On the subprime crisis and the Latin American financial markets: A regime switching skew-normal approach

Diego Ferreira*　　　Andreza A. Palma†

Área 4 - Macroeconomia, Economia Monetária e Finanças

Abstract

This paper analyzes the potential occurrence of financial contagion in Latin American markets from the recent US subprime crisis. Distinctively from the usual empirical approaches for contagion analyses, a regime-switching skew-normal (RSSN) model is implemented in order to assess both correlation and coskewness contagion as well as investigate the occurrence of structural breaks in the moments of the mean, variance and skewness. Even though correlation contagion was observed in all selected Latin American markets, coskewness contagion was only detected in Brazil. Variance structural breaks were found in all financial markets while structural breaks in the mean were only detected in Argentinian, Mexican and the US markets. Yet, joint contagion and structural break tests suggested the occurrence of these phenomena in all considered markets.

Keywords: Financial Contagion; Latin America; Regime Switching; Skew-Normal Distribution; Bayesian Estimation.

JEL Classification: C11; C34; N26.

Resumo

O objetivo do presente trabalho é analisar a ocorrência de contágio financeiro nos mercados latino-americanos durante a recente crise do *subprime*. De forma distinta das abordagens empíricas usuais para análise de contágio, utilizamos um modelo *regime-switching skew-normal* (RSSN) que permite avaliar o contágio em correlação e em coassimetria, bem como a existência de quebras estruturais na média, variância e assimetria (primeiro, segundo e terceiro momentos). Apesar do contágio em correlação ter sido observado em todos os mercados estudados, o contágio em coassimetria foi observado apenas no Brasil. Quebras estruturais na variância foram encontradas em todos os mercados enquanto as quebras estruturais na média foram observadas apenas na Agertina, México e EUA. Além disso, os testes de quebra estrutural e contágio conjuntos apontaram para a existência desses fenômenos em todos os mercados analisados.

Palavras-chave: Contágio Financeiro; América Latina; Mudança de Regime; Distribuição normal assimétrica; Estimação Bayesiana.

*PhD candidate at the Department of Applied Social Sciences, Graduate Program in Development Economics (PPGDE), Federal University of Paraná (UFPR), Curitiba, Brazil. E-mail: diegoferreira.eco@gmail.com. Phone: (+55 41) 99947-7494.

†Professor at the Department of Economics, Federal University of São Carlos (UFSCar), Sorocaba, Brazil. E-mail: drepalma@gmail.com.

1 Introduction

After a period of low volatility, the advent of the subprime mortgage crisis in mid 2007, which was originated due to the reversion process of the last residential construction cycle in the US, was one of the most severe crisis in the American economy, with spillover effects on a variety of other developed and emerging markets (Horta et al., 2008; Dooley and Hutchison, 2009; Lahet, 2009). The current process of globalization as well as technological advances have contributed to a higher degree of financial market integration, which is largely responsible for the propagation of international crises in the last decades (Dornbush et al., 2000). Notwithstanding the existence of numerous benefits arising from such higher integration, some disadvantages also emerge as the byproduct of this process. Financial contagion is one of them. Being potentially responsible for the worsening of a market vulnerability to external shocks (Bekaert et al., 2003; Collins and Biekpe, 2003), financial contagion might also reduce the effectiveness of portfolio diversification (Sharma and Seth, 2012) as well as hamper policymakers' ability of monitoring and maintaining the financial stability of their countries.

Despite the relevance of financial contagion for both academics and practitioners, there still remains no consensus in the literature on the concept of contagion. According to Rotta and Valls Pereira (2016), the World Bank provides three different definitions of contagion: broad (can occur during both good and bad times), restrictive (excess of comovement) and very restrictive (changes in the transmission mechanism in turbulent times, i.e., shift-contagion). In the present paper, we follow the definition perpetrated by Forbes and Rigobon (2002), which is equivalent to the shift-contagion principle, that is, contagion is understood as a statistically significant change in the correlation coefficient of two (or more) financial assets in a crisis period compared to a non-crisis period. Usually, during periods of crisis, the correlation between asset returns tends to increase.

In terms of methodological procedures, most applied studies on financial contagion are based on multivariate volatility models (such as DCC-GARCH, BEKK, CCC, among others), which lie within the class of models originally proposed by Bollerslev et al. (1988). Some recent studies in this methodological branch are Marçal and Valls Pereira (2008) and Filleti et al. (2008). These models are particularly useful in verifying the occurrence of contagion given that they model the correlation structure between variables. However, overparameterization as well as the need of imposing proper restrictions in order to proceed with estimation are underlying limitations of such models. For instance, the Constant Conditional Correlation (CCC) model developed by Bollerslev (1990) – considered to be one of the most common models within this class – assumes that the conditional correlations are constant over time. Although several improvements were proposed to these models (see e.g. Galeano and Ausin (2010)), estimation from the frequentist standpoint is still challenging.

Against this background, the present paper applies the regime switching skew-normal (RSSN) model developed by Chan et al. (2017) to assess the potential occurrence of financial contagion between the US and four main Latin American economies: Argentina, Brazil, Chile and Mexico. The proposed model is an extension of Hamilton (1989) and is particularly adequate to evaluate contagion. First, the model assumes data is non-normally distributed, which is an important feature of financial series – usually, financial series are characterized by heavy tails, that is, their distribution is leptokurtic, reflecting the higher likelihood of extreme events compared to the normal distribution. Moreover, by considering regime switching features, the model is also able to capture comovement shifts between asset returns due to regime transitions, which is the exact definition of contagion considered in this paper. Given the rather large amount of parameters and latent variables, the Bayesian approach is considered to be more appropriate for this type of models. More specifically, we applied Markov Chain Monte Carlo (MCMC) techniques in order to retrieve the posterior estimates of the switching parameters and then perform the contagion tests. Also, distinctively from the multivariate volatility models, the regime transition in the RSSN model is endogenous. As discussed by Chan et al. (2017), by defining strict periods of crisis and non-crisis without a endogenous mechanism of transition, one might obtain misleading results. Hwang et al. (2011) assert that another limitation in empirical studies on contagion is their assessment of only correlation shifts (see also Pukthuanthong and Roll (2009)). Given that the correlation coefficient is a linear measure of dependency between distributions, such coefficient might not reflect the proper dependency relationship since the definition of contagion is based on a non-normal non-linear structure of dependency. In this sense, the proposed model also allows for the evaluation of higher-order moment contagion (e.g. coskewness) given that it can capture changes in the joint distribution of the asset returns. The financial literature has in fact discussed the importance of equity return skewness and coskewness for portfolio management. For instance, during crises, negative return skewness tends to become positive since risk averse investors recompose their portfolios to include assets with this characteristic (Fry et al., 2010). Assets with positive skewness (i.e. tail is on the right side) have fewer negative returns with higher probability. The coskewness coefficient is defined as the covariance between an asset return and the squared portfolio return, thus being related to the systematic contribution of this asset to the portfolio skewness. Consequently, if an asset return and a portfolio present positive coskewness, they will usually present extreme positive returns in excess of market returns at the same time, which ultimately leads to lower expected returns. Conversely, negative coskewness implies higher probability of underperformance relative to market returns at the same time.

