The Effects of the Subprime Crisis on the Latin American Financial Markets: An Empirical Assessment

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Abstract

The aim of this article is to answer the following question: can the considerable rise in the volatility of the LAC stock markets in the aftermath of the 2007/2008 crisis be explained by the worsening financial environment in the US markets? To this end, we rely on a time-varying transition probability Markov-switching model, in which "crisis" and "non-crisis" periods are identified endogenously. Using daily data from January 2004 to April 2009, our findings do not validate the "financial decoupling" hypothesis since we show that the financial stress in the US markets is transmitted to the LAC's stock market volatility, especially in Mexico.

JEL Classification: C13, C22, G01, G15.

Key Words: Stock markets, volatility, financial stress, regime-switching, Markov-switching model.

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1. Introduction

This paper examines empirically the relationship between the rise in volatility of the Latin American countries (LAC) and the worsening in the financial environment in the US market in the aftermath of the 2007/2008 crisis. We study the respective roles of local factors (regional volatility) and US financial stress factors in the dynamics of the stock market volatility of five LAC (Brazil, Chile, Colombia, Mexico, and Peru). We show that the financial stress in the US markets is transmitted to these countries' stock market volatility, but not in the same scale. Our findings support the idea of heterogeneity among the LAC markets, in the sense that the 2007/2008 subprime crisis did not equally affect all the countries, despite the fact that high volatility of the equity prices was observed everywhere. This is in accordance with the two views that have been at the centre of the policy debate in Latin America regarding the vulnerability of the financial markets to the subprime crisis.

On the one hand, one may claim that the LAC's banking and financial sectors showed resilience to the crisis and put forward the thesis of a financial decoupling with respect to the rest of the world (see Powell and Martinez (2008) and Pereira Valadao and Gico Jr. (2009) among others). Although the countries initiated vast liberalization reforms of their financial markets, they still had a low market capitalization, a weak financial depth and the banking intermediation represented almost 90% of the non-financial corporate financing before the crisis. The spectacular development of market capitalization was the fact of only a few big companies. Furthermore, many domestic banks remained solvent and profitable, had healthy capital adequacy ratios and median return on equity. Above all, the domestic banks held few of the "toxic assets" that triggered the subprime crisis. According to this view, the crisis in the LACs was essentially the consequence of a factor that is not related to a "financial channel", namely the precipitous decline in prices of raw materials which reversed the growth rates of the last five years.[2] So, a downward movement in the terms of trade was the dominant factor of the economic collapse (IMF (2008), Powell and Martinez (2008) and Pereira Valadao and Gico Jr. (2009)).

On the other hand, one can think about the influence of financial factors, given the degree of integration between the LAC's financial markets and the United States'. Empirical papers studying the co-movements across stock markets report increasing correlations during the past five years, especially since 2007 (see Gonzalez-Hermosillo and Hesse (2009)). Studies by the IMF (2008) also point to spillover effects from the US financial markets to the LAC's through different channels (equity market channel, market risk premium, global credit, etc.). Besides, there are cross-border effects implying that LAC financial markets are integrated with advanced economies. Indeed, many LAC have endured the sharp decrease in the US liquidity market (a typical example is Mexico), have suffered from funds withdrawals (as foreign banks transferred resources to their central offices), and the equity markets accumulate losses that threat the life of some companies (examples are Chile and Colombia).

We do not examine in this paper the question as whether the financial stress in the US during the subprime crisis propagated to the LAC through real or financial channels. Recent studies show that these channels were in fact intertwined (for an illustration, see Paiva (2009)). We rather concentrate on the financial linkage and examine empirically the link between the US

[2] In this paper we focus our attention on the "financial channel" and on testing the financial decoupling hypothesis. While interesting, the question as whether the LAC equity markets were affected by the subprime crisis through raw materials or real channels is beyond the scope of the paper.

subprime crisis and the volatility of the LAC stock markets. There are several motivations to focus our attention on volatility. First, volatility of equity prices is usually viewed as an indicator of financial stress for the different segments of financial markets. Secondly, over the last ten years, the volatility of LAC financial markets has become a key determinant for explaining the risk-taking behaviors of investors, especially the substitution in their portfolios between different categories of securities (corporate and government bonds). Thirdly, as volatility tends to decline (resp. increase), it releases (resp. augments) risk budgets of financial firms and encourages (resp. discourages) position-taking. In particular, during the subprime crisis, the observed changes in volatility determined adjustments in domestic balance sheets and leverage conditions.

We thus aim at answering the following question: can the considerable rise in the volatility of the LAC equity markets in the aftermath of the 2007/2008 crisis be explained by the worsening financial environment in the US markets? As previously mentioned, the answer to this question is not straightforward. Indeed, due to the disastrous consequences of the financial crises they faced during the decades of 1990 and 2000, LAC's policymakers adopted measures aiming at insulating their markets from external shocks. Firstly, they adopted macroeconomic policies to avoid future crises due to flawed fundamentals.[3] Secondly, there was a passionate debate among the policymakers regarding the opportunity of adopting measures such as capital controls as a management tool in times of crises. Mexico and Argentina opted for a total liberalization, while Brazil, Chile and Colombia chose to adopt capital controls during the years preceding the 2007 crisis. The question of financial decoupling is still a debated issue in Latin America.

Several econometric models have been used in the literature to study the coupling and decoupling between the LAC stock markets and financial stress in international capital markets. Recent studies have looked at this issue during the subprime crisis (Frank et al. (2008), Berglof et al. (2009), Gonzalez-Hermilloso and Hesse (2009), Rose and Spiegel (2009)). In terms of model specification, many of them rely on VAR models, multivariate GARCH models, or time-varying common factor models. In this paper, we re-examine this issue using a more powerful econometric tool, namely a time-varying transition probability Markov-switching model (TVPMS) proposed by Kim et al. (2008). Compared to the previous ones, this model has the advantage of being helpful in investigating whether the impact of the financial stress indicators is nonlinear, with an influence differing between crisis and non-crisis episodes. Crisis and non-crisis regimes are identified endogenously, and the switch from one regime to the other can happen at any time. In other words, contrasting with structural break models, the time of the changes is not forced *a priori*, and we do not separate, *ex ante*, the sample into two parts with respect to a given time. Our study therefore contributes to the empirical literature on financial contagion, as it investigates the transmission mechanisms of crises.[4]

The rest of the paper is organized as follows. Section 2 presents the data, some stylized facts on the volatility of the LAC equity markets and their links with the US market. They suggest both the presence of an asymmetric dynamics and co-movements with the financial stress indicators in the US markets. In Section 3, methodological concerns relating to TVPMS

[3] The IMF economic outlooks for LAC in 2007 and 2008 show that these countries had good economic fundamentals during the subprime turmoil.

[4] For other recent contributions, see Dungey et al. (2010), Aloui et al. (2011), Barba and Ceretta (2011), Breuss (2011).

models are outlined. In Section 4, we estimate and comment the different TVPMS models. Finally, Section 5 concludes.

2. Data and stylized facts on the volatility of LAC stock markets in the aftermath of the subprime crisis

2.1. Data

We investigate the links between the financial markets of the US and five Latin American countries for which we have a complete database: Brazil, Chile, Colombia, Mexico, and Peru. To this end, we use daily data for the following series: equity market indices for the five considered Latin American countries. To ensure that our results are not specific to a particular stock price series, two equity indices are considered for each country. On the one hand, we rely on the S&P/IFCI price indices, that are subsets of S&P/IFCG indices,[5] and measure the returns of stocks that are legally and practically available to foreign investors. On the other hand, we use the following stock market indices: (i) BOVESPA price index for Brazil, (ii) Chile INTER10 price index for Chile, (iii) IGBC price index for Colombia, (iv) BOLSA price index for Mexico, and (v) LIMA SE price index for Peru.

To choose the financial variables that could have affected the LAC equity price volatility, we refer to the literature[6] suggesting that several adverse spillover effects may explain the transmission of the global crisis to the LAC's financial sectors: (i) the slowdown in total lending by foreign parent banks to their local affiliates due to liquidity constraints in interbank markets (credit crunch transmission channel), (ii) sudden stop effects implied by liquidity risks in the international markets and inducing withdrawals of liabilities owed to nonresidents, (iii) the lack of access to foreign borrowing, (iv) the losses associated with foreign exchange derivative positions, and (v) banks' exposure to stock market fluctuations. As the global crisis originated in the financial markets of the industrialized countries, these channels are expected to be closely tied with financial stress indicators, particularly those reflecting market and liquidity risks: ABCP (asset-backed commercial papers) and CDS (credit default swap) spreads, bank funding liquidity, stock market liquidity. We use the US S&P 500 stock market index whose squared returns act as a proxy of the US market volatility.[7] The endogenous variables are the respective volatility of LAC's stock markets, defined as the squared returns of the first-difference of the logged stock indices. Data are extracted from Datastream and span the period from January 2004 to April 2009.

2.2. How strong was the link with the US stock markets?

The heterogeneous response of the LAC to the subprime crisis resulted from different degrees of interdependency with the US financial markets. The two extreme cases are, on the one hand, Mexico which has the closest ties given its membership to NAFTA and cross-border capital flows, and, on the other hand, Brazil whose regulatory framework imposes constraints

[5] S&P/IFCI indices typically cover a high percentage of the stocks in the S&P/IFCG indices.

[6] See IMF (2008) and Berkmen et al. (2009).

[7] The complete description of data is given in Appendix 1. For Colombia, many data on the S&P/IFCI equity index were lacking, so for this country we only consider the IGBC stock index series. The series are transformed into first-difference since the unit root tests show that they are I(1) (results available upon request to the authors).

on risk-taking behaviors. Regarding the presence of foreign banks in the domestic banking sector, their share varies from only 15% in Peru to 80% in Mexico, thereby implying that the banking disturbances in the US have had less impact in some countries relative to others. In Brazil, for instance, the market share of foreign banks in local banking system is only 30%, 20% in Colombia, while it is 50% in Chile and Mexico. Contagion effects from the subprime crisis were also different across countries due to differences in financial regulation. For instance, the Brazilian government has imposed strict transparency requirements on the report of net asset values of hedge and equity funds so that investors did not choose to long lock up for their investments and rarely take illiquid positions. Conversely, up until the 2008 crisis, private equity funds were less regulated in Mexico, and contagion effects are more important because investors are under pressure not to outperform their competitors in the US and in the sub-region. Besides, compared with Mexico, countries like Brazil, Chile and Peru did not experience a major financial crisis for the following reason. As shown by the ECLAC (2009), countries that were the most affected by the financial turmoil in the US market were also those which were the more severely hit by the adverse shocks on export earnings. Due to their tightest link with the Asian emerging countries, Brazil, Chile and Peru have continued to export towards the Asian markets that showed a decoupling from the rest of the world. As a consequence, there was less uncertainty in these countries' stock markets relative to Colombia or Mexico, because the impact on growth of the adverse shocks due to the drop of export earnings was weaker. In Mexico, growth deceleration was characterized by a drop in GDP from 3.3% in 2007 to 1.3% in 2008 and -7% in 2009. By contrast, in Brazil, the GDP decreases from 5.5% to 5.1% between 2007 and 2008 and to -0.8% in 2009. In Chile, the growth rate was respectively 5.1%, 3.2% and -1.0% in 2007, 2008 and 2009, and in Peru 9.0%, 9.8% and 2%.

