-Box autocorrelation test including six lags. This also tests the first two moments of the standardized residuals to validate consistent estimations of the QML procedure from deviations to normality. .***, **, and * represent significance at 1%, 5%, and 10% levels.

*Table 4.- Estimations for the MSCI index using the GJR- GARCH-M and GJR- RS-GARCH-methodology. (T-stats in parenthesis). ***,**,* represents significance at 1%, 5% and 10%.*

This table shows the estimations for the intercept, the risk aversion parameter and the shock persistence in the emerging markets considered using the asymmetric variance specification. T-stats in parenthesis. ***, **, and * represent significance at 1%, 5%, and 10% levels.

	GARCH-M			**RS-GARCH-M**					
				State k=1			**State k=2**		
Parameter *(t-stat)*	c	λ_1	Persistence	c	λ_1	Persistence	c	λ_1	Persistence
Argentina	**0.2465** *(1.1983)*	**-0.0104**** *(-1.9959)*	**0.9927**	**-0.5065** *(-0.4848)*	**0.0906**** *(2.0931)*	**0.9746**	**0.6784** *(-0.9280)*	**-0.0078** *(-0.4925)*	**0.1855**
Brazil	**1.2171***** *(2.9806)*	**-0.0621***** *(-4.7613)*	**0.9813**	**-3.8809*** *(-1.7449)*	**0.3277**** *(1.9818)*	**0.9719**	**-0.3739** *(-0.4412)*	**-0.0356** *(-1.1505)*	**0.2463**
Peru	**-0.2428** *(-1.0764)*	**0.0267** *(1.0729)*	**0.9583**	**-2.0797***** *(-3.7862)*	**0.0929***** *(2.8484)*	**0.9920**	**1.2368***** *(3.8078*	**-0.0287** *(1.2978)*	**0.8909**
Mexico	**0.5719** *(0.2266)*	**-0.0235** *(0.0145)*	**0.9231**	**-2.5091***** *(-3.6486)*	**0.0981***** *(2.8791)*	**0.8766**	**0.7778***** *(3.8334)*	**-0.0109** *(-0.8750)*	**0.6242**
Chile	**-0.2428** *(-1.0764)*	**0.0267** *(1.0729)*	**0.9586**	**-1.0830*** *(-1.9072)*	**0.0830**** *(1.9850)*	**0.9231**	**0.6728***** *(3.3803)*	**-0.0215** *(-1.3274)*	**0.9075**
China	**0.3981** *(0.5491)*	**-0.0142** *(-0.7097)*	**0.9746**	**-1.2315** *(-1.3072)*	**0.1910*** *(1.7866)*	**0.9857**	**-0.5112** *(-0.7200)*	**-0.0026** *(-0.1183)*	**0.2833**
Indonesia	**0.2201** *(1.1952)*	**-0.0050** *(-0.7771)*	**0.9777**	**-8.4867** *(-1.0467)*	**1.0324***** *(3.0577)*	**0.9874**	**-1.0759** *(-0.3190)*	**0.0072** *(0.0436)*	**0.0484**
Malasia	**0.1032** *(1.0026)*	**0.0028** *(0.3204)*	**0.9935**	**0.6455***** *(3.6438)*	**0.0032** *(0.2612)*	**0.9807**	**-0.2349** *(-1.2471)*	**0.0054** *(0.3606)*	**0.9721**
Thailand	**0.1284** *(0.5397)*	**-0.0051** *(-0.4463)*	**0.9871**	**-0.2359** *(-0.4102)*	**0.0674***** *(2.1222)*	**0.9832**	**-0.3847** *(-0.6931)*	**-0.0137** *(-0.7104)*	**0.8897**
India	**0.2772** *(1.2178)*	**-0.0025** *(-0.1666)*	**0.9687**	**-11.225***** *(-20.2009)*	**0.1619***** *(3.7981)*	**0.9999**	**0.1439** *(0.6080)*	**0.0234** *(1.3371)*	**0.7360**