The present study contributes to the existing literature by assessing the existence of financial contagion in the Latin American economies in the aftermath of the recent global financial crisis not only through correlation (linear or non-linear) but also through coskewness in the context of endogenous regime transitions. To the best of our knowledge, no study has attempted to use such approach to investigate both correlation and coskewness contagion effects in Latin America during the recent US financial crisis. Given the highly volatile nature of these markets, analyzing the potential occurrence of financial contagion is essential, especially in the presence of non-linear behavior. Calvo and Reinhart (1996), Chen et al. (2002) and Coronado et al. (2016) describe the specific characteristics of financial markets in Latin America.

The obtained results confirm the hypothesis of correlation contagion in the selected Latin American markets, with probability of 100%. Hence, we found evidences of a statistically significant increase in the correlation between the US and each Latin American market during the 2007 global financial crisis. The assessment of coskewness showed that such coefficient increased for all five considered countries, even becoming positive for Brazil and Mexico, that is, these financial markets shifted toward a more risk-averse profile than in the pre-crisis period, with investors seeking safety strategies (lower volatility and lower expected return). Regarding the interrelationship with the US, only Argentina depicted a less risk averse behavior, indicating greater risk appetite. As for the existence of coskewness contagion, such phenomenon was only observed in Brazil, suggesting that risk-averse investors tended to migrate their investments from the Brazilian market to the US during the crisis. Consequently, these findings indicate that, among the selected Latin American countries, the Brazilian market apparently endured the most significant negative effects of the recent crisis. The occurrence of structural breaks in the moments of the mean, variance and skewness was also analyzed. Structural breaks in the mean were only present in Argentina and the US whereas the probability of variance structural break was 100% for the five financial markets. As for skewness structural breaks, decisive support of such phenomenon was only found in Mexico. Overall, these findings reaffirm the relevance of financial contagion in Latin America.

Besides this introduction and the concluding remarks, the paper is organized in three sections. First, Section 2 describes the RSSN model as well as the contagion and structural break tests. Section 3 presents the data and the posterior estimates of the switching parameters. Finally, Section 4 addresses the results for the contagion tests and the occurrence of moment structural breaks.

2 A regime switching skew-normal model for asset returns

According to Hamilton (1989), nonlinear stationary processes are intrinsic features of macroeconomic time series. By amending the parameters of an autoregression to allow for a discrete-state Markov process, the regime switching model departed from the restrictions imposed by linearity. Yet, others still remained. As discussed in Chan et al. (2017), financial time series are usually characterized by asymmetry, heavy tails and heteroskedasticity. In order to circumvent such restraints, the latter authors extended the regime switching model of Hamilton (1989) to a multivariate skew-normal framework, following the skew-normal distribution developed by Sahu et al. (2003). This so-called regime switching skew-normal (RSSN) model is argued to better represent the intricacies of high frequency data.

Let y_t be a set of asset returns skew-normally distributed with regime-dependent parameters, that is,

$$y_t = \mu_{s_t} + \Omega_{s_t} Z_t + \varepsilon_t, \tag{1}$$

$$\varepsilon_t \overset{iid}{\sim} N(0, \Sigma_{s_t}), \tag{2}$$

$$Z_t \overset{iid}{\sim} N(c1_m, I_m)\mathbb{1}(Z_{jt} > c, j = 1, \dots, m), \tag{3}$$

where $y_t = (y_{1t}, \dots, y_{mt})'$ is an m-dimensional vector with $t = 1, \dots, T$; $s_t \in \{0; 1\}$ is an unobserved random binary variable representing the regime that the process was in at time t; μ_{s_t} is an $m \times 1$ regime-dependent vector of constants; Ω_{s_t} is a symmetric $m \times m$ regime-dependent skewness-coskewness matrix; $Z_t = (Z_{1t}, \dots, Z_{mt})'$ is an m-dimensional latent random vector; ε_t is an $m \times 1$ innovation vector; Σ_{s_t} is an $m \times m$ regime-dependent variance-covariance matrix; 1_m is an $m \times 1$ column of ones; I_m is an $m \times m$ identity matrix; and $\mathbb{1}(\cdot)$ is an indicator function with takes a value of 1 if all Z_{jt} are greater than c and 0 otherwise. Following Chan et al. (2017), c is set to be $-\sqrt{2/\pi}$ so that the unconditional expectation of y_t is not affected by Z_t.

As in Hamilton (1989), the state of the regime s_t is modeled as the outcome of an unobserved two-state Markov chain, so that the standard Markov transition is given by

$$\begin{aligned} \Pr(s_t = 1 \mid s_{t-1} = i) &= p_{it} \\ \Pr(s_t = 0 \mid s_{t-1} = i) &= 1 - p_{it} \end{aligned} \tag{4}$$

with $i \in \{0; 1\}$; and p_{it} being probabilities that vary with time.