2.3. How did the volatility evolve during the crisis?

INSERT FIGURE 1 ABOUT HERE

Figure 1 summarizes preliminary evidence regarding the squared returns of the stock indices,[8] by highlighting a huge increase in volatility during the year 2008. The figures also show higher volatility before the onset of the subprime crisis period ("local" peaks). Moreover, the highly leptokurtic distributions of the squared returns suggest a non-constant and time-dependent volatility. To account for these characteristics, we estimate alternative GARCH-type models to see whether they capture a phenomenon of volatility clustering. Figure 2 shows the graphs of the volatility derived from a simple GARCH model.

INSERT FIGURE 2 ABOUT HERE

The GARCH specification puts forward the existence of changing regimes in the volatility of stock markets. Indeed, in September 2008, the stock returns volatility increases strongly in the five countries. The collapse of Lehman Brothers entailed a wave of stress on LAC stock markets. However, the countries show some peculiarities, which are revealed by the different graphs.

[8] Similar patterns are obtained with the S&P/IFCI indices, but have not been reported here to save space.

Consider first the case of Brazil. During the crisis, the volatility increases at exceptional levels and reaches a maximum around 45[9] at the beginning of October 2008. However, this peak of volatility is not long-lasting, because the volatility falls once after (achieving levels close to 5). The crisis thus induced a sudden increase in volatility, but of low duration, in the Brazilian stock market. Turning to Chile, the movements of volatility are a little bit different. We indeed notice a surge in October 2008, but also a strong increase at the beginning of the year. The market underwent a situation of stress before the collapse of the world stock markets. We also observe that the amplitude of the volatility is not the same as in Brazil, because, in non-crisis periods, the volatility varies between 0.5 and 2 depending upon whether the market is in a phase of low or high volatility. From the year 2008, the volatility increases, until reaching a peak around 15 in October, and then decreases smoothly at levels comparable to those preceding the year 2008.

Regarding Colombia, the pattern exhibits differences in comparison with the other countries. This country experienced a very sudden acceleration of its volatility during the months of May and June 2006, achieving a level of 70. This period was characterized by a strong fall of the stock market returns. Indeed, a 10% fall in the index forced the stock market authorities in Bogota to suspend their operations for the first time of their history. After this period, the volatility stabilizes near 2. A second period of stress appears at the beginning of 2008, but of much weaker intensity, since the volatility reaches "only" a level of 23. Finally, like the other countries, Colombia underwent the effects of the fall of the world stock markets in October 2008, and its volatility increased quickly. Like Colombia, Mexico experienced a situation of financial stress on its stock market during the month of June 2006, but in a much lesser proportion (its volatility was only near 8). However, the volatility increased at the end of the years 2007 and 2008.

Finally, Peru underwent episodes of exceptional volatility during the financial crisis, particularly after the fall of Lehman Brothers: the volatility reaches a level equal to 125 in October 2008, increasing the risk of variations of the short-term returns. A strong period of volatility also appears at the end of the year 2007 till the middle of 2008, caused by the important phase of stress during which the stock market decreased by 70 %.

2.4. Evidencing the regime-dependent characteristic of volatility

We estimate alternative GARCH-family models to investigate whether the squared returns show time-varying dynamics in the volatility of stock returns. In particular, we are interested in detecting asymmetric dynamics, regime-dependent behaviors, smooth and rapid transition from low (resp. high) to high (resp. low) volatility, and highly persistent volatility regimes during a period that includes the months of the subprime crisis. Tables A1 and A2 in Appendix 2 display the values of the information criteria corresponding to the different estimated models.[10] They show an overwhelming evidence that the models that account for regime-dependent volatility uncover the data better than the others. For the S&P/IFCI series,

[9] These figures regarding the level of volatility are given only for comparison purposes across countries (they have no unit).

[10] The estimated GARCH models are the following: GARCH, Exponential GARCH (EGARCH), Power GARCH (PGARCH), Logistic and Exponential Smooth Transition GARCH (LSTGARCH and ESTGARCH), Asymmetric Nonlinear Smooth Transition GARCH (ANST-GARCH) and Quadratic GARCH (QGARCH). To avoid too many tables, and because this paper focuses on alternative regime-dependent models, the estimates are not reported but are available upon request to the authors.

both the LSTGARCH and ESTGARCH nonlinear models indeed yield the lowest values of the information criteria and the highest maximum likelihood. For the other stock returns series, the LSTGARCH model is also the best specification for Colombia, Mexico and Peru, while the Q-GARCH and EGARCH models fit better the nonlinear asymmetric behavior of the squared returns of Brazil and Chile.

The nonlinear GARCH models provide evidence that we should rely on regime-dependent volatility models to account for the properties of the squared returns. However, regarding our main objective—testing the hypothesis of a link between the degradation of US financial markets and the volatility of the LAC stock markets—using autoregressive models is not enough. Indicators of financial stress in the US markets can be considered as "common factors" to the LAC countries, explaining why we observe "explosion" of volatility at the same dates in the five equity markets (2006 for Colombia and Mexico, 2007 and 2008 for all the countries). These common factors are, for instance, the ABCP and CDS spreads, the US market liquidity, or the interbank market rates. Figures 3 through 6 show that these variables exhibit a high variability during the periods of increasing volatility in the equity markets in the five Latin American countries.

INSERT FIGURES 3 THROUGH 6 ABOUT HERE

Common markets factors are not easily handled in standard GARCH-family models[11] because they imply strong restrictions for the conditions of stationarity and non-negativity of the variance (see for instance Hwang and Satchell (2005)). Alternative models have thus been suggested in the literature, such as factor models which have been found very successful.[12] These models are however not suited for our goal. Indeed, we do not seek to discriminate between countries' volatility changes induced respectively by idiosyncratic and common components. We focus on components related to worldwide variables and want to see how they affect the volatility regime. We accordingly consider an alternative framework—time-varying probability Markov-switching model—to investigate whether the regime-dependent property of the volatility can be explained by the financial stress indicators in the US market.

To ensure that the volatility of all stock returns is well described by nonlinear, Markov-switching processes and not by structural changes, we test the hypothesis of linearity against the alternative of a Markov-switching model following the methodology proposed by Carrasco et al. (2009). Their testing approach covers the class of Markov-switching models where the parameters vary according to an unobservable Markov chain and for which the standard approaches do not apply (due to the presence of nuisance parameters). The test requires the estimation of the model under the null hypothesis of parameter stability and relies upon bootstrap simulations in order to compute the critical values. Results are reported in Table A3 in Appendix 2 and show that, for all the countries and all the endogenous variables, the null hypothesis of no regime change is strongly rejected in favor of the alternative of two-state Markov-switching models.

[11] Such models are called GARCHX models.

[12] See, among many others, Engle et al. (1990), Campbell et al. (2001), Connor et al. (2006), Clements and Collet (2008).

3. TVPMS models of the volatility of the LAC stock returns

3.1. Motivation and main characteristics

We estimate time-varying probability Markov-switching (TVPMS) models in order to account for changes in volatility regimes. We adopt the framework proposed by Kim et al. (2008) which has the advantage of considering the correlation between the two noises that respectively define the process under examination and the transition probabilities. We consider "ordinary" regimes characterized by low variations of the price indices, and identify "crisis" or "turbulent" regimes when they manifest with large price deviations (high volatility). The TVPMS models are more suited for our analysis than other early warning systems or signal extraction models (logit/probit models, event analysis, signal approach) for the following reasons.

First, the signal approach requires an *ex ante* definition of a threshold level above which one considers that a crisis is triggered. Similarly, the logit/probit analysis requires the definition of a crisis dummy, with possible misspecifications. One advantage of the TVPMS model is that we let the model determine endogenously which days correspond to low and high volatility.

Secondly, the TVPMS model can be considered as the autoregressive representation of a probabilistic nonlinear GARCH model, and is thus more general than a usual deterministic nonlinear GARCH model. This model mimics the volatility as resulting from a learning phenomenon with investors making a Bayesian inference on the process that governs volatility changes. The volatility dynamics is time-varying, with the volatility today being influenced by its past level according to the value taken by a third variable. The latter is unobserved, and the way in which regime shifts from low to high volatility occur is not known with certainty. For instance, regarding the numerous factors that usually affect the equity price volatility in the LAC (economic policies, speculation, contagion channels stemming from trade or financial linkages), we cannot say *a priori* that the turmoil in the American financial markets was the root cause of the observed increased volatility of the LAC equity markets during 2008. The only thing we can say is that this may have been the case with a given likelihood. The TVPMS model precisely tries to evaluate this likelihood.

Thirdly, since we are looking for changes in volatility regimes that are associated with the crisis, the kind of underlying regime change is assumed to happen only occasionally and to take the form of discrete events. Such changes are not adequately captured by standard nonlinear GARCH models since the latter assume that changes occur continuously over the sample.

3.2. The empirical model

We define the endogenous variable y_t ($t = 1, \ldots, T$) as the first-difference of the squared stock returns. The TVPMS model is defined as follows:

$$y_t = \begin{cases} \alpha_1 + \beta_1 y_{t-1} + \sigma_1 \varepsilon_t, & \text{with a probability } p_{1j}(z_t) \\ \alpha_2 + \beta_2 y_{t-1} + \sigma_2 \varepsilon_t, & \text{with a probability } p_{2j}(z_t) \end{cases}, \tag{1}$$

where $\varepsilon_t \backsim \text{i.i.N}(0,1)$. $\alpha_1, \alpha_2, \beta_1, \beta_2, \sigma_1, \sigma_2$ are scalars. y_t is assumed to "visit" two regimes: a high volatility regime corresponding to crisis periods, and a low volatility regime capturing non-crisis or "normal" periods. The occurrence of a regime is referred by an unobserved state variable s_t that takes two values: 1 if the observed regime is 1 and 2 if it is regime 2.[13]

s_t is conditioned by $s_{t-1}, s_{t-2}, \cdots, s_{t-k}$. At any time $\tau < t$, the regime that will be observed at time *t* is not known with certainty. We thus introduce a probability *P* of occurrence of s_t given the past regime. We assume, for purpose of simplicity, that s_t is a first-order Markov chain with transition probabilities:

$$P\{s_t = i/s_{t-1} = j, z_t\} = p_{ij}(z_t), \qquad (2)$$

where z_t is a vector of predetermined "transition" variables that govern the transition from one regime to the other (stress indicators in the US market).

Assuming a Probit specification[14] for the occurrence of z_t on s_t, we have:

$$s_t = \begin{cases} 1, & \text{if } \eta_t < a_1(s_{t-1}) + b_1(s_{t-1})z_t \\ 2, & \text{if } \eta_t \geq a_2(s_{t-1}) + b_2(s_{t-1})z_t \end{cases}, \qquad (3)$$

where $\eta_t \sim \text{i.i.} N(0,1)$. We also suppose that $\begin{bmatrix} \varepsilon_t \\ \eta_t \end{bmatrix} \sim N(0, \Sigma)$, $\Sigma = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$ and $\text{cov}(\varepsilon_t, \eta_{t\pm h}) = 0, \forall h \neq 0$.