Korea	**0.0009** *(0.0054)*	**0.0021** *(0.2946)*	**0.9747**	**-0.8469**** *(-2.3028)*	**0.0242*** *(1.6435)*	**0.9793**	**0.7807**** *(1.9605)*	**0.0013** *(0.0619)*	**0.9943**
Phillipines	**0.0798** *(0.3046)*	**-0.0013** *(-0.0769)*	**0.9587**	**-0.3445** *(-0.4684)*	**0.1107*** *(1.6971)*	**0.9739**	**-1.9929***** *(-3.5068)*	**0.0456** *(1.6290)*	**0.8012**
Taiwan	**0.2141** *(0.9112)*	**-0.0068** *(-0.4135)*	**0.9708**	**-1.7062**** *(-2.2161)*	**0.0601*** *(1.6903)*	**0.9247**	**0.5258** *(1.1218)*	**0.0387** *(0.5164)*	**0.2266**
Egypt	**0.0139** *(1.5272)*	**-0.1422** *(-1.3135)*	**1.0071**	**-0.8151***** *(-4.2283)*	**0.0267** *(1.5545)*	**0.9999**	**1.3689***** *(3.7862)*	**-0.0238** *(-0.9963)*	**0.9242**
Morocco	**0.1287** *(0.0243)*	**0.0065** *(0.0243)*	**0.9382**	**-0.7708***** *(-3.4016)*	**0.0830*** *(1.7333)*	**0.9349**	**0.8995***** *(2.8602)*	**-0.0463** *(-0.8154)*	**0.9186**
South Africa	**0.0001** *(0.0006)*	**0.0025** *(0.1469)*	**0.9231**	**-1.5907***** *(-2.5682)*	**0.0663*** *(1.9340)*	**0.9772**	**0.4485** *(1.9100)*	**0.0236** *(1.1818)*	**0.5980**
Hungary	**0.2227** *(0.8450)*	**-0.0068** *(-0.6371)*	**0.9433**	**-1.5550** *(-1.2636)*	**0.1707*** *(1.9258)*	**0.9684**	**-1.4575**** *(-2.2946)*	**0.0309** *(1.6154)*	**0.3432**
Poland	**0.0369** *(0.1440)*	**0.0007** *(0.0738)*	**0.9591**	**-1.9868**** *(-2.1793)*	**0.0397*** *(1.6503)*	**0.8209**	**0.0898** *(0.0181)*	**0.0277** *(0.0689)*	**0.0397**
Turkey	**0.4060** *(1.0651)*	**-0.0143**** *(-2.144)*	**0.9703**	**-2.1126** *(-1.3860)*	**0.0762*** *(1.6858)*	**0.9881**	**-0.2158** *(-0.2913)*	**-0.0191*** *(-1.9397)*	**0.7428**
Czech Republic	**0.3981*** *(1.6908)*	**-0.0142** *(-0.8269)*	**0.9082**	**0.2329** *(0.2211)*	**0.0719** *(0.4884)*	**0.9305**	**-1.1934**** *(-2.1098)*	**0.0215** *(1.0363)*	**0.1772**
Russia	**0.4428** *(1.6442)*	**-0.0037** *(-0.5830)*	**0.9893**	**-0.1313** *(-0.2300)*	**-0.0002** *(-0.0203)*	**0.9944**	**1.1275*** *(1.8828)*	**-0.0043** *(-0.2979)*	**0.9330**
MSCI Asia	**0.1637** *(1.3389)*	**-0.0101** *(-0.8105)*	**0.9716**	**-1.2134** *(-1.2538)*	**0.4734*** *(1.7354)*	**0.9871**	**0.1510** *(0.4284)*	**-0.0307** *(-1.1566)*	**0.1339**
MSCI Europe	**0.0125** *(0.0698)*	**-0.0038** *(-0.3297)*	**0.9660**	**-1.3635**** *(-2.3256)*	**0.0711**** *(2.0025)*	**0.9649**	**0.5780**** *(2.0865)*	**-0.0221** *(-1.5195)*	**0.9450**
MSCI Latin America	**-0.0082** *(-0.5151)*	**0.0805** *(0.3399)*	**0.9163**	**-1.7886***** *(-2.9394)*	**0.1509** *(0.3485)*	**0.9547**	**-10.4221** *(-0.3296)*	**0.0245** *(1.3025)*	**0.0402**