Note that the RSSN model allows the means (μ_{s_t}), coskewness (Ω_{s_t}), and the error cross-covariances (Σ_{s_t}) to change in accordance to shifts in regime. Hence, given the existence of two regimes, there are two sets of regime-dependent parameters, namely ($\mu_0, \Omega_0, \Sigma_0$) and ($\mu_1, \Omega_1, \Sigma_1$). Chan et al. (2017) argue that changes in the parameters of correlation and coskewness during the second regime are to be understood as contagion whereas changes in the moment parameters of the mean, variance and skewness in the second regime are to be understood as structural breaks.

The econometric representation of equations (1) to (3) is defined as

$$y_t = X_t \beta_{s_t} + \varepsilon_t, \tag{5}$$

$$\varepsilon_t \overset{iid}{\sim} N(0, \Sigma_{s_t}), \tag{6}$$

where $X_t = (I_m, I_m \otimes Z_t')$, $\beta_{s_t} = (\mu_{s_t}', \omega_{s_t}')'$ and $\omega_{s_t} = \mathrm{vec}(\Omega_{s_t}')$. The dimensions of μ_{s_t}, ω_{s_t} and β_{s_t} are m, m^2 and $m(m+1)$, respectively. The underlying likelihood function is then specified as

$$f(y \mid Z, \Theta, s) = (2\pi)^{-\frac{mT}{2}} \prod_{t=1}^{T} |\Sigma_{s_t}|^{-\frac{1}{2}} \exp\left\{ -\frac{1}{2} \sum_{t=1}^{T} [y_t - X_t\beta_{s_t}]' \Sigma_{s_t}^{-1} [y_t - X_t\beta_{s_t}] \right\} \tag{7}$$

with $\Theta = (\beta_0, \beta_1, \Sigma_0, \Sigma_1)$ being the parameters of the RSSN model; and $s_t \in \{0; 1\}$.

In terms of the Bayesian estimation procedure, Markov Chain Monte Carlo methods are performed as to obtain draws from the posterior distribution. The priors for the model parameters are set as

$$\beta_{s_t} \sim N(\underline{\beta}, \underline{V}_{\beta}), \tag{8}$$

$$\Sigma_{s_t} \sim IW(\underline{\tau}_{\Sigma}, \underline{S}_{\Sigma}), \tag{9}$$

$$\Pr(s_t = 1 \mid s_{t-1} = i) = p_{it}, \quad \Pr(s_t = 0 \mid s_{t-1} = i) = 1 - p_{it}, \tag{10}$$

where $IW(\underline{\tau}_{\Sigma}, \underline{S}_{\Sigma})$ represents the inverse-Wishart distribution with degree of freedom $\underline{\tau}_{\Sigma}$ and scale matrix $\underline{S}_{\Sigma}$. Also, $\underline{\beta} = (\underline{\mu}', \underline{\omega}')'$ and $\underline{V}_{\beta} = \left[\begin{smallmatrix} \phi_\mu I_m & 0 \\ 0 & \phi_\omega I_k \end{smallmatrix}\right]$, with $k = m^2$.

As proposed by Chan et al. (2017), the posterior distribution is obtained by the Gibbs sampler method. As the joint posterior distribution is proportional to the product of the likelihood function and the joint prior density (i.e. the Bayes rule), we have that

$$\pi(\Theta, Z, s \mid y) \propto f(y \mid Z, \Theta, s) f(Z) f(s \mid \Theta) \pi(\Theta) \tag{11}$$

where $f(Z)$, $f(s \mid \Theta)$ and $f(y \mid Z, \Theta, s)$ are depicted by equations (3), (4) and (7), respectively. In addition, $\pi(\Theta)$ represents the prior density function whereas $\pi(\Theta, Z, s \mid y)$ is the posterior density function. Prior independence between β and Σ is assumed, so that

$$\pi(\Theta) = \pi(\beta_0)\pi(\beta_1)\pi(\Sigma_0)\pi(\Sigma_1). \tag{12}$$

Following Chan et al. (2017), the posterior draws from the joint posterior distribution are obtained by performing the following Gibbs sampler:

- **Step 1:** Starting values for $\Theta^{(0)} = \left(\beta_0^{(0)}, \beta_1^{(0)}, \Sigma_0^{(0)}, \Sigma_1^{(0)}\right)$ and $Z^{(0)}$ are defined, where $\beta_l^{(0)} = \left(\mu_l^{(0)\prime}, \omega_l^{(0)\prime}\right)^\prime$ with $l = 0, 1$. The counter is set as $loop = 1, \ldots, n$, where n is the number of iterations.
- **Step 2:** The $s^{(loop)}$ is generated from $\pi\left(s \mid y, Z^{(loop-1)}, \Theta^{(loop-1)}\right)$, where $\Theta^{(loop)} = \left(\beta^{(loop)}, \Sigma^{(loop)}\right)$.
- **Step 3:** The $\beta_l^{(loop)}$ is generated from $\pi\left(\beta_l \mid y, Z^{(loop-1)}, \Sigma_l^{(loop-1)}, s^{(loop)}\right)$.
- **Step 4:** $\Sigma_l^{(loop)}$ is generated from $\pi\left(\Sigma_l \mid y, Z^{(loop-1), \beta_l^{(loop)}, s^{(loop)}}\right)$.
- **Step 5:** $Z^{(loop)}$ is generated from $\pi\left(Z \mid y, \Theta^{(loop)}, s^{(loop)}\right)$.
- **Step 6:** The counter is reset to $loop = loop + 1$. Return to Step 2.

As described in Step 1, this algorithm is iterated n times. In order to allow the Markov Chain to converge to a stationary distribution, the n_0 first draws are discarded as burn-in draws while the remaining n_1 are retained to compute the parameter estimates. For the full conditional distributions, their derivations and further technical details, refer to Chan et al. (2017).

Testing for financial contagion and structural breaks requires restrictions on the RSSN model parameters as well as the evaluation of underlying hypotheses. Assume the RSSN model as the unrestricted model (M_u). This model embodies two sets of regime-specific parameters, which are comprised of regime-specific mean vectors μ_0 and μ_1, covariance matrices Σ_0 and Σ_1, and coskewness matrices Ω_0 and Ω_1. The correlation coefficient $\rho_{ij,l}$ is obtained by the ratio of the covariance $\Sigma_{ij,l}$ and the product of the square root of the variances $\Sigma_{ii,l}$ and $\Sigma_{jj,l}$, that is,

$$\rho_{ij,l} = \frac{\Sigma_{ij,l}}{\sqrt{\Sigma_{ii,l}}\sqrt{\Sigma_{jj,l}}}. \tag{13}$$

Note that the subscript (ij, l) refers to the ij-th element of the respective matrix in the regime l.