We accordingly define the transition probabilities as follows:

$$\begin{cases} P\{s_t = 1/s_{t-1} = j\,, z_t\} = p_{1j}(z_t) = \Phi(a_1(s_{t-1}) + b_1(s_{t-1})z_t) \\ P\{s_t = 2/s_{t-1} = j\,, z_t\} = p_{2j}(z_t) = 1 - \Phi(a_2(s_{t-1}) + b_2(s_{t-1})z_t) \end{cases}, \qquad (4)$$

where Φ is the standard Normal cumulative distribution function.

The usual probabilistic properties for the ergodicity and the invertibility of the TVPMS model applies if we assume that y_t and z_t are covariance-stationary.[15]

The above model can be generalized to a higher number of states (see Kim et al. (2008)) and encompasses several classes of Markov-switching models previously proposed in the literature. It is very similar to the time-varying probability models introduced by Goldfeld and Quandt (1973), Diebold et al. (1994), Filardo (1994), but it is more general by assuming that the two processes ε_t and η_t are correlated ($\rho \neq 0$) and that the variances across regimes are not the same. When $b_j = 0$, the model reduces to the constant probability model proposed by Goldfeld and Quandt (1973) and Hamilton (1989).

[13] We do not discuss here the question as whether the number of states is equal to or different from 2. The interested reader may refer to Hamilton (1991), Hansen (1992), and Garcia (1998).

[14] Any functional form of the transition probabilities that maps the transition variables into the unit interval would be a valid choice for a well-defined log-likelihood function: logistic or Probit family of functional forms, Cauchy integral, piecewise continuously differentiable variables. We consider here the Normal law because this choice is common wisdom in the applied literature (see Kim et al. (2008)).

[15] See Hamilton (1989).

3.3. Estimation and methodological issues

The above model is estimated via the maximum likelihood (henceforth ML) method with relative minor modifications to the nonlinear iterative filter by Hamilton (1989). We define the following vectors: $\Omega_t = (Y'_{t-1}, Z'_t)$' the vector of observations of *y* and *z* up to time *t-1* and *t* respectively, $\xi_t = (y_t, y_{t-1}, \dots, y_1)$' the vector of observations of the endogenous variable, and $\theta = (\alpha_1, \alpha_2, \beta_1, \sigma_1, a_1, b_1, \beta_2, \sigma_2, a_2, b_{2,}\rho)$' the vector of parameters.

The conditional likelihood function of the observed data ξ_t is defined as

$$L(\theta) = \prod_{t=1}^{T} f(y_t/\Omega_t, \xi_{t-1}; \theta) \tag{5}$$

where

$$\begin{aligned} f(y_t/\Omega_t, \xi_{t-1}; \theta) = \textstyle\sum_i \sum_j f(y_t/s_t = i, s_{t-1} = j, \Omega_t, \xi_{t-1}; \theta) \\ \times P(s_t = i, s_{t-1} = j/\Omega_t, \xi_{t-1}; \theta). \end{aligned} \tag{6}$$

The weighting probability in (6) is computed recursively by applying Bayes' rule:

$$\begin{aligned} P(s_t = i, s_{t-1} = j/\Omega_t, \xi_{t-1}; \theta) &= P_{ij}(z_t) P(s_{t-1} = j/\Omega_t, \xi_{t-1}; \theta) \\ &= P(s_t = i/s_{t-1} = j, z_t) P(s_{t-1} = j/\Omega_t, \xi_{t-1}; \theta) \\ &= P_{ij}(z_t) P(s_{t-1} = j/\Omega_t, \xi_{t-1}; \theta) \end{aligned} \tag{7}$$

We also have

$$\begin{aligned} P(s_t = i/\Omega_{t+1}, \xi_t; \theta) &= P(s_t = i/\Omega_t, \xi_t; \theta) \\ &= \frac{1}{f(y_t/\Omega_t, \xi_{t-1}; \theta)} \textstyle\sum_j f(y_t/s_t = i, s_{t-1} = j, \Omega_t, \xi_{t-1}; \theta) \\ &\quad \times P(s_t = i, s_{t-1} = j/\Omega_t, \xi_{t-1}; \theta) \end{aligned} \tag{8}$$

To complete the recursion defined by Equations (6) and (8), we need the regime-dependent conditional density functions:

$$f(y_t/s_t = 1, s_{t-1} = j, \Omega_t, \xi_{t-1}; \theta) = \frac{\phi\left(\frac{y_t - \alpha_1 - \beta_1 y_{t-1}}{\sigma_1}\right) \Phi\left(\frac{a_j + z'_t b_j - \rho\left((y_t - \alpha_1 - \beta_1 y_{t-1})/\sigma_1\right)}{\sqrt{1-\rho^2}}\right)}{\sigma_1 P_{1j}(z_t)} \tag{9a}$$

$$f(y_t/s_t = 2, s_{t-1} = j, \Omega_t, \xi_{t-1}; \theta) = \frac{\phi\left(\frac{y_t - \alpha_2 - \beta_2 y_{t-1}}{\sigma_2}\right) \Phi\left(\frac{-\left(a_j + z'_t b_j\right) + \rho\left((y_t - \alpha_2 - \beta_2 y_{t-1})/\sigma_2\right)}{\sqrt{1-\rho^2}}\right)}{\sigma_2 P_{2j}(z_t)}, \tag{9b}$$

where ϕ is the standard normal probability distribution.

The parameters of Equations (1) and (4) are thus jointly estimated with ML methods for mixtures of Gaussian distributions. As compared with other estimators (for instance, the EM algorithm or the Gibbs sampler[16]), the ML estimator has the advantage of computational ease. As shown by Kiefer (1978), if the errors are distributed as a normal law, then the ML yields

[16] See Diebold et al. (1994) and Filardo and Gordon (1998).

consistent and asymptotically efficient estimates. Further, the inverse of the matrix of second partial derivatives of the likelihood function at the true parameter values is a consistent estimate of the asymptotic variance-covariance matrix of the parameter values.

It should be noticed that two specifications are encompassed with the TVPMS model, depending upon the value of ρ. If $\rho = 0$, there is no correlation between ε_t and past values of the state variable. In other words, the state variable is exogenous. On the contrary, $\rho \neq 0$ corresponds to the endogenous switching case. A test of the null hypothesis that the state variable is exogenous can thus be derived by testing the null hypothesis $\rho = 0$ (see Hamilton (1994) and Kim et al. (2008)).

The influence of z_t on P_{1j} and P_{2j} gives information about the way the transition variables influence the probability of being in either regime or another. For instance, suppose that regime 1 is the crisis regime with the highest volatility. A positive (resp. negative value) of b_1 (resp. b_2) implies that the transition variable rises the probability of being in the high-volatility regime at time t and decreases the probability of being in the low-volatility regime, regardless of the economy's state at time t

4. Main results

4.1. Marginal contributions

The marginal advantage of the time-varying specification over the constant transition probability model can be assessed by computing the marginal contribution of the transition probabilities.[17] To measure whether the contribution of time-varying is important, we compute the following weighted transition probability series for both states 1 and 2:

$$\mathrm{MC}(p_t) = \{[P(s_t = i/s_{t-1} = i)] - \bar{p}\} \times P\left(s_{t-1} = i/y_t, y_{t-1}, \cdots, y_{t-p}\right), \quad i = 1,2 \tag{10}$$

where $\bar{p}$ is the mean of the transition probabilities. One advantage of $\mathrm{MC}(p_t)$ is that it helps detecting when the time variation is important, or the years when the transition variables give most information on the different regimes. Figures 7a to 7c reproduce the marginal contributions for Brazil, in the case where the transition variables have a significant influence on the probabilities, namely bank funding illiquidity, the S&P 500 volatility and the volatility of the other LAC emerging markets. The marginal contribution is evidenced by the deviations from zero. For the first two transition functions, we observe that the spikes correspond generally to the years 2008 and 2009, thereby supporting the assumption that these variables are providing important information about changes in volatility occurring during the subprime crisis and less information for the years before (Figures 7a and 7b). The case of the third variable (changes in the volatility in other LAC equity markets) is even more interesting (Figure 7c). It acts as a "fine" detector of turning points in the variations of volatility by revealing more spikes in the whole sample (not only during the years 2008 and 2009). The domestic market seems to be much more sensitive to contagion effects stemming from the regional equity markets than from other US indicators of financial stress. As a consequence, this variable helps better to track the changes occurring in the volatility.

[17] The graphs of this contribution are easier to interpret than those of the probabilities of the different regimes.

INSERT FIGURES 7a THROUGH 7c ABOUT HERE

INSERT FIGURES 8a THROUGH 8c ABOUT HERE

In the case of Mexico, an examination of the figures showing the marginal contribution series (Figures 8a through 8c) reveals that the volatility of the other LAC markets convey less information on the occurrence of the high volatility change regime (state 2) than the liquidity of the US market. The cases of Peru and Chile are very similar to Brazil (Figures 9a to 10b), while Colombia resembles Mexico (Figures 11a and 11b).

INSERT FIGURES 9a, 9b, 10a, 10b, 11a, 11b ABOUT HERE

4.2. Detailed results for countries

The results of the estimation of our TVPMS models are contained in Tables 1a through 5.[18] As previously mentioned, the endogenous variable is the changes in volatility for each Latin American market. Various transition variables are considered that aim at representing financial characteristics such as market liquidity, funding liquidity, default risk and attitudes towards risk.[19] To proxy these concepts, the following six transition variables are used:[20] (i) ABCP spreads, which is an indicator of funding liquidity conditions in the ABCP market segment, (ii) an indicator of bank funding liquidity, (iii) the volatility of the S&P 500 stock index, which acts as a proxy for market volatility, (iv) the CDS spreads acting as a measure of bank's default risk, (v) a proxy for overall US market liquidity conditions, and (vi) a measure of the volatility of the LAC stock returns, defined, for each country i, by the mean of the volatility of the other j LAC ($i \neq j$).

The significance of time variation is captured by the coefficients a_1, a_2, b_1 and b_2.[21] The regime-switching parameters are α_1, α_2, β_1, β_2, σ_1 and σ_2. For all the regressions, the model with endogeneity is retained, since the null hypothesis of no correlation between ε_t and η_t is always rejected ($\rho \neq 0$).

Brazil

Because the endogenous variable is the first-difference of the squared returns (changes in volatility), the model dichotomizes into regimes that exhibit peaks (the volatility decreases hugely after achieving very high levels) and no peaks (changes in volatility are not very

[18] The models are estimated using the first-difference of all the variables. Indeed, we applied unit root tests and found that all the variables were I(1). We do not report the results here to save place, but they are available upon request to the authors.

[19] Note that market liquidity is an asset-specific concept referring to the ease with which a position in an asset may be liquidated without significantly altering its price, whereas funding liquidity is an institution-specific characteristic related to the ability of a financial intermediary to service its liabilities (for a detailed presentation of these concepts, see Frank et al. (2008)).

[20] See Appendix 1.