*Table 5.- Estimations for the MSCI index using the GARCH-M and RS-GARCH-methodology without including constant. (T-stats in parenthesis). ***,**,* represents significance at 1%, 5% and 10%.*

LATINOAMERICA									
Parameter *(std. error)*	***GARCH-M***			***RS-GARCH-M***					
				State k=1			***State k=2***		
Country	*BRA*	*ARG*	*PER*	*BRA*	*ARG*	*PER*	*BRA*	*ARG*	*PER*
λ_1	**-0.0034** *(-0.9746)*	**-0.0164***** *(-4.5717)*	**0.0100** *(1.0480)*	**0.0299***** *(2.5970)*	**0.0227**** *(2.5276)*	**0.0306**** *(2.3202)*	**-0.0046** *(-1.5287)*	**-0.0103** *(-1.2474)*	**0.0018** *(0.1471)*
Country	*CHI*	*MEX*	*MSCI LATIN*	*CHI*	*MEX*	*MSCI LATIN*	*CHI*	*MEX*	*MSCI LATIN*
	0.0029 *(0.2870)*	**0.0142*** *(1.9421)*	**0.0046** *(0.5831)*	**0.0416**** *(2.2275)*	**0.0509**** *(2.3994)*	**0.0502**** *(2.0400)*	**-0.0091** *(-0.7313)*	**-0.0081** *(-0.6510)*	**-0.0247** *(-1.5677)*
ASIA									
Parameter *(std. error)*	***GARCH-M***			***RS-GARCH-M***					
				State k=1			***State k=2***		
Country	*CHI*	*INDON*	*MAL*	*CHI*	*INDON*	*MAL*	*CHI*	*INDON*	*MAL*
λ_1	**0.0033** *(0.4884)*	**0.0059** *(1.2332)*	**0.0104** *(1.5173)*	**0.0275**** *(2.0109)*	**0.0592***** *(4.0240)*	**0.0820***** *(4.4463)*	**-0.0162**** *(-2.0097)*	**-0.0085** *(-1.4869)*	**-0.0087** *-(1.0901)*
Country	*THAI*	*INDIA*	*KOR*	*THAI*	*INDIA*	*KOR*	*THAI*	*INDIA*	*KOR*
λ_1	**0.0040** *(0.6330)*	**0.0155*** *(1.8953)*	**0.0089*** *(1.6602)*	**0.0245*** *(1.9556)*	**0.0650**** *(2.2727)*	**0.0337***** *(2.8609)*	**-0.0110** *(-1.4344)*	**-0.0243** *(-0.8771)*	**-0.0030** *(-0.3862)*
Country	*PHIL*	*TAIW*	*MSCI ASIA*	*PHIL*	*TAIW*	*MSCI ASIA*	*PHIL*	*TAIW*	*MSCI ASIA*
λ_1	**0.0090** *(1.1150)*	**0.0109** *(1.3831)*	**0.0132** *(1.3269)*	**0.0397***** *(3.1041)*	**0.0457**** *(2.4795)*	**0.0853***** *(3.9435)*	**-0.0173*** *(-1.8609)*	**-0.0138** *(-0.9572)*	**-0.0227**** *(-2.0111)*
EUROPE									
Parameter *(std. error)*	***GARCH-M***			***RS-GARCH-M***					
				State k=1			***State k=2***		
Country	*CZECH*	*HUNG*	*POL*	*CZECH*	*HUNG*	*POL*	*CZECH*	*HUNG*	*POL*
λ_1	**0.0156*** *(1.8596)*	**0.0086** *(1.4797)*	**0.0025** *(0.4875)*	**0.0427***** *(2.7466)*	**0.0281**** *(2.0847)*	**1.1154***** *(3.6167)*	**-0.0150** *(-1.0595)*	**-0.0193**** *(-2.1362)*	**-0.0055** *(-1.0552)*
Country	*RUSS*	*TURK*	*MSCI EURO*	*RUSS*	*TURK*	*MSCI EURO*	*RUSS*	*TURK*	*MSCI EURO*
λ_1	**0.0033** *(0.8056)*	**-0.0072*** *(-1.8645)*	**-0.0014** *(-0.1990)*	**0.0184*** *(1.7901)*	**-0.0055** *(-0.7175)*	**0.0205** *(1.3067)*	**-0.0014** *(-0.2689)*	**-0.0098*** *(-1.6814)*	**-0.0084** *(-0.9834)*
AFRICA									
Parameter *(std. error)*	***GARCH-M***			***RS-GARCH-M***					
				State k=1			***State k=2***		
Country	*MOR*	*EGYP*	*SOU AF*	*MOR*	*EGYP*	*SOU AF*	*MOR*	*EGYP*	*SOU AF*
λ_1	**0.0104** *(1.5173)*	**0.0040** *(0.6218)*	**0.0089** *(1.1349)*	**0.0539*** *(1.6552)*	**0.0130** *(1.2054)*	**0.0616***** (3.5583)	**0.0223** *(1.4414)*	**-0.0096** *(-0.4153)*	**-0.0132** *(-1.0773)*