For the specific case of financial contagion, five alternative tests are performed. First, contagion between financial markets is detected if the correlation coefficient increased in the regime $s_t = 1$ in comparison to the regime $s_t = 0$. In mathematical terms, we test whether

$$\rho_{ij,s_t=1} - \rho_{ij,s_t=0} > 0 \tag{14}$$

for $i \neq j$. Chan et al. (2017) argue that such hypothesis is based on the idea perpetrated by Forbes and Rigobon (2002) that markets are expected to behave more similarly during a crisis. The probability associated to the correlation contagion between markets i and j is defined as

$$\Pr\left(\rho_{ij,s_t=1} - \rho_{ij,s_t=0} > 0 \mid y, M_u\right) \tag{15}$$

and is calculated from the MCMC draws.

Second, joint correlation contagion between the $m-1$ pairs of asset returns with market j can also be tested for. In this case, we obtain the sum of the individual correlation coefficients $\Upsilon_l = \sum_{i=1}^m \sum_{j\neq i}^m \rho_{ij,l}$ for each regime and then test for joint correlation contagion, that is, whether $\Upsilon_0 \leq \Upsilon_1$. Similarly to the previous case, such joint probability of correlation contagion is estimated based on the MCMC draws.

A third alternative test is the coskewness contagion test which relies on the idea that contagion occurs when the asymmetric dependence of returns i and j changes across regimes. According to Chan et al. (2017), this test is compatible with the bivariate coskewness statistics for contagion developed by Fry et al. (2010). The coskewness contagion test is given by

$$\omega_{ij,s_t=0} \neq \omega_{ij,s_t=1} \tag{16}$$

for $i \neq j$. Hence, the restricted model (M_r) for the coskewness test is set as $\omega_{ij,s_t=0} = \omega_{ij,s_t=1}$, for $i \neq j$. As the test involves equality restrictions, we depart from the probability decision to Bayesian model comparison methods. Following Chan et al. (2017), the natural logarithm of the Bayes factor is used as the decision statistics and the model selection threshold follows the scale proposed by Jeffreys (1961).[1] Evidence in favor of M_u supports the hypothesis of bivariate coskewness contagion.

It is also possible to test for joint coskewness contagion in which we investigate whether there were shifts in coskewness across all m asset markets. In this case, the joint coskewness contagion test is defined as

$$\sum_{i=1}^{m} \sum_{j \neq i}^{m} \omega_{ij,s_t=0} \neq \sum_{i=1}^{m} \sum_{j \neq i}^{m} \omega_{ij,s_t=1}. \tag{17}$$

Thus, the restriction imposed to the model is comprised of $\sum_{i=1}^{m} \sum_{j \neq i}^{m} \omega_{ij,s_t=0} = \sum_{i=1}^{m} \sum_{j \neq i}^{m} \omega_{ij,s_t=1}$. As the previous case, the natural logarithm of BF_{ru} is computed. Evidences in favor of M_u indicates the existence of joint coskewness contagion.

In addition, both correlation and coskewness contagion can be jointly tested for. The procedure consists of imposing both restrictions to the RSSN model and then computing the natural logarithm of BF_{ru}. However, despite knowing the prior distributions of the associated parameters, the density in the simultaneous presence of such restrictions is usually not known. Therefore, Chan et al. (2017) propose a Gaussian kernel estimation to approximate such unknown densities, following Geweke (2010).[2] Once again, evidences in favor of M_u indicates the simultaneous occurrence of both types of contagion.

Yet, the RSSN model also allows for the testing of structural breaks in the mean, variance and skewness for asset market i during $s_t = 1$ compared to $s_t = 0$. For the first case, testing the existence of a structural break in the mean for asset market i relies on the idea that the mean decreases in financial crisis periods given that expected returns are lower. Hence, the probability for market i is defined as

[1] Despite being an alternative to classical hypothesis testing, the choice of Bayesian model comparison is driven by the fact that it is also a suitable approach for comparing non-nested models. The Bayes factor is defined as

$$BF_{ru} = \frac{p(y|M_r)}{p(y|M_u)} \iff \ln\big(BF_{ru}\big) = \ln\big(p(y|M_r)\big) - \ln\big(p(y|M_u)\big)$$

with $p(y|M_r)$ and $p(y|M_u)$ being the marginal likelihoods of the data under models M_r and M_u, respectively. For technical details on computing the marginal likelihoods, refer to Chan et al. (2017). Note that the marginal likelihood of M_r will be small if the data are improbable under such model. Hence, the BF_{ru} indicates which model better fits the given data.

[2] For technical details on the Gaussian kernel estimator, refer to Chan et al. (2017) and Geweke (2010).

$$\Pr\left(\mu_{i,s_t=1} - \mu_{i,s_t=0} < 0 \mid y, M_u\right) \tag{18}$$

and is estimated from the MCMC draws. The extension to a joint version across all m asset markets is achieved by considering the whole mean vectors $\mu_{s_t=1}$ and $\mu_{s_t=0}$, so that the associated probability is

$$\Pr\left(\sum_{i=1}^{m} \mu_{i,s_t=1} - \sum_{i=1}^{m} \mu_{i,s_t=0} \leq 0 \;\middle|\; y, M_u\right) \tag{19}$$

and can also be estimated from the MCMC draws.