[21] Recall that if b_j=0, the TVPMS reduces to the constant transition probability model. The significance levels associated with these coefficients are reported in Tables 1a through 5 and allow us to test if the hypothesis of constant probabilities is rejected in favor of the alternative of time-varying probabilities. In the majority of the cases (see detailed results in the tables), the time-varying transition probability model is preferred to the constant probability specification, confirming the findings obtained in Section 4.1.

important). Consider first the case of the Brazilian S&P/IFCI series. In Table 1a, we see that the estimate of the mean volatility change in regime 1 (α_1) is statistically not significant, while it is significantly negative in regime 2 (α_2). This suggests that there are phases in the dynamics of volatility characterized by high peaks, notably in the second regime. The interesting point is that, in the latter, changes in volatility are of much higher magnitude than in the first regime, as illustrated by the high values of σ_2 in comparison with σ_1. We propose to label regime 1 as a low-change volatility regime and regime 2 as a high-change volatility regime.

Regarding the transition variables, three of them influence the switches of the volatility changes between the two regimes: bank funding illiquidity, the changes in volatility of the S&P 500 and the volatility changes of the other LAC's equity markets. Indeed, the significance of the parameters b_1 and b_2 indicates whether the transition variables contain information about the probability of being in either regime or the other. Our results show that b_1 and/or b_2 are statistically significant in respectively the third, fourth and seventh columns. An increase in the volatility changes in either the US S&P 500 market or the regional equity markets (other LAC's) decreases the probability of small changes in the Brazilian equity market volatility (b_1 is significantly negative). This result is in line with the intuition of a contagion effect between the volatility changes of the different markets. For bank funding illiquidity, at first glance we obtain somewhat counter-intuitive, respectively positive and negative signs for b_1 and b_2. Indeed, when banks in the US interbank markets are facing liquidity problems we would expect them to repatriate capitals from their affiliates in Brazil, thereby causing higher changes in volatility (thus, we would expect $b_1 < 0$ and $b_2 > 0$). However, one explanation to the reversed signs could be that the signs are not showing a causality phenomenon, but a correlation. Indeed, the share of foreign banks in the banking sector total assets is low in Brazil (less than 30%, as compared, for instance, with Mexico where this proportion is nearly 80%). In the aftermath of the subprime crisis, the enterprises in the equity markets had to find alternative sources of financing and thereby increased the proportion of corporate bonds. Corporate spreads, although they increased, have been less volatile than other spreads at short maturities, because the Brazilian firms showed more resilience to the crisis than firms in the industrialized countries. As a consequence, the positive sign of b_1 reflects a situation in which, as the US markets were showing a higher volatility, the Brazilian companies made a substitution in their sources of financing.

The other financial stress indicators in the US markets reveal little information about the future state of the volatility changes (the coefficients b_1 and b_2 are not statistically significant for the CDS spreads or the US market liquidity).

The next step is to investigate whether the time-varying inferred probabilities are correlated with the chronology of the volatility changes observed in reality. In this view, Table 1a also contains the percentage of probabilities above 0.5 for each regime and each year. The results are as expected. Indeed, in state 1 (low changes in the volatility), the probabilities are very high in 2004, 2005, 2006, and then, they decrease from 2007 onwards. Conversely, we observe low probabilities in state 2 during the years 2004 to 2006, and they increase substantially in 2008 and 2009. All these findings also apply for the BOVESPA stock returns. The difference is that the volatility variables (S&P 500 and other LAC) are the only ones playing a significant role in influencing the probability of being in either regime or the other (see Table 1b).

INSERT TABLES 1a and 1b ABOUT HERE

Mexico

The case of Mexico's equity markets shows a contrasted view, as compared with the Brazilian situation (Table 2a). Indeed, given the high degree of integration between the US and Mexican financial markets, we find a significant influence of all the transition variables, with significant coefficients for b_1 and/or b_2. Except the inversed signs of the variable "banking funding illiquidity" that we already noticed for Brazil, for the other variables, b_1 is negative while b_2 is either positive or statistically non-significant. Therefore, more financial stress in the US market reduces the probability of not observing important peaks (and huge downturns) in the volatility changes. Interestingly, the probabilities reported in Table 2a reveal that, in the aftermath of the crisis, the deterioration of the financial conditions in the US markets increased importantly the probability of a high volatility change regime (for instance, the percentage of probabilities above 0.5 is higher than 70% in general, in comparison with 50% in the case of Brazil). Comparing the findings obtained for the Mexican S&P/IFCI series with those using the BOLSA stock returns, we obtain very similar results (Table 2b).

INSERT TABLES 2a and 2b ABOUT HERE

Chile, Colombia and Peru

The situation of the other countries in our sample resembles that of either Mexico or Brazil, despite some differences. In Chile, with the exception of market liquidity, the domestic markets are in general influenced by the US financial stress indicators (see Tables 3a-3b). However, the latter do not perform quite well as "leading indicators" of times of crisis (when changes in volatility are characterized by high peaks with troughs of high magnitude), since they do not have a stronger explanatory power on the probability of being in regime 2. Indeed, if we compare the case of Mexico with that of Chile, the percentages of probabilities above 0.5 in the second regime are quite low, even during the years 2008 and 2009.

The situation of Peru is very close to that of Brazil, with only an influence of the US and LAC's volatility changes driving the domestic volatility switches (Tables 4a-4b). Turning to Colombia, it is in an intermediate situation between Brazil and Mexico with the CDS being the only statistically significant transition variable in addition to the market volatility series (but with smaller probabilities above 0.5 in regime 2); see Table 5 and Figures 11a and 11b.

INSERT TABLES 3a, 3b, 4a, 4b and 5 ABOUT HERE

4.3. What explains the observed differences between the LAC and what are the implications in terms of financial regulation?

Our findings globally put forward the importance of US financial stress indicators on the volatility of the LAC stock markets. They are in line with those obtained by Dooley and Hutchinson (2009) showing that the emerging markets (among which Brazil, Chile, Colombia and Mexico) indeed reacted to a host of bad news on the US economy, such as the bankruptcy of Lehman Brothers, the write-downs of equities in US financial institutions, or housing market developments. These factors had the effect of raising the CDS spread basis in the LAC financial markets, because they were providing bad news about the liquidity problems facing the US banks and credit markets. The changes in the CDS spreads were then transmitted to the volatility of the equity markets with more or less magnitude depending upon the strength of the LAC market interdependence with the US markets. During episodes of heightened volatility and intensive financial stress in the US markets, "irrational" moods (caused by liquidity needs) were the predominant factor of contagion. In this context, changes in the equity prices' volatility took the form of clearly identifiable, discrete events happening only occasionally. Markov-switching models appear adequate to model such contagion shifts.

Though for all the countries the model dichotomizes into two regimes of respectively low and high changes in volatility, the above results point to two main differences between the Latin American countries. A first difference is that in Chile and Mexico, the interest rate spreads in the US markets (CDS, ABCP, bank funding liquidity) were at play to account for high changes in the volatility during the crisis in addition to market volatility variables, while Brazil, Colombia and Peru seem to be more sensitive to the volatility of the regional financial markets. Secondly, the relevance of the different financial variables in accounting for the evolution into the second regime (characterized by high volatility changes) is important for Mexico (to a less extent for Brazil) and of somewhat less importance for Chile, Colombia and Peru (for which we find quite small percentages of probabilities above 0.5 in regime 2 during the years 2008 and 2009).

These differences are in line with the observed stylized facts. Firstly, some countries have increased domestic securization and implemented regulatory framework that have made it difficult to domestic bank to buy asset-backed securities in the US markets. This concerns mainly the four countries other than Mexico. Because their banks' balance sheets were not as exposed to the toxic assets as in the industrialized countries, the stock market volatilities showed more resilience to the increased financial stress in the US. Another point needs to be mentioned. In Peru, Colombia, Chile and Brazil, a substantial share of capitalization in the equity markets is linked to commodity and energy activities. This means that the peaks observed in the changes of volatility did not only stem from the financial stress in the US markets, but also from the huge drop in the prices of raw materials, commodities, oil that was observed at the beginning of the crisis.[22] Therefore, the stock valuations appeared to decline in line with the low performance of the world commodity markets. Conversely, in Mexico, the channel of contagion from the US financial stress is predominant because of the importance of cross-border funding flows for the Mexican companies.

Several comments are worth making regarding the implications of the above results in terms of financial regulation. According to us, the dependence to the US capital markets does not necessarily imply a return to past capital controls. Though some countries may be tempted to adopt such policies (for instance, Brazil has a low degree of financial openness as compared to many LAC), one way to counter the contagion effects from the US market would be to revive the intra-regional integration of capital markets and to adopt risk-sharing schemes between countries. Those experiencing moderate losses from the financial shocks could provide capital transfers to others more severely hit. This is possible in a context of huge accumulation of reserves by countries like Peru or Brazil which are exporters of raw materials. Another adequate policy to smooth the contagion effects in the dependent countries (Mexico and Colombia) could be to adopt an "insurance" mechanism by improving the external accounts during calm or financial boom periods and use the proceeds as protection

[22] An extension of the present study would be to investigate the role of commodity price volatility, but this is beyond the scope of the paper and left for future research.

during the downswings of markets. This strategy has been useful in Brazil, and helped the authorities to dampen the volatility of capital outflows and thereby of stock prices. A third solution to make the LAC become more immune to the turmoil in the US financial markets may be to increase financing through multilateral institutions' facilities (IMF or regional banks such as the inter-American development bank). Colombia and Mexico benefited from such credit lines in 2009.

5. Conclusion

How extensive were the financial linkages between the Latin American countries and the United States during the subprime crisis? This paper attempts to answer this question by using a new empirical approach based on time-varying probability Markov-switching models. Our estimations show that a broad range of stress indicators in the US financial market can cause abrupt changes in the volatility of the LAC stock markets. These US factors had the effect of raising the CDS spread basis in the LAC financial markets, because they were notably providing bad news about the liquidity problems facing the US banks and credit markets. The changes in the CDS spreads were then transmitted to the volatility of the equity markets with more or less magnitude depending upon the strength of the LAC market interdependence with the US markets. We find that Mexico is the most vulnerable to the US financial stress, since this country has the closer links with the US financial markets; all the US transition variables being informative about the dynamics of the Mexican stock market volatility. A similar conclusion holds for Chile, although not all the transition variables were statistically significant. The other countries seem to be much more sensible to the activity in the regional financial markets (Colombia, Peru and Brazil).

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Appendix

Appendix 1. Data description

Source: Datastream for all series.

Frequency: Daily. Period: January 1, 2004 to April 7, 2009. Number of observations: 1374.

Financial stress indicators

- ABCP spreads: Spread between the yield of 3-month ABCP and that of 3-month US Treasury bill. This is an indicator of funding liquidity conditions in the ABCP market segment.
- Bank funding liquidity: Spread between the 3-month US interbank rate and the US federal funds rate. This is an indicator of bank funding liquidity.
- Market volatility: Volatility of the S&P 500 index, which is a proxy of market volatility, measured by the square of S&P 500 stock returns.
- Market liquidity: two proxies of overall market liquidity conditions are used: (i) Spread between the US 30-year Treasury bonds and the US 10-year Treasury bonds, and (ii) Spread between the US 5-year Treasury bonds and the US 2-year Treasury bonds.
- CDS spreads: 5-year US bank sector CDS. This is a measure of banks' default risk.