This table shows the estimations for the risk aversion parameter in the emerging markets considered in the symmetric case omitting the constant term in the mean equation. T-stats in parenthesis. ***, **, and * represent significance at 1%, 5%, and 10% levels.

*Table 6.- Estimations for the MSCI index using the GJR-GARCH-M and GJR- RS-GARCH-methodology without including constant. (T-stats in parenthesis). ***,**,* represents significance at 1%, 5% and 10%.*

LATINOAMERICA									
Parameter *(std. error)*	***GARCH-M***			***RS-GARCH-M***					
				State k=1			***State k=2***		
Country	*BRA*	*ARG*	*PER*	*BRA*	*ARG*	*PER*	*BRA*	*ARG*	*PER*
λ_1	**-0.0336**** *(-7.0351)*	**-0.0073*** *(-1.7552)*	**0.0064** *(0.6470)*	**0.0214** *(1.3816)*	**0.0070** *(0.5363)*	**0.0326**** *(2.3744)*	**-0.0413** *(-0.5913)*	**-0.0093** *(-0.7125)*	**-0.0160** *(-1.376)*
Country	*CHI*	*MEX*	*MSCI LATIN*	*CHI*	*MEX*	*MSCI LATIN*	*CHI*	*MEX*	*MSCI LATIN*
	0.2910 *(0.2741)*	**0.0056** *(0.7745)*	**-0.0038** *(-0.431)*	**0.0312**** *(1.7331)*	**0.0323**** *(1.7605)*	**0.0255** *(1.3195)*	**-0.0260** *(-1.5689)*	**-0.0113** *(-1.2577)*	**-0.0159** *(-1.578)*
ASIA									
Parameter *(std. error)*	***GARCH-M***			***RS-GARCH-M***					
				State k=1			***State k=2***		
Country	*CHI*	*INDON*	*MAL*	*CHI*	*INDIA*	*MAL*	*CHI*	*INDIA*	*MAL*
λ_1	**-0.0027** *(-0.4240)*	**-0.0004** *(-0.0884)*	**0.0076** *(1.0269)*	**0.0428**** *(2.9401)*	**0.0217*** *(1.7528)*	**0.0278** *(1.2406)*	**-0.0439***** *(3.2648)*	**-0.0164** *(-1.186)*	**-0.0033** *(-0.2599)*
Country	*THAI*	*INDIA*	*KOR*	*THAI*	*INDIA*	*KOR*	*THAI*	*INDIA*	*KOR*
λ_1	**-0.0004** *(-0.0611)*	**0.0137** *(1.6408)*	**0.0021** *(0.3429)*	**0.0199** *(1.4150)*	**0.0561**** *(2.2478)*	**0.0209** *(1.2333)*	**-0.0098** *(-1.2041)*	**-0.0064** *(-0.5194)*	**-0.0102** *(-0.9600)*
Country	*PHIL*	*TAIW*	*MSCI ASIA*	*PHIL*	*TAIW*	*MSCI ASIA*	*PHIL*	*TAIW*	*MSCI ASIA*
λ_1	*0.0033* *(0.4033)*	*0.0062* *(0.7689)*	*-0.0032* *(-0.431)*	**0.0297**** *(2.1527)*	**0.0434**** *(2.2992)*	**0.0463**** *(2.0185)*	**-0.0131** *(-1.1998)*	**-0.0129** *(-1.218)*	**-0.0112** *(-0.9485)*
EUROPE									
Parameter *(std. error)*	***GARCH-M***			***RS-GARCH-M***					
				State k=1			***State k=2***		
Country	*CZECH*	*HUNG*	*POL*	*CZECH*	*HUNG*	*POL*	*CZECH*	*HUNG*	*POL*
λ_1	**0.0098** *(1.0895)*	**0.0003** *(0.0517)*	**0.0018** *(0.2997)*	**0.0450***** *(2.8740)*	**0.0200** *(-0.688)*	**0.0054** *(0.3914)*	**-0.0217** *(-1.5636)*	**-0.0062** *(1.2479)*	**0.0038** *(0.4984)*
Country	*RUSS*	*TURK*	*MSCI EURO*	*RUSS*	*TURK*	*MSCI EURO*	*RUSS*	*TURK*	*MSCI EURO*
λ_1	**0.0067** *(0.8658)*	**-0.0081**** *(-2.0835)*	**-0.0032** *(-0.431)*	**0.0192**** *(1.9619)*	**0.0020** *(0.3037)*	**0.0084** *(0.5263)*	**-0.0190** *(-1.4980)*	**-0.0159** *(-1.419)*	**-0.0076** *(-0.9216)*
AFRICA									
Parameter *(std. error)*	***GARCH-M***			***RS-GARCH-M***					
				State k=1			***State k=2***		
Country	*MOR*	*EGYP*	*SOU AF*	*MOR*	*EGYP*	*SOU AF*	*MOR*	*EGYP*	*SOU AF*
λ_1	**0.0263*** *(1.9221)*	**0.0067** *(0.8658)*	**0.0025** *(0.3150)*	**0.0424** *(0.9808)*	**0.0541***** *(3.8911)*	**0.0491***** *(2.1914)*	**0.0257** *(1.2030)*	**-0.046***** *(-2.869)*	**-0.0065** *(-0.5017)*