The structural break test for the variance of the returns of market i is obtained by testing the hypothesis that $\Sigma_{ii,s_t=1} - \Sigma_{ii,s_t=0} > 0$ since the variance of returns is expected to increase in the financial crisis regime. Therefore, the underlying probability has the form

$$\Pr\left(\Sigma_{ii,s_t=1} - \Sigma_{ii,s_t=0} > 0 \mid y, M_u\right) \tag{20}$$

which is also calculated from the MCMC draws. The joint test version for all m asset markets is computed by evaluating the proportion of times $\Sigma_{s_t=1} - \Sigma_{s_t=0} > 0$ in the MCMC draws, where $\Sigma_{s_t=1} = \sum_{i=1}^{m} \Sigma_{ii,s_t=1}$ and $\Sigma_{s_t=0} = \sum_{i=1}^{m} \Sigma_{ii,s_t=0}$. Consequently, the associated probability is given by

$$\Pr(\Sigma_{s_t=1} - \Sigma_{s_t=0} > 0 \mid y, M_u) \tag{21}$$

and is obtained from the MCMC draws.

The last set of structural break tests consists of evaluating potential changes in the skewness of asset returns in regime $s_t = 1$ compared to regime $s_t = 0$. The individual test for asset market i is based on the hypothesis that $\omega_{ii,s_t=0} \neq \omega_{ii,s_t=1}$. Yet, Chan et al. (2017) argue that there still remains no macroeconomic consensus on the direction of skewness changes during a crisis. Therefore, they propose an agnostic stance regarding such movements, recognizing both positive and negative changes as possible outcomes. Formally, the latter hypothesis is tested by imposing $\omega_{ii,s_t=1} = \omega_{ii,s_t=0}$ to the RSSN model and comparing the unrestricted model to the restricted one through the Bayes factor. Note that in M_u all regime-specific parameters are free to vary across regimes whereas M_r considers no skewness changes for the asset market i. Similarly to the previous cases, evidences in favor of M_u suggest the occurrence of a structural break in the return skewness for market i. On the other hand, the joint evaluation of a potential structural break in the return skewness of all m asset markets is performed by imposing the assumption that $\omega_{ii,s_t=1} = \omega_{ii,s_t=0}$, for all $i = 1, \ldots, m$, to the RSSN model. The Bayes factor is then computed and evaluated.

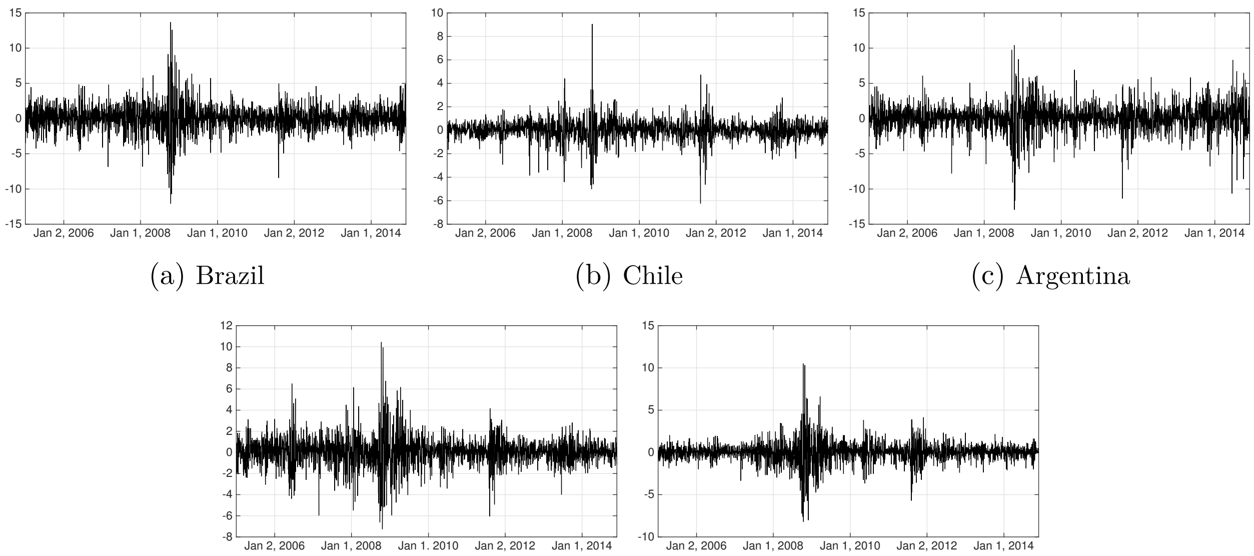
Finally, the RSSN model also allows for the testing of the simultaneous occurrence of contagion and structural breaks by simultaneously imposing the necessary restrictions to the RSSN model and evaluating the Bayes factor. For instance, one can evaluate the coexistence of a joint structural break (i.e. simultaneous mean, variance and skewness structural break) for the asset market i with a joint bivariate contagion (i.e. correlation and coskewness contagion) between asset markets i and j. Note that the occurrence of joint contagion and structural breaks across all asset markets is also possible under the RSSN framework. Yet, as previously discussed, there still remains concerns about the associated densities in the presence of such restrictions. These unknown densities are also estimated by a Gaussian kernel estimator.

3 Data and econometric estimates

We investigate the potential occurrence of contagion effects between the equity returns of the US and four Latin American markets (Argentina, Brazil, Chile, and Mexico – the LA-4) during the recent subprime crisis. To this end, daily equity market indices for the latter markets were collected from the Bloomberg financial database. More specifically, we use the following stock market indices: (i) Sao Paulo Stock Exchange Ibovespa index for Brazil (IBOV:IND), (ii) Santiago Stock Exchange IGPA index for Chile (IGPA:IND), (iii) Buenos Aires Stock Exchange Merval index for Argentina (MERVAL:IND), (iv) S&P/BMV IPC index for Mexico (MEXBOL:IND), and (v) Dow Jones Industrial Average index for the US (INDU:IND). The daily percentage returns are computed as the difference of natural logarithms of the daily equity indices, multiplied by 100, that is, $r_t = 100 \times \left[\ln(y_t) - \ln(y_{t-1})\right]$, where r_t is the daily percentage return of an equity index at time t, and y_t and y_{t-1} are the daily equity indices at time t and $t-1$, respectively. In addition, given that different stock markets are subjected to different holiday schedules, missing equity indices are carried forward from the last observed index as to make the calendar compatible across the five selected countries. Finally, following Chan et al. (2017), the residuals of a VAR(5) are used as the data during the estimation procedure.