Equity indexes

Two series of equity indices are considered for each country (except for Colombia):

- S&P IFCI price indices. S&P/IFCI (Investable) indices are subsets of S&P/IFCG indices and measure the returns of stocks that are legally and practically available to foreign investors. Note that S&P/IFCI indices typically cover a high percentage of the stocks in the S&P/IFCG indices.
- The following stock indices: (i) BOVESPA price index for Brazil, (ii) Chile INTER10 price index for Chile, (iii) IGBC price index for Colombia, (iv) BOLSA price index for Mexico, and (v) LIMA SE price index for Peru.

Appendix 2

Table A1. Information criteria on nonlinear GARCH models: S&P/IFCI indices

		Brazil	Chile	Mexico	Peru
GARCH	LM	-2617.06	-1708.23	-2310.17	-2603.35
	AIC	3.8685	2.5251	3.4149	3.8482
	BIC	3.9058	2.5677	3.4575	3.8855
EGARCH	LM	-2626.29	-1712.17	NC	-2605.62
	AIC	3.8821	2.5309	NA	3.8516
	BIC	3.9248	2.5788	NA	3.8942
PGARCH	LM	NC	-1715.50	-2538.56	-2604.21
	AIC	NA	2.5358	3.7525	3.8495
	BIC	NA	2.5891	3.8057	3.8975
LSTGARCH	LM	-2611.96	NC	-2308.63	-2603.07
	AIC	3.8609	NA	3.4126	3.8478
	BIC	3.9089	NA	3.4659	3.8958
ESTGARCH	LM	-2621.56	-1707.23	-2310.11	-2603.26
	AIC	3.9178	2.5236	3.4148	3.8481
	BIC	3.8752	2.5769	3.4680	3.8961
ANST-GARH	LM	-2621.49	-1707.37	-2309.83	NC
	AIC	3.9284	2.5238	3.4143	NA
	BIC	3.8751	2.5877	3.4783	NA
QGARCH	LM	-2617.48	-1708.20	-2308.97	-2603.26
	AIC	3.8692	2.5250	3.4130	3.8480
	BIC	3.9065	2.5730	3.4610	3.8900

Note: LM: maximum likelihood, AIC: Akaike, BIC: Schwarz.

Table A2. Information criteria on nonlinear GARCH models: other stock indices

		Brazil	Chile	Colombia	Mexico	Peru
GARCH	LM	-2701.71	-2001,09	-2271.43	-2263.42	-2432.34
	AIC	3.9936	2.9422	3.3576	3.3457	3.5954
	BIC	4.0309	2.9795	3.4162	3.3884	3.6434
EGARCH	LM	-2711.11	-1987.68	-2279.28	-2273.53	-2441.37
	AIC	4.0075	2.9381	3.3692	3.3607	3.6088
	BIC	4.0501	2.9808	3.4331	3.4086	3.6621
PGARCH	LM	NC	-1987.86	-2275.59	-2272.33	-2444.98
	AIC	NA	2.9384	3.3637	3.3589	3.6141
	BIC	NA	2.9864	3.4330	3.4122	3.6727
LSTGARCH	LM	NC	-1988.40	-2270.30	-2259.20	-2429.50
	AIC	NA	2.9392	3.3559	3.3395	3.5912
	BIC	NA	2.9872	3.4252	3.3928	3.6499
ESTGARCH	LM	-2700.26	-1988.31	-2271.43	-2263.19	NC
	AIC	3.9915	2.9391	3.3576	3.3454	NA
	BIC	4.0394	2.9870	3.4269	3.3987	NA
ANST-GARH	LM	-2701.36	-1989.55	-2272.96	-2263.07	-2431.77
	AIC	3.9931	2.9409	3.3598	3.3452	3.5946
	BIC	4.0517	2.9995	3.4398	3.4092	3.6639
QGARCH	LM	-2696.45	-1988.93	-2270.42	-2260.68	-2431.18
	AIC	3.9850	2.9400	3.3560	3.3410	3.5930
	BIC	4.0280	2.9820	3.4200	3.3890	3.6470

Note: LM: maximum likelihood, AIC: Akaike, BIC: Schwarz.

Table A3. Testing linearity against the alternative of Markov-switching models

		SupTS	1% cv	5% cv	10% cv
Brazil					
	S&P/IFCI returns	8.9336	5.3050	4.2377	3.7161
	BOVESPA returns	9.1763	5.3077	4.2251	3.7173
Chile					
	S&P/IFCI returns	116.6136	5.8430	4.5243	3.8978
	INTER 10 returns	127.9986	5.7403	4.5380	3.8196
Colombia					
	IGBC returns	23.1380	5.3762	4.4219	3.7544
Mexico					
	S&P/IFCI returns	10.1714	5.3646	4.4201	3.7563
	BOLSA returns	8.9262	5.4008	4.4334	3.7716
Peru					
	S&P/IFCI returns	13.6802	5.4050	4.4473	3.8101
	LIMA SE returns	11.2773	5.8345	4.5198	3.8474

Note: Empirical critical values (cv) are computed from 500 iterations for a sample size equal to the size of the original data set. The statistic, SupTS, is obtained by searching the maximum over two nuisance parameters, h (h is a vector specifying the direction of the alternative) and $\rho = p + q - 1$ (p and q are transition probabilities under the alternative); it is computed by drawing h uniformly over the unit sphere (20 values used) and by taking the values of ρ in an equally spaced grid (30 values used).

Table 1a. Estimation of TVPMS model – Brazil – S&P/IFCI returns

	ABCP spreads	Bank funding	S&P 500 volatility	CDS spreads	US market liquidity	Other LAC volatility
α_1	0.01	0.01	-0.09	0.0059	0.01	-1.18*
α_2	-9.46*	-9.12*	-6.03*	-8.79*	-9.21*	22.89*
β_1	-0.40*	-0.39*	-0.43*	-0.39*	-0.40*	-0.86*
β_2	-0.64*	-0.65*	-0.61*	-0.64*	-0.64*	-0.22*
σ_1	2.54*	2.52*	2.49*	2.50*	2.50*	5.30*
σ_2	21.85*	21.67*	21.73*	21.64*	21.75*	21.01*
a_1	1.41*	1.43*	1.96*	1.43*	1.41*	0.68*
a_2	-0.76*	-0.79*	-0.72*	-0.78*	-0.76*	41.84
b_1	0.11	1.64*	-0.45*	-0.02	-5.65	-0.08*
b_2	0.20	-0.98**	0.02*	-0.001	-1.26	-6.50
ρ	0.64*	0.65*	0.58*	0.62*	0.63*	-0.94*
	Percentage of probabilities higher than 0.5					
	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)
2005	93.46 (6.54)	92.31 (7.69)	93.65 (6.15)	93.46 (6.54)	93.46 (6.54)	95.77 (4.23)
2006	86.54 (13.46)	86.54 (13.46)	89.23 (10.77)	86.54 (13.46)	86.54 (13.46)	93.08 (6.92)
2007	81.23 (18.77)	81.23 (18.77)	78.93 (21.07)	80.84 (19.16)	80.84 (19.16)	87.74 (12.26)
2008	57.63 (42.37)	57.25 (42.75)	53.82 (46.18)	57.25 (42.75)	56.87 (43.13)	72.14 (27.86)
2009	43.48 (56.52)	44.93 (55.07)	40.58 (59.42)	43.48 (56.52)	43.48 (56.52)	68.12 (31.88)

Table 1b. Estimation of TVPMS model – Brazil – BOVESPA returns

	ABCP spreads	Bank funding	S&P 500 volatility	CDS spreads	US Market liquidity	Other LAC volatility
α_1	0.02	0.02	-0.13	0.02	0.02	-0.19**
α_2	-12.51*	-12.25*	-7.01*	-12.29*	-12.34*	-4.79**
β_1	-0.45*	-0.44*	-0.46*	-0.45*	-0.45*	-0.47*
β_2	-0.64*	-0.35*	-0.61*	-0.64*	-0.64*	-0.63*
σ_1	3.10*	3.12*	3.02*	3.12*	3.03*	3.39*
σ_2	25.18*	25.12*	24.67*	25.31*	24.92*	27.49*
a_1	1.40*	1.42*	1.96*	1.42*	1.38*	2.34*
a_2	-0.63*	-0.64*	-0.63*	-0.64*	-0.62*	-0.60*
b_1	0.14	0.66	-0.46*	0.0053	-4.90	-0.30*
b_2	0.05	-0.78	0.02*	0.0019	-1.05	0.02*
ρ	0.64*	0.64*	0.55*	0.63*	0.64*	0.39*
	Percentage of probabilities higher than 0.5					
	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)
2005	91.54 (8.46)	91.54 (8.46)	93.46 (6.54)	91.92 (8.08)	91.54 (8.46)	96.15 (3.85)
2006	90.77 (9.23)	90.38 (9.62)	91.15 (8.85)	90.77 (9.23)	90.38 (9.62)	92.69 (7.31)
2007	85.44 (14.56)	85.82 (14.18)	83.14 (16.86)	85.82 (14.18)	85.06 (14.94)	87.74 (12.26)
2008	63.74 (36.26)	63.36 (36.64)	60.69 (39.31)	63.74 (36.26)	62.21 (37.79)	65.65 (34.35)
2009	55.07 (44.93)	55.07 (44.93)	50.72 (49.28)	55.07 (44.93)	52.17 (47.83)	55.07 (44.93)

Note: * and ** indicate that the estimated coefficients are statistically significant at the 5% and 10% significance level, respectively.

Table 2a. Estimation of TVPMS model – Mexico – S&P/IFCI returns

	ABCP spreads	Bank funding	S&P 500 volatility	CDS spreads	US market liquidity	Other LAC volatility
α_1	0.0114	0.0086	-0.037	0.009	0.0083	-0.02
α_2	-3.50*	-3.91*	-2.66*	-3.75*	-3.73*	-3.06*
β_1	-0.49*	-0.48*	-0.47*	-0.49*	-0.48*	-0.48*
β_2	-0.55*	-0.55*	-0.53*	-0.55*	-0.55*	-0.54*
σ_1	1.40*	1.41*	1.44*	1.41*	1.40*	1.46*
σ_2	14.52*	14.59*	15.12*	14.60*	14.53*	15.14*
a_1	1.69*	1.63*	2.27*	1.69*	1.69*	2.06*
a_2	-1.06*	-1.04*	-0.91*	-1.04*	-1.05*	-1.01*
b_1	-3.58*	1.96*	-0.51*	-0.05*	-13.93*	-0.19*
b_2	0.04	-0.59	0.01*	-0.0009	-2.19	0.0061
ρ	0.50*	0.53*	0.45*	0.52*	0.53*	0.48*
	Percentage of probabilities higher than 0.5					
	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)
2005	93.08 (6.92)	93.08 (6.92)	94.23 (5.77)	93.08 (6.92)	93.08 (6.92)	93.08 (6.92)
2006	80.38 (19.62)	80.77 (19.23)	81.54 (18.46)	80.77 (19.23)	80.38 (19.62)	82.31 (17.69)
2007	73.95 (26.05)	74.33 (25.67)	76.25 (23.75)	74.71 (25.29)	74.71 (25.29)	76.63 (23.37)
2008	59.94 (40.46)	59.92 (40.08)	57.25 (42.75)	59.16 (40.84)	58.78 (41.22)	60.69 (39.31)
2009	26.09 (73.91)	27.54 (72.46)	27.54 (72.46)	27.54 (72.46)	26.09 (73.91)	27.54 (72.46)