This table shows the estimations for the risk aversion parameter in the emerging markets considered in the asymmetric case omitting the constant term in the mean equation. T-stats in parenthesis. ***, **, and * represent significance at 1%, 5%, and 10% levels.

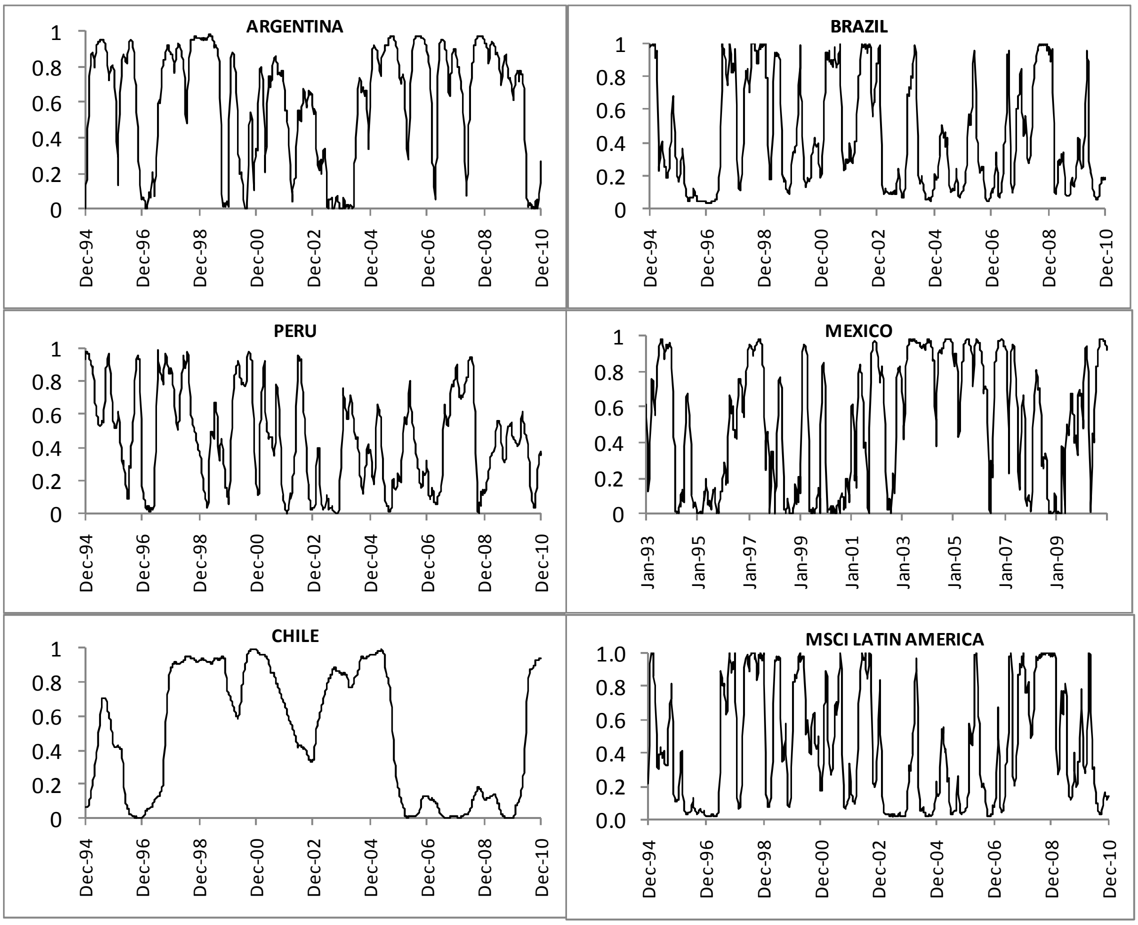

Figure 1.A.- Charts showing the smooth probability of being in a low volatility state in each country during the period 1995–2010 in Latin American Emerging Markets.