Data span the period from January 4, 2005 to November 28, 2014. Following Chan et al. (2017), the period from January 4, 2005 to July 25, 2007 is defined as the Great Moderation whereas the Global Financial Crisis corresponds to the period from March 3, 2008 to November 28, 2014. Consequently, from July 26, 2007 to February 29, 2008, both the selected Latin American and the US markets are in transition from the former period to the latter one. In fact, preliminary visual inspection of the financial time series in Figure 1 suggests that the fluctuation of equity returns increased from 2008 onwards, especially in Argentina, Chile and the US. Such fluctuation increase also indicates the potential presence of a non-constant and time-dependent volatility.

Figure 1: Daily Percentage Equity Returns of Selected Latin American Markets and the US



(a) Brazil (b) Chile (c) Argentina

(d) Mexico (e) US

Yet, priors for the hyperparameters in Equations (8) to (10) need to be specified in order to proceed with the Bayesian estimation. Following Chan et al. (2017), we set $\underline{\beta} = 0$, $\phi_\mu = 0.01$, $\phi_\omega = 1$, $\underline{\tau}_\Sigma = 20 + m + 1$, $\underline{S}_\Sigma = (\underline{\tau}_\Sigma - m - 1) \times I_m$, with $m = 5$. Note that the priors for the variances (i.e. ϕ_μ and ϕ_ω) are relatively small as to guarantee the prior distributions are proper and slightly informative. Regarding the priors for the transition probabilities, it is first assumed that $\Pr(s_t = 1 \mid s_{t-1} = 0) = \Pr(s_t = 1 \mid s_{t-1} = 1) = p_t$. Then, following Chan et al. (2017), the initial value for the probability of being in the Great Moderation regime is defined as $\Pr(s_t = 0) = 0.99$ for the period between January 4, 2005 and July 25, 2007. In contrast, the probability of being in the Global Financial Crisis regime is defined as $\Pr(s_t = 1) = 0.99$ for the period between March 3, 2008 and November 28, 2014. One should note that the probability of being in the Great Moderation regime decreases linearly from 0.99 on July 26, 2007 to 0.01 on March 3, 2008.

As in Chan et al. (2017), we also restrict the coskewness matrix Ω of Equation (1) to be a symmetric matrix so that the dimension of ω becomes $k = m(m+1)/2$. Further, the constant term c in Equation (3) is defined as $c = -\sqrt{2/\pi}$, which leads to $E(Z_t) = 0$ and $V(Z_t) = (\pi - 2)/\pi$ and ensures that the inclusion of latent variables (i.e. Z_t) has no effect on the (unconditional) expectation of y_t.

We performed 200,000 iterations of the MCMC algorithm with the first 10,000 draws being discarded in the burn-in period. Given that MCMC sampling methods are commonly associated to autocorrelation and, consequently, biased Monte Carlo standard errors, we only retain every 10th iteration in order to circumvent such issues. Hence, posterior means are computed based on 20,000 MCMC draws. Table 1 presents the posterior means of the switching parameters for the selected Latin American markets and the US during both the Great Moderation and the Global Financial Crisis regimes.

In terms of correlation and coskewness, the obtained results show considerable variation between regimes (Table 1). Correlation was found to be higher during the Global Financial Crisis regime in comparison to the period of Great Moderation. This result is in line with the evidences presented by the international literature on financial market linkages during crises (see e.g. Roll (1988), Hamao et al. (1990), King and Wadhwani (1990), Malliaris and Urrutia (1992), Erb et al. (1994), Lin et al. (1994), Solnik et al. (1996), Ramchmand (1998), Cizeau et al. (2001), Longin and Solnik (2001), Ang and Chen (2002), Butler and Joaquin (2002), Bartram and Wang (2005), Meric et al. (2008), among others). Accordingly, such cross-market correlation rise in the context of high volatility ultimately reduced the benefits of risk diversification in the Latin American markets in the aftermath of the United States subprime mortgage crisis.

When compared to the Great Moderation period, coskewness between all pairs of Latin American markets became less negative during the Global Financial Crisis, with coskewness between Mexico and Brazil even becoming positive (Table 1). Given that positive coskewness reduces the risk of the portfolio in high volatile periods (Harvey and Siddique, 2000; Adesi et al., 2004; Guidolin and Timmermann, 2008), these findings suggest that the Latin American financial markets shifted toward a more risk-averse profile than in the pre-crisis period. Yet, regarding the interrelationship with the US, coskewness became positive for almost all selected Latin American markets. Similar results were also found in recent studies for the European markets and the US (Fry et al., 2010; Fry-McKibbin et al., 2014; Chan et al., 2017). Note that the Argentina-US pair is the only exception, with the value of coskewness falling from -0.327 to -0.858. Thus, while most of Latin American markets presented a more risk-averse profile relative to the US during the subprime crisis, investors in Argentina seem to have become even less risk averse.

The obtained results for the moments of the mean, variance and skewness are also regime-dependent (Table 1). During the Great Moderation, mean returns for the five considered markets were positive, with Mexico and Brazil exhibiting the highest values: 0.086% and 0.080%,

Table 1: Posterior Means of the Switching Parameters for the Selected Latin American Markets and the US