Table 2b. Estimation of TVPMS model – Mexico – BOLSA returns

	ABCP spreads	Bank funding	S&P 500 volatility	CDS spreads	US Market liquidity	Other LAC volatility
α_1	0.0001	-0.0011	-0.04	-0.0051	0.0014	-0.029
α_2	-3.89*	-3.81*	-2.27**	-3.58*	-3.71*	-2.62*
β_1	-0.52*	-0.52*	-0.51*	-0.52*	-0.52*	-0.52*
β_2	-0.54*	-0.55*	-0.53*	-0.54*	-0.54*	-0.54*
σ_1	1.32*	1.33	1.39*	1.32*	1.33*	1.42*
σ_2	13.86*	13.91*	14.62*	13.81*	13.84*	14.72*
a_1	1.60*	1.64*	2.13*	1.66*	1.68*	2.11*
a_2	-1.00*	-1.02	-0.91*	-1.02*	-1.03*	-0.95*
b_1	-0.77	2.29*	-0.38*	-0.04*	-13.13	-0.19*
b_2	-0.08	-0.56	0.0094	0.0004	-4.38	0.0046
ρ	0.52*	0.53*	0.37*	0.51*	0.53*	0.41*
	Percentage of probabilities higher than 0.5					
	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)
2005	93.46 (6.54)	93.85 (6.15)	94.23 (5.77)	93.46 (6.54)	93.85* (6.15)	94.62 (5.38)
2006	81.15 (18.85)	81.54 (18.46)	83.08 (16.92)	81.15 (18.85)	80.77 (19.23)	83.08 (16.92)
2007	75.48 (24.52)	75.48 (24.52)	77.39 (22.61)	74.71 (25.29)	75.48 (24.52)	79.31 (20.69)
2008	62.98 (37.02)	63.74 (36.26)	62.60 (37.40)	62.21 (37.79)	62.60 (37.40)	63.36 (36.64)
2009	28.99 (71.01)	28.99 (71.01)	28.99 (71.01)	28.99 (71.01)	27.54 (72.46)	30.43 (69.57)

Note: * and ** indicate that the estimated coefficients are statistically significant at the 5% and 10% significance level, respectively.

Table 3a. Estimation of TVPMS model – Chile – S&P/IFCI returns

	ABCP spreads	Bank funding	S&P 500 volatility	CDS spreads	US market liquidity	Other LAC volatility
α_1	-0.0016	-0.0007	-0.01	-0.008	-0.0005	-0.01
α_2	-3.57*	-3.31*	-2.97*	-3.41*	-3.76*	-2.77*
β_1	-0.45*	-0.46*	-0.43*	-0.45*	-0.543*	-0.43*
β_2	-0.41*	-0.41*	-0.40*	-0.41*	-0.41*	-0.40*
σ_1	0.70*	0.71*	0.75*	0.637*	0.70*	0.73*
σ_2	13.69*	13.79*	14.62*	13.30*	13.77*	14.19*
a_1	1.80*	1.87*	2.28*	1.92*	1.78*	2.11*
a_2	-0.93*	-0.97*	-0.80*	-0.88*	-0.91*	-0.92*
b_1	-1.32*	-3.07	-0.28*	-0.09*	2.57	-0.1*
b_2	-0.19	0.16	0.003	0.003	-3.72	0.0015
ρ	0.41*	0.40*	0.38*	0.44*	0.41*	0.35*
	Percentage of probabilities higher than 0.5					
	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)
2005	98.08 (1.92)	98.08 (1.92)	98.85 (1.15)	97.69 (2.31)	98.08 (1.92)	98.46 (1.54)
2006	96.92 (3.08)	96.92 (3.08)	97.69 (2.31)	96.54 (3.46)	96.92 (3.08)	96.92 (3.08)
2007	79.31 (20.69)	80.08 (19.92)	82.38 (17.62)	78.54 (21.46)	79.69 (20.31)	82.38 (17.62)
2008	62.60 (37.40)	65.27 (34.73)	66.03 (33.97)	61.45 (38.55)	63.36 (36.64)	65.65 (34.35)
2009	62.32 (37.68)	62.32 (37.68)	60.87 (39.13)	56.52 (43.48)	62.32 (37.68)	60.87 (39.13)

Table 3b. Estimation of TVPMS model – Chile – Chile INTER 10 returns

	ABCP spreads	Bank funding	S&P 500 volatility	CDS spreads	US Market liquidity	Other LAC volatility
α_1	-0.01	-0.01	-0.04	-0.01	-0.01	-0.03
α_2	-6.00*	-5.66*	-5.39*	-5.79*	-6.08*	-5.10*
β_1	-0.44*	-0.43*	-0.45*	-0.45*	-0.44*	-0.45*
β_2	-0.43*	-0.43*	-0.41*	-0.42*	-0.43*	-0.43*
σ_1	1.07*	1.08*	1.03*	1.06*	1.06*	1.03*
σ_2	17.34*	17.41*	17.11*	17.21*	17.25*	17.00*
a_1	1.66*	1.71*	1.78*	1.68*	1.65*	1.75*
a_2	-0.82*	-0.85*	-0.66*	-0.80*	-0.81*	-0.74*
b_1	0.24	1.94**	-0.17*	-0.01*	-3.37	-0.06*
b_2	0.22	-0.17	0.0051	0.005	-2.98	0.0001
ρ	0.47*	0.47*	0.46*	0.47*	0.49*	0.43*
	Percentage of probabilities higher than 0.5					
	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)
2005	94.23 (5.77)	94.62 (5.38)	94.23 (5.77)	94.23 (5.77)	94.23 (5.77)	93.85 (6.15)
2006	96.15 (3.85)	96.15 (3.85)	95.77 (4.23)	95.77 (4.23)	96.15 (3.85)	95.38 (4.62)
2007	81.61 (18.39)	81.61 (18.39)	80.84 (19.16)	81.61 (18.39)	81.61 (18.39)	80.84 (19.16)
2008	58.78 (41.22)	58.78 (41.22)	57.25 (42.75)	58.78 (41.22)	58.40 (41.60)	57.63 (42.37)
2009	84.06 (15.94)	84.06 (15.94)	73.91 (26.09)	84.06 (15.94)	82.61 (17.39)	75.36 (24.64)

Note: * and ** indicate that the estimated coefficients are statistically significant at the 5% and 10% significance level, respectively.

Table 4a. Estimation of TVPMS model – Peru – S&P/IFCI returns

	ABCP spreads	Bank funding	S&P 500 volatility	CDS spreads	US market liquidity	Other LAC volatility
α_1	0.08	0.08	0.08	0.09	0.09	0.01
α_2	-10.01*	-10.13*	-10.28*	-10.45*	-10.12*	-8.12*
β_1	-0.31*	-0.31*	-0.32*	-0.31*	-0.31*	-0.34*
β_2	-0.52*	-0.51*	-0.50*	-0.51*	-0.52*	-0.49*
σ_1	2.22*	2.22*	2.22*	2.23*	2.22*	2.20*
σ_2	22.45*	22.39*	22.15*	22.40*	22.41*	22.09*
a_1	1.37*	1.36*	1.38*	1.35*	1.35*	1.57*
a_2	-0.75*	-0.75*	-0.70*	-0.75*	-0.74*	-0.75*
b_1	0.7**	-0.78	-0.07*	-0.008	0.28	-0.13*
b_2	0.15	0.39	0.01*	0.009	1.23	0.02*
ρ	0.64*	0.65*	0.68*	0.66*	0.65*	0.63*
	Percentage of probabilities higher than 0.5					
	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)
2005	88.85 (11.15)	88.46 (11.54)	88.46 (11.54)	88.85 (11.15)	88.85 (11.15)	88.85 (11.15)
2006	79.23 (20.77)	79.23 (20.77)	79.23 (20.77)	79.23 (20.77)	79.23 (20.77)	80.00 (20.00)
2007	83.52 (16.48)	83.52 (16.48)	83.14 (16.86)	83.52 (16.48)	83.14 (16.86)	83.91 (16.09)
2008	65.27 (34.73)	65.27 (34.73)	64.12 (35.88)	65.27 (34.73)	65.27 (34.73)	62.60 (37.40)
2009	47.83 (52.17)	47.83 (52.17)	44.93 (55.07)	47.83 (52.17)	47.83 (52.17)	43.48 (56.52)

Table 4b. Estimation of TVPMS model – Peru – LIMA SE returns

	ABCP spreads	Bank funding	S&P 500 volatility	CDS spreads	US Market liquidity	Other LAC volatility
α_1	-0.03	-0.03	-0.01	-0.03	-0.03	-0.04
α_2	-5.13*	-4.92*	-6.76*	-5.07*	-5.00*	-5.26*
β_1	-0.41*	-0.42*	-0.31*	-0.41*	-0.42*	-0.38*
β_2	-0.41*	-0.41*	-0.41*	-0.41*	-0.42*	-0.40*
σ_1	1.62*	1.59*	1.65*	1.60*	1.62*	1.60*
σ_2	23.84*	23.57*	24.10*	23.72*	23.78*	23.67*
a_1	1.57*	1.56*	1.52*	1.58*	1.56*	1.65*
a_2	-1.07*	-1.10*	-0.98*	-1.07*	-1.09*	-1.03*
b_1	-1.57*	-0.98	-0.04*	-0.03*	-3.63	-0.10*
b_2	-0.11	0.48	0.01*	0.0028	-3.20	0.01**
ρ	0.44*	0.43*	0.52*	0.44*	0.43*	0.47*
	Percentage of probabilities higher than 0.5					
	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)
2005	94.23 (5.77)	94.23 (5.77)	93.85 (6.15)	94.23 (5.77)	94.23 (5.77)	93.85 (6.15)
2006	73.46 (26.54)	72.69 (27.31)	74.23 (25.77)	73.08 (26.92)	73.08 (26.92)	72.69 (27.31)
2007	75.10 (24.90)	75.10 (24.90)	77.39 (22.61)	75.48 (24.52)	75.10 (24.90)	75.10 (24.90)
2008	50.76 (49.24)	51.15 (48.85)	51.15 (48.85)	48.85 (51.15)	51.91 (48.09)	50.00 (50.00)
2009	50.72 (49.28)	53.62 (46.38)	53.62 (46.38)	52.17 (47.83)	56.52 (43.48)	50.72 (49.28

Note: * and ** indicate that the estimated coefficients are statistically significant at the 5% and 10% significance level, respectively.