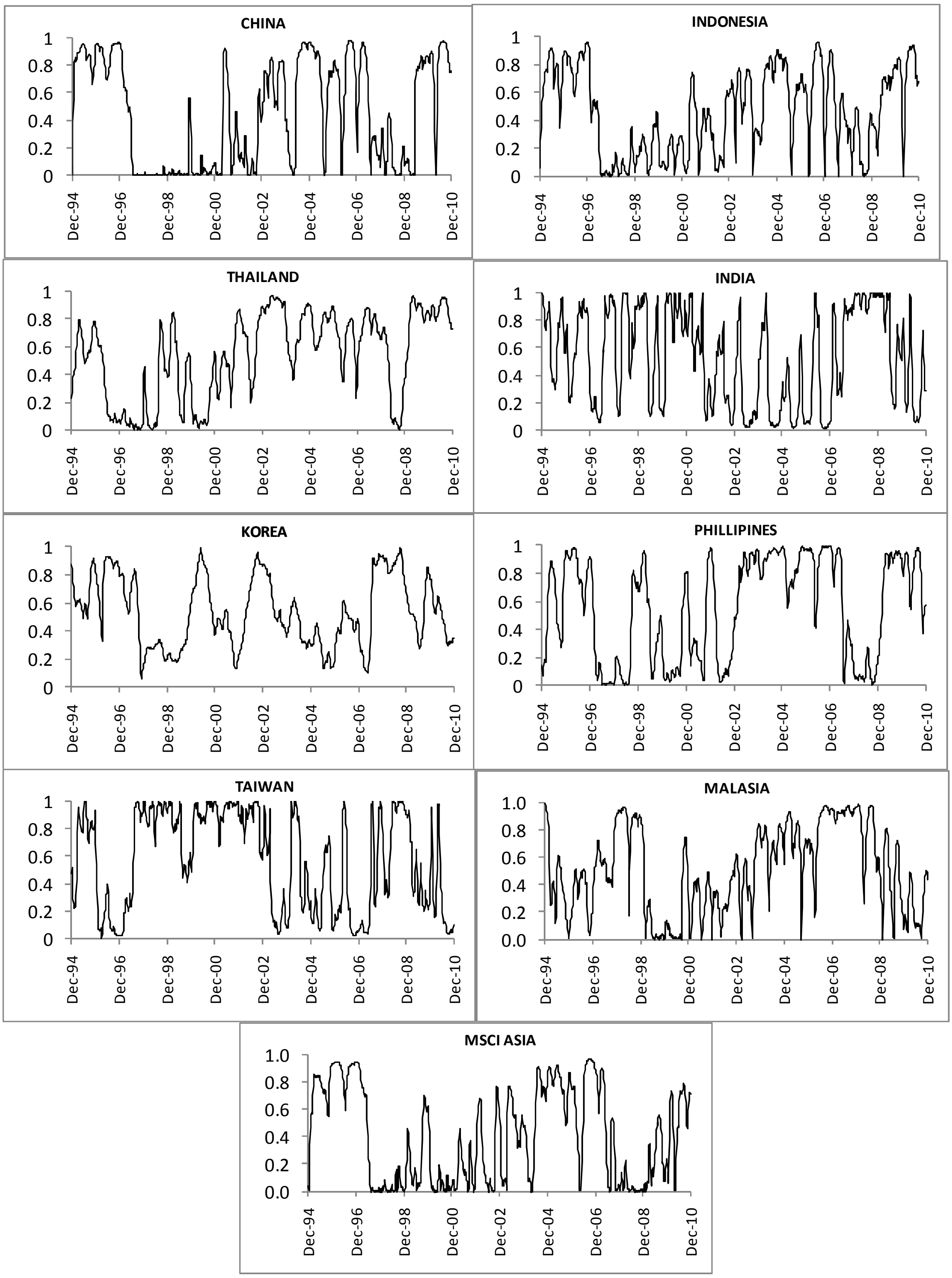

Figure 1.B- Charts showing the smooth probability of being in a low volatility state in each country during the period 1995–2010 in Asian Emerging Markets.