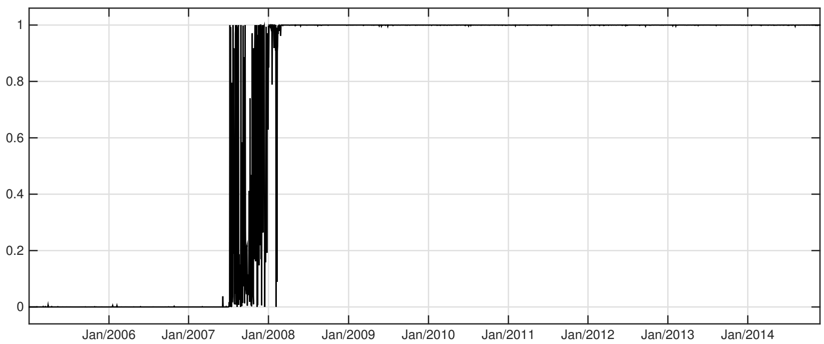
Parameters	Markets	Brazil	Chile	Argentina	Mexico	US
Great Moderation Regime ($s_t = 0$)						
Covariance ($\sum_{ij,0}$)	Chile	0.095				
	Argentina	0.190	0.046			
	Mexico	0.403	0.120	0.154		
	US	0.210	0.052	0.107	0.204	
Correlation ($\rho_{ij,0}$)	Chile	0.168				
	Argentina	0.168	0.085			
	Mexico	0.390	0.239	0.155		
	US	0.355	0.181	0.190	0.388	
Coskewness ($\omega_{ij,0}$)	Chile	-0.272				
	Argentina	-1.064	-0.222			
	Mexico	-0.782	-0.210	-0.707		
	US	-0.356	-0.087	-0.327	-0.252	
Mean ($\mu_{i,0}$)	—	0.080	0.065	0.033	0.086	0.021
Variance ($\sum_{ii,0}$)	—	1.131	0.272	1.001	0.908	0.300
Skewness ($\omega_{ii,0}$)	—	-1.054	-0.182	-0.889	-0.525	-0.119
Global Financial Crisis Regime ($s_t = 1$)						
Covariance ($\sum_{ij,1}$)	Chile	0.892				
	Argentina	2.334	0.926			
	Mexico	1.628	0.681	1.525		
	US	1.457	0.563	1.387	1.055	
Correlation ($\rho_{ij,1}$)	Chile	0.615				
	Argentina	0.704	0.588			
	Mexico	0.743	0.654	0.642		
	US	0.769	0.625	0.672	0.775	
Coskewness ($\omega_{ij,1}$)	Chile	-0.083				
	Argentina	-0.319	-0.093			
	Mexico	0.238	-0.138	-0.337		
	US	0.583	0.338	-0.858	0.135	
Mean ($\mu_{i,1}$)	—	-0.017	0.008	0.047	0.011	0.011
Variance ($\sum_{ii,1}$)	—	3.054	0.690	3.599	1.571	1.180
Skewness ($\omega_{ii,1}$)	—	-0.225	-0.148	-0.489	0.223	0.224

Notes: By their nature, both variance-covariance and skewness-coskewness matrices are symmetrical. Therefore, only the main diagonal and the lower entry estimates are reported. Data span from January 4, 2005 to November 28, 2014, comprising 2584 daily observations.

respectively. However, as expected, mean returns decreased in the aftermath of the subprime crisis, with the Brazilian mean return even becoming negative (-0.017%). The variance of daily equity returns considerably increased in the Global Financial Crisis regime relative to the Great Moderation regime. For instance, while the Argentinian and Brazilian variances substantially increased after the subprime crisis (from 1.001 to 3.599 and from 1.131 to 3.054, respectively), Chile presented the lowest increase among the considered markets (from 0.272 to 0.690). As for skewness, negative parameters were found for all five selected markets during the pre-crisis period. Still, the obtained results for the Global Financial Crisis regime shows that the skewness parameters shifted toward less negative magnitudes in Brazil, Chile and Argentina. In the case of Mexico and the US, even though the same direction of change was observed, skewness parameters turned positive. Based on the Arrow-Pratt notion of risk aversion (Pratt, 1964; Arrow, 1971), right-skewed (positive skewness) payoffs are preferable to left-skewed (negative skewness) ones in the context of risk-averse investors. Therefore, the positive skewness parameters for Mexico and the US imply that investors considered these markets to be relatively safer than Brazil, Chile and Argentina. Similar results for the European markets and the US were found by Fry et al. (2010) and Fry-McKibbin et al. (2014).

But how did the probability of the model being in a certain regime change over time? Figure 2 displays the posterior probability of being in the Global Financial Crisis regime during the sample period. The regime transition was apparently initiated in mid 2007, period in which the US economy severely suffered from increases in risk spreads, wealth contractions, and shortage of liquidity in the credit market (Goodhart, 2008; Reinhart and Rogoff, 2008). Such transitions across regimes were unstable until February of 2008, settling into the crisis regime thereafter. Note that the transition to the Global Financial Crisis regime for the selected Latin American markets took place before the collapse of the Bear Stearns Hedge Group in March of 2008, an event considered as a main trigger of the subsequent financial crisis. Using the same econometric framework, Chan et al. (2017) found similar results for the European markets and the US.

Figure 2: Posterior Probability of the Global Financial Crisis Regime



4 Addressing contagion and structural breaks

Even though the regime-dependent nature of both our low- and high-order moment estimates is readily observable, properly identifying potential contagious linkages arising from the US equity market on Latin America during the Global Financial Crisis is still imperative. The first panel of Table 2 presents individual and joint contagion tests for the correlation and coskewness channels. First, note that correlation contagion is characterized as a statistical significant increase in the correlation parameter during the Global Financial Crisis relative to the previous regime. That being said, the obtained results provide strong evidence of correlation contagion between the US and Latin American returns, with $p = 1.00$. Even when jointly considering the US and all Latin American markets, the contagion tests still indicate the occurrence of such contagion mechanism ($p = 1.00$).

However, coskewness contagion was only observed for the Brazil-US pair, with a value of the log of the Bayes factor $\ln(BF_{ru})$ of -8.54. Consequently, this result suggests that risk-averse investors tended to migrate their investments from the Brazilian market to the US during the crisis. As discussed in Chan et al. (2017), the presence of coskewness contagion in only some of the considered markets indicates the relative severity of the crisis in the financial sector of these economies relative to the other markets. Thus, the US subprime crisis spillovers seem to have affected the Brazil more severely than the rest of the Latin American markets. Interestingly, when considering the coskewness test for all markets ($\forall i$), there is decisive evidence of contagion, with the value of the log of the Bayes factor $\ln(BF_{ru})$ being -172.22.

The jointly occurrence of both the correlation and coskewness contagion is tested in the bottom row of the first panel of Table 2. For each US-Latin American market pair, the joint contagion tests provided decisive support for both phenomena during the Global Financial Crisis regime. The same conclusion is obtained when jointly considering all Latin American markets and the US.