Table 5. Estimation of TVPMS model – Colombia – IGBC returns

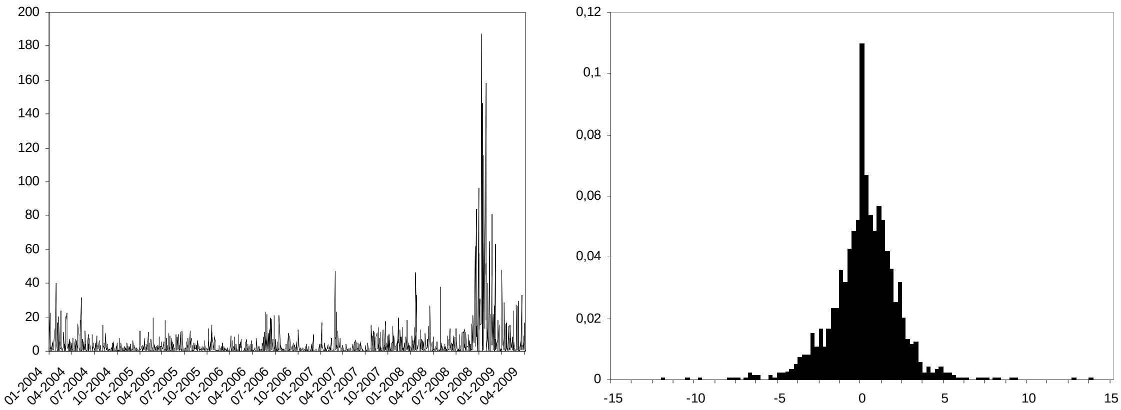
	ABCP spreads	Bank funding	S&P 500 volatility	CDS spreads	US Market liquidity	Other LAC volatility
α_1	0.0021	-0.0013	0.0034	-0.0052	-0.0005	-0.01
α_2	-7.77*	-7.70*	-8.08*	-7.65*	-7.72*	-6.91*
β_1	-0.41*	-0.40*	-0.41*	-0.40*	-0.41*	-0.39*
β_2	-0.55*	-0.55*	-0.55*	-0.55*	-0.55*	-0.55*
σ_1	1.59*	1.58*	1.58*	1.56*	1.58*	1.59*
σ_2	23.37*	23.29*	23.46*	23.09*	23.28*	23.40*
a_1	1.65*	1.63*	1.63*	1.63*	1.63*	1.72*
a_2	-0.76*	-0.75*	-0.71*	-0.74*	-0.74*	-0.75*
b_1	-0.44	0.18	0.02*	0.01*	0.43	-0.05*
b_2	0.52	0.69	0.0	0.01	-1.28	0.0017
ρ	0.45*	0.44*	0.45*	0.45*	0.44*	0.42*
	Percentage of probabilities higher than 0.5					
	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)	Regime 1 (Regime 2)
2005	87.31 (12.69)	86.15 (13.85)	86.92 (13.08)	86.15 (13.85)	86.15 (13.85)	87.31 (12.639)
2006	73.85 (26.15)	73.46 (26.54)	74.23 (25.77)	73.08 (26.92)	73.85 (26.15)	73.46 (26.54)
2007	90.42 (9.58)	90.42 (9.58)	90.42 (9.58)	90.42 (9.58)	90.42 (9.58)	90.04 (9.96)
2008	79.77 (20.23)	79.39 (20.61)	79.39 (20.61)	78.24 (21.76)	79.39 (20.61)	79.01 (20.99)
2009	100.0 (0.0)	98.55 (1.45)	100 (0.0)	98.55 (1.45)	98.55 (1.45)	97.10 (2.90)

Note: * and ** indicate that the estimated coefficients are statistically significant at the 5% and 10% significance level, respectively.

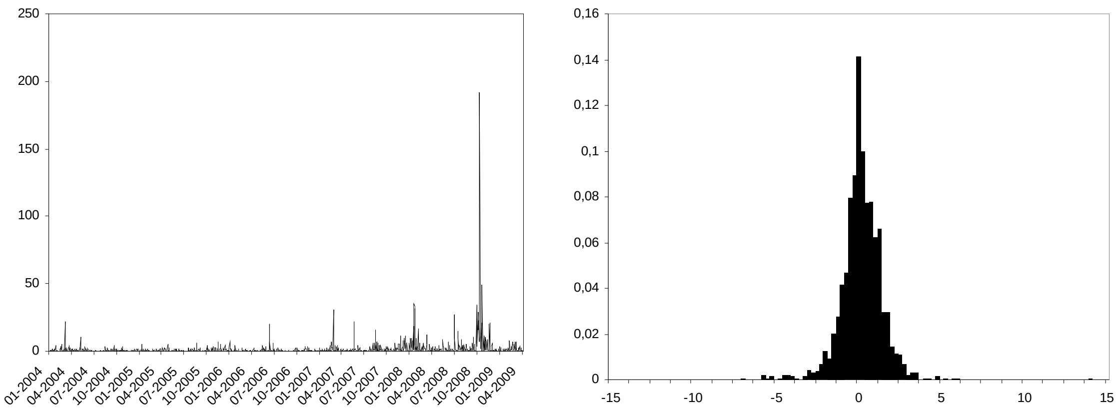
Figure 1. Squared returns (left) and their distribution (right) - stock markets

This figure reports the evolution of the squared returns of the five considered stock indexes, together with their distribution.

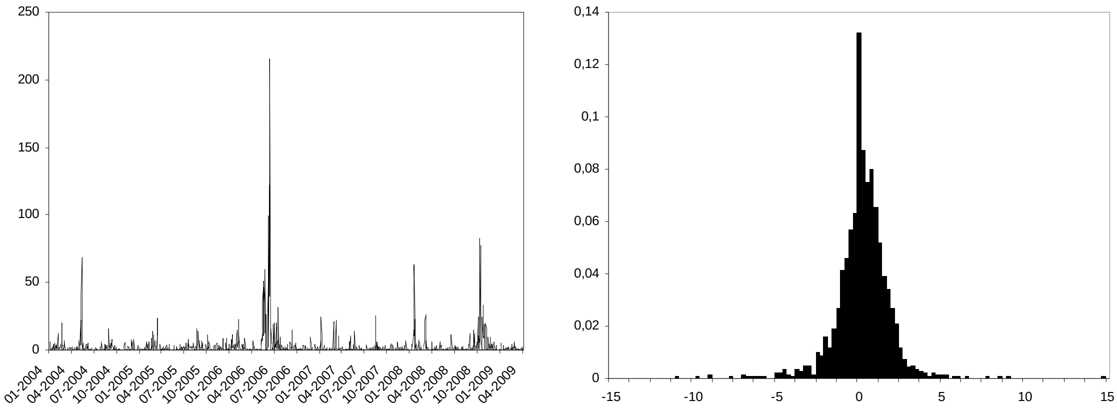
Brazil



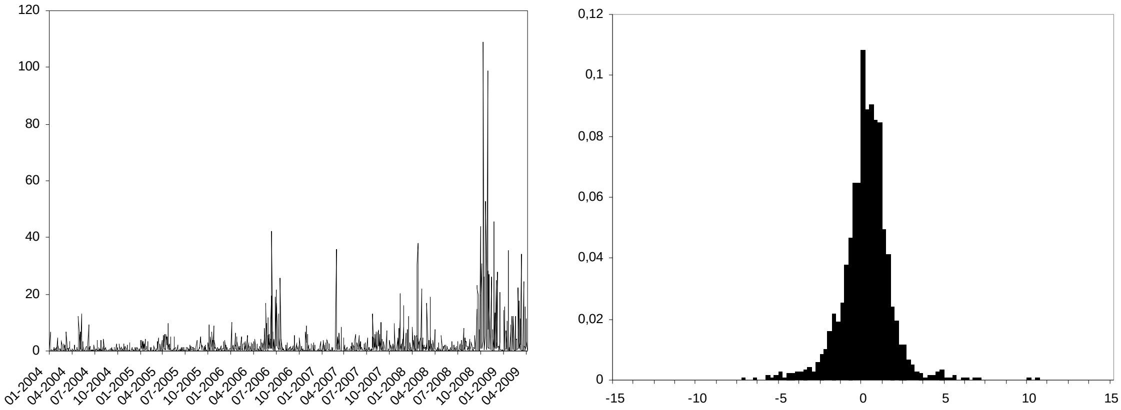
Chile



Colombia



Mexico



Peru

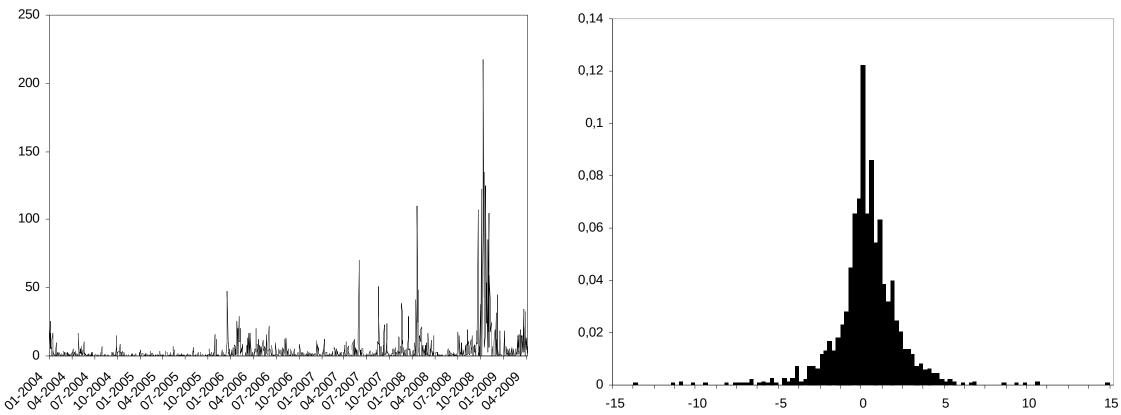


Figure 2. Stock returns volatility estimated from a GARCH-type model

This figure reports the volatility (VOL) of stock returns estimated from a GARCH model for the five considered countries: Brazil (BR), Chile (CH), Colombia (CO), Mexico (ME) and Peru (PE).