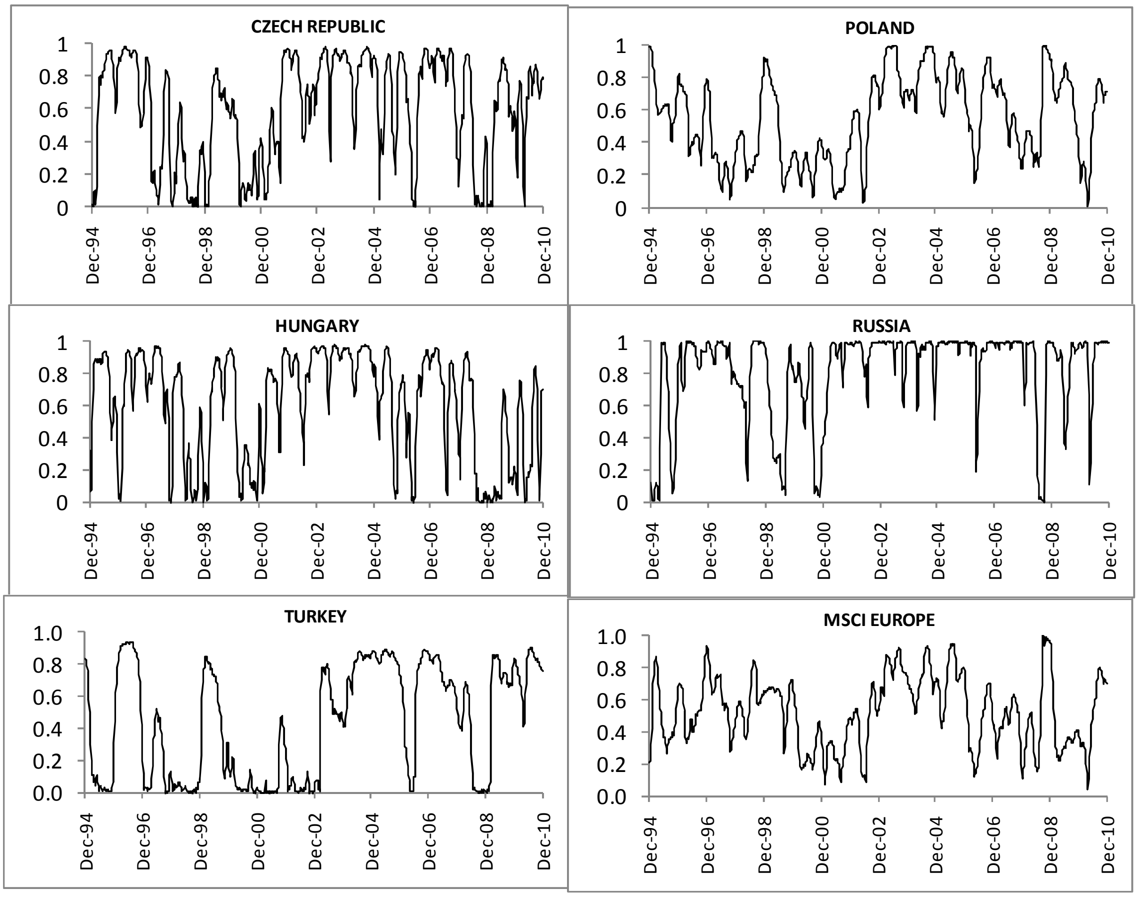

Figure 1.C- Charts showing the smooth probability of being in a low volatility state in each country during the period 1995–2010 in European Emerging Markets.