Table 2: Contagion and Structural Break Tests for the Equity Returns of Selected Latin American Markets and the US during the Global Financial Crisis

	Method	Brazil	Chile	Argentina	Mexico	US	$\forall i$
Contagion Tests ($i \neq j$)							
Correlation	p	**1.00**	**1.00**	**1.00**	**1.00**	—	**1.00**
Coskewness	BF	**-8.54**	-2.24	-0.87	-2.11	—	**-172.22**
Correlation and Coskewness	BF	**-19.98**	**-28.37**	**-9.91**	**-54.03**	—	**-288.75**
Structural Break Tests (i)							
Mean	p	0.57	0.58	**0.99**	0.71	**0.99**	**0.98**
Variance	p	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Skewness	BF	-1.65	1.33	0.62	**-2.56**	-0.37	**-5.28**
Mean, Variance and Skewness	BF	**-144.60**	**-213.55**	**-116.57**	**-15.29**	**-450.01**	**-813.94**
Joint Contagion ($i \neq j$) *and Structural Break Tests* (i)							
All	BF	**-668.62**	**-494.58**	**-229.76**	**-497.85**	—	**-1102.7**

Notes: Contagion tests are performed with respect to the US market. Data span from January 4, 2005 to November 28, 2014, comprising 2584 daily observations. Note that p and BF refer to decision methods based on probability and the Bayes Factor, respectively. The bold results indicate the presence of contagion or structural break.

As a second step, we also investigate the likelihood of moment structural breaks in the mean, variance and skewness for each equity return. The second panel of Table 2 presents such results. Even though the structural break tests suggest only Argentina and the US individually presented such phenomenon, the test considering all five markets combined indicate a structural break in the moment of the mean during the Global Financial Crisis period ($p = 0.98$). Note that this latter result might reflect the strong evidences of such structural breaks in Argentina ($p = 0.99$) and the US ($p = 0.99$).

In regards to the second moment, the probability of a structural break for all equity markets is 100% (Table 2). As expected, when considering all five markets jointly, the structural break test for the variance confirms the individual results, with probability of 100%. These results are in line with the stylized fact of higher equity return volatility during crisis periods.

The results for the presence of a structural break in skewness are decisive only for Mexico, with the value of the log of the Bayes factor $\ln(BF_{ru})$ being -2.56 (Table 2). Yet, similar to the test of a structural break in the moment of the mean, the results for skewness considering all five markets also suggest a statically significant shift in the parameter in the aftermath of the US subprime crisis, with $\ln(BF_{ru}) = -5.28$.

For each market, joint tests were also performed in order to assess whether the mean, variance and skewness, jointly, presented structural breaks. The obtained results are summarized in the last row of the second panel of Table 2. Note that the values of the natural log of the Bayes factor for all five markets, both individually and jointly, provide decisive evidence of structural breaks. Still, it is important to highlight the fact that, in general, the structural break in the variance emerges as the most important one for all five equity markets.

Finally, we also considered the concomitant occurrence of both contagion and structural breaks for each market as well as all the five markets jointly. The last panel of Table 2 reports the joint test estimates. Given that the US is considered the source of the crisis, there is no test statistics for this market. Overall, our findings provide decisive evidence of joint contagion and structural breaks for each individual Latin American market and for the five combined markets. However, these results must be interpreted with caution. As the joint tests for contagion and structural breaks consider a variety of comoment and moment changes between regimes, the sole use of their results might induce misleading conclusions. For instance, even though the joint contagion and structural break test indicates the occurrence of both phenomena in Chile, the results of individual tests suggest neither coskewness contagion nor mean or skewness structural break. Still, these joint tests are appealing tools in order to further validate the individual results.

5 Concluding remarks

This article investigated the potential occurrence of financial contagion between the US and selected Latin American equity markets during the recent US-based global financial crisis. More specifically, through the application of the regime switching skew-normal (RSSN) model developed by Chan et al. (2017), we evaluated the likelihood of contagion by considering potential changes in the comoments of correlation and coskewness in the Global Financial Crisis regime compared to the Great Moderation regime. As a second step, we also tested for the presence of structural breaks in the moments of the mean, variance and skewness. Assessing the possibility of these phenomena is relevant in order to better comprehend the intricacies in the behavior of risk averse investors in Latin America during the recent crisis.

First, the posterior estimates of the switching parameters revealed their regime-dependent nature. Indeed, correlation between Latin American markets and the US increased during the Global Financial Crisis regime in comparison to the Great Moderation regime, which ultimately reduced the benefits of risk diversification in these emerging markets. Moreover, with exception of Argentina, the observed rise in coskewness during the crisis period suggests that the Latin American markets shifted toward a more risk-averse profile relative to the US than in the pre-crisis period. While the variance of equity returns of all five considered markets increased considerably during the crisis regime, the mean equity returns presented a rather substantial decreased, with the Brazilian mean even becoming negative. As for skewness, daily equity returns exhibited less negative coefficients during the financial crisis relative to the pre-crisis period. In fact, positive skewness parameters were even found for Mexico and the US. Consequently, these results for skewness imply that risk averse investors considered Mexico and the US to be relatively safer markets than Brazil, Chile and Argentina in the aftermath of the recent financial crisis.

Both the individual and joint contagion tests provided significant evidence of correlation contagion from the US for all the selected Latin American markets, with probability of 100%. Yet, coskewness contagion was only decisively observed for the Brazil-US pair. Furthermore, structural breaks in the mean were only present in Argentina and the US whereas the probability of variance structural break was 100% for the five financial markets. As for skewness structural breaks, decisive support of such phenomenon was only found for Mexico. Yet, joint contagion and structural tests provided decisive evidence of their occurrence for each individual Latin American market and for the five combined markets.

The results found in the present paper contribute to the recent debate on the occurrence of contagion and on potential restructuring policies for the international financial system. Determining the existence of financial contagion is of major concern for investors given its effect on portfolio risk management and portfolio expected return. On the other hand, the evaluation of financial contagion is also important to policymakers as to design proper macroprudential strategies in order to minimize potential financial spillovers on economies during crisis as well as discuss the resilience and efficiency of the financial system in the context of high-volatility returns.

6 Compliance with Ethical Standards

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

Diego Ferreira declares that he has no conflict of interest.

Andreza Aparecida Palma declares that she has no conflict of interest

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