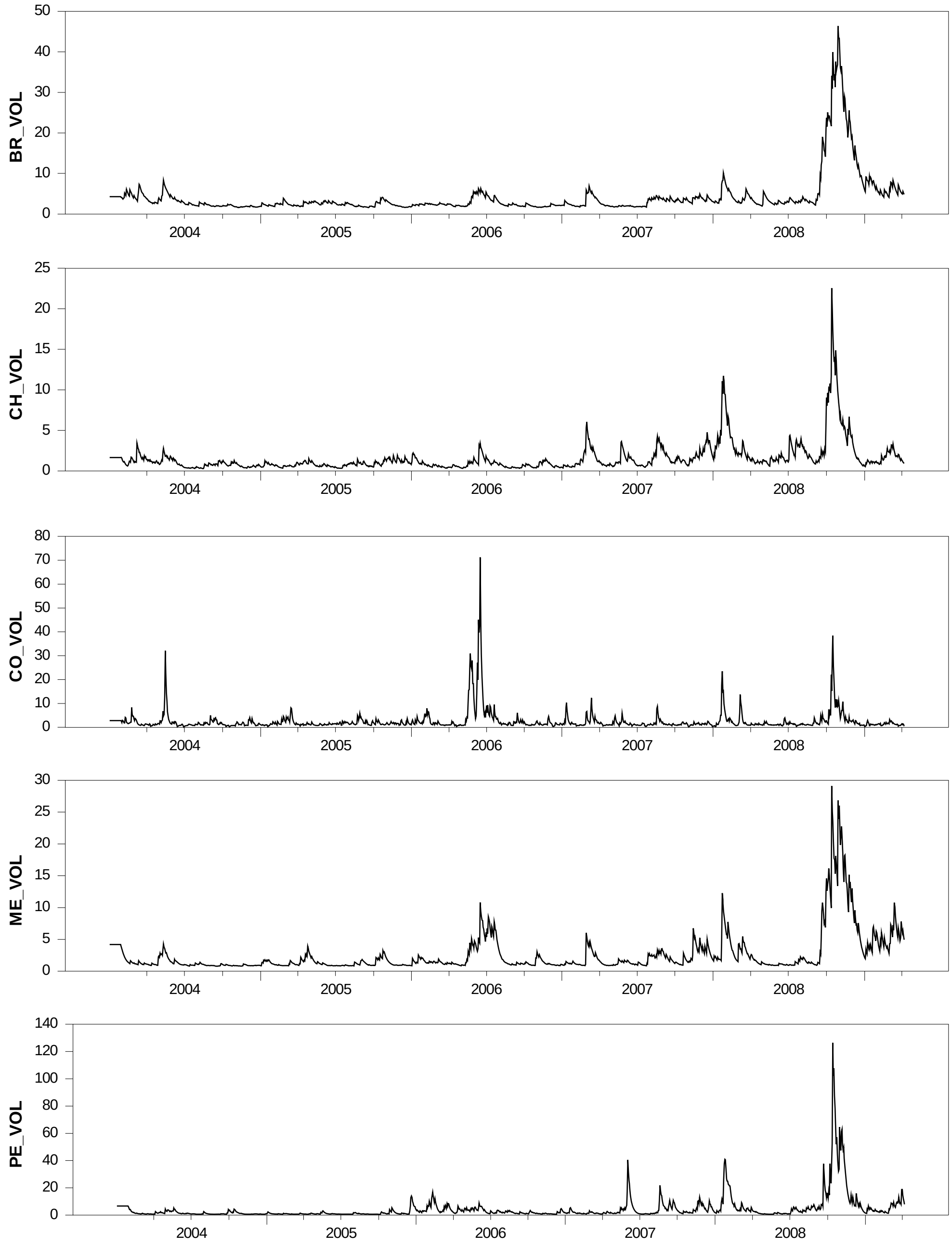


Figure 3. ABCP spreads

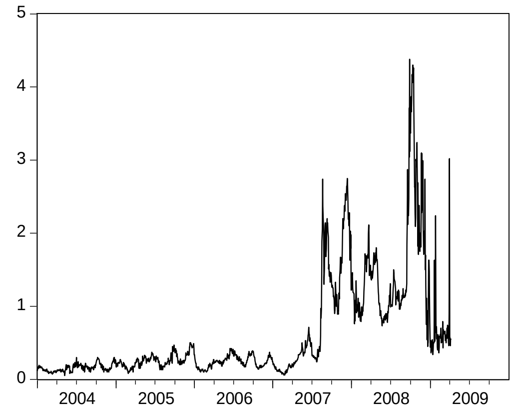


Figure 4. CDS spreads

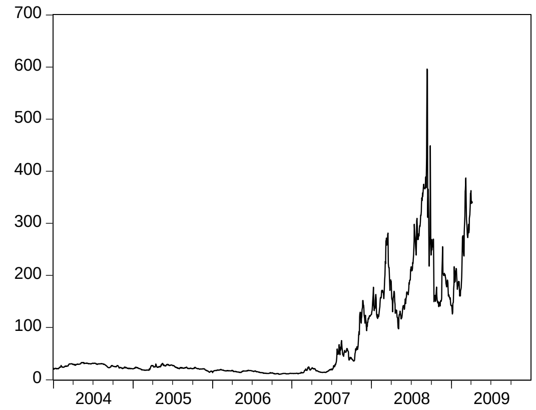
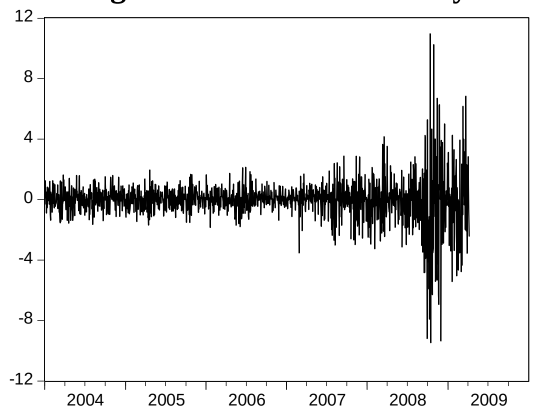


Figure 5. US Market liquidity

Figure 6. S&P 500 Volatility



Figures 7 and 8. Marginal contribution of the transition variables

Figure 7a. Brazil – Bank funding

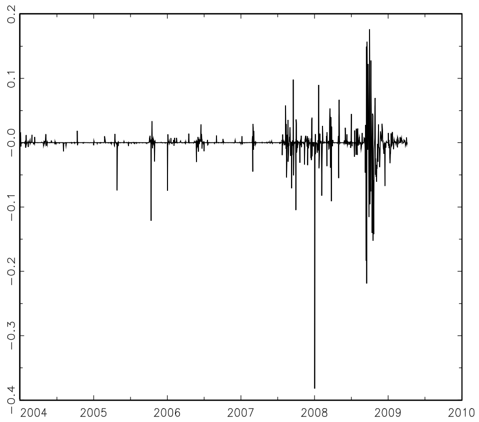


Figure 7b. Brazil – S&P 500 volatility

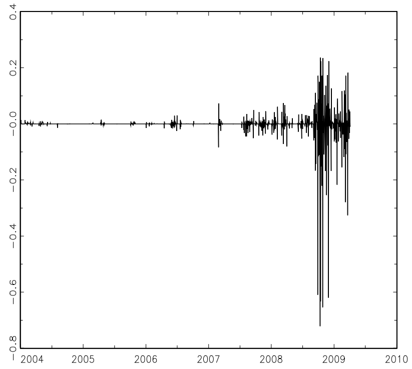


Figure 7c. Brazil – Other LAC volatility

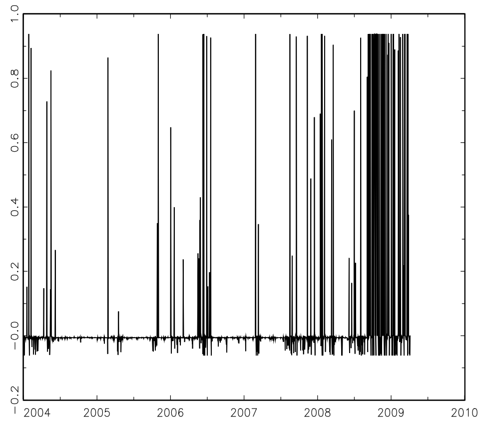


Figure 8a. Mexico – ABCP spreads

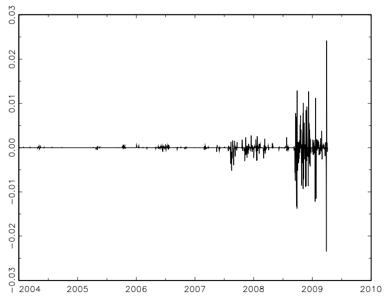


Figure 8b. Mexico – US market liquidity

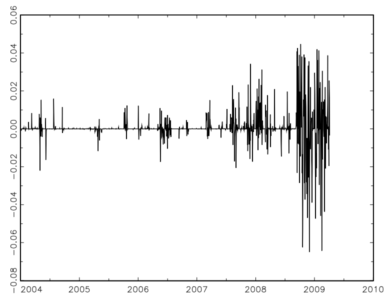
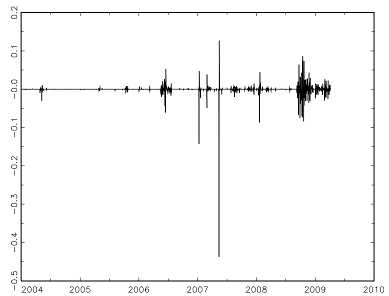


Figure 8c. Mexico – Other LAC volatility



Figures 9, 10 and 11. Marginal contribution of the transition variables

Figure 9a. Chile – ABCP spreads

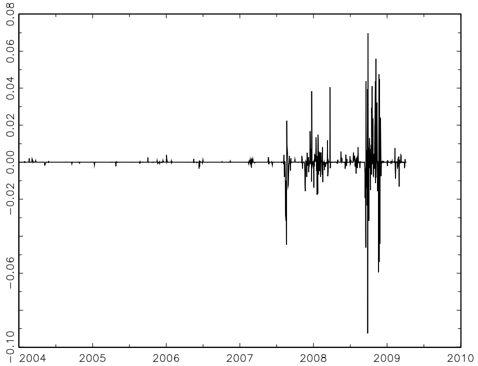


Figure 9b. Chile – CDS spreads

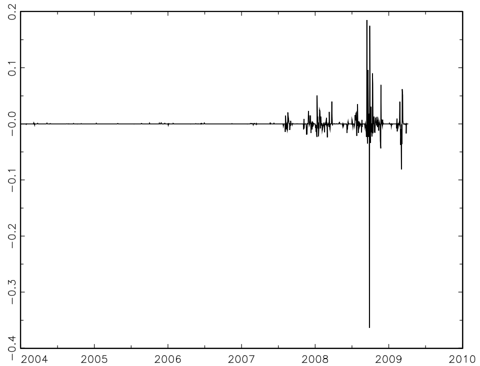


Figure 10a. Peru – S&P 500 volatility

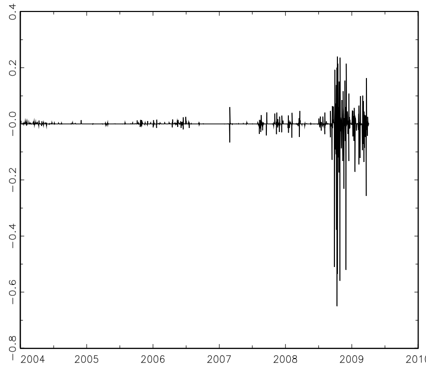


Figure 10b. Peru – Other LAC volatility

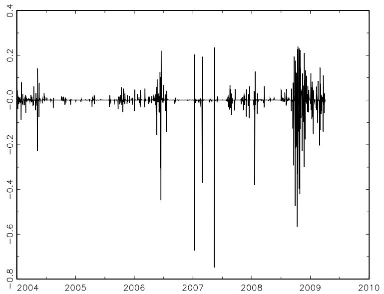


Figure 11a. Colombia – CDS spreads

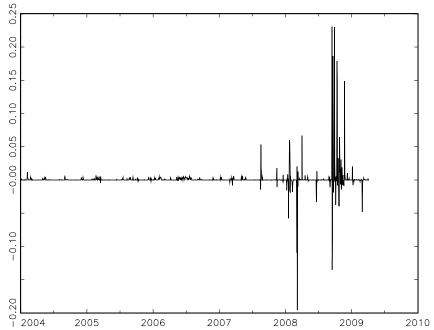


Figure 11b. Colombia – Other LAC volatility