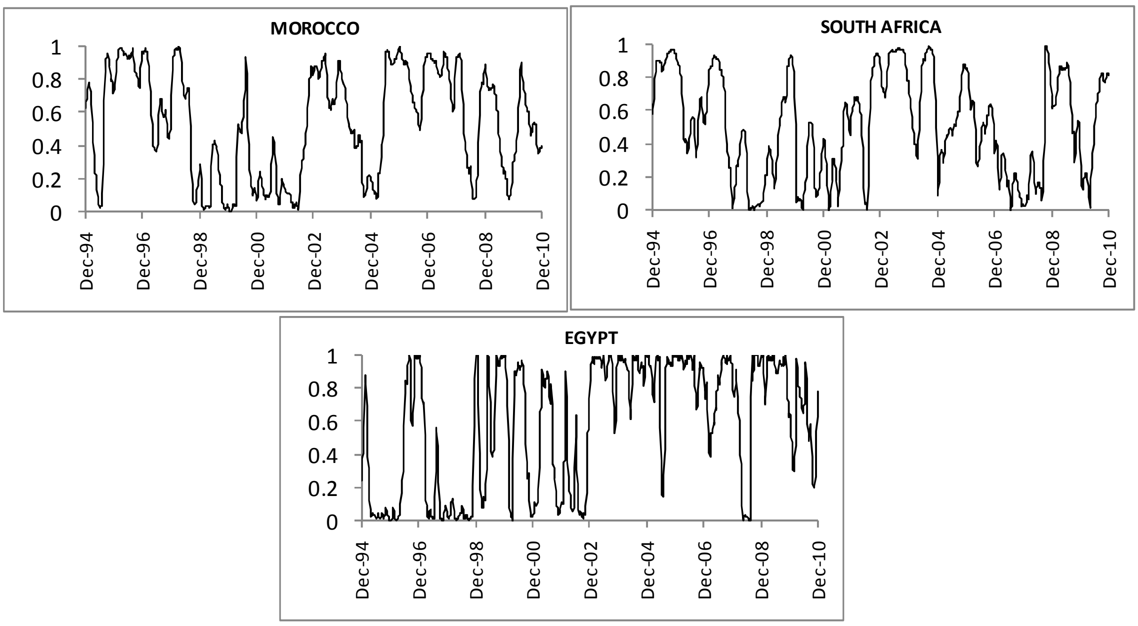

Figure 1.D- Charts showing the smooth probability of being in a low volatility state in each country during the period 1995–2010 in African Emerging Markets.