Comovements and Contagion in Emergent Markets: Stock Indexes Volatilities

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ABSTRACT The past decade has witenessed a series of (well accepted and defined) financial crises periods in the world economy. Most of these events are country specific and eventually spreaded out across neighbor countries, with the concept of vicinity extrapolating the geographic maps and entering the *contagion* maps. Unfortunately, what contagion represents and how to measure it are still unanswered questions.
In this article we measure the transmission of shocks by cross-market correlation coefficients following Forbes and Rigobon's (2000) notion of *shift-contagion*. Our main contribution relies upon the use of traditional factor model techniques combined with stochastic volatility models to study the dependence among Latin American stock price indexes and the North American index. More specifically, we concentrate on situations where the factor variances are modeled by a multivariate stochastic volatility structure.
From a theoretical perspective, we improve currently available methodology by allowing the factor loadings, in the factor model structure, to have a time-varying structure and to capture changes in the series' weights over time. By doing this, we believe that changes and interventions experienced by those five countries are well accommodated by our models which *learns* and *adapts* reasonably fast to those economic and idiosyncratic shocks.
We empirically show that the time varying covariance structure can be modeled by one or two common factors and that some sort of contagion is present in most of the series' covariances during periods of economical instability, or *crises*. Open issues on real time implementation and natural model comparisons are thoroughly discussed.

1 Introduction

The aim of this paper is to investigate, and possibly to explain, how the financial crises observed during the last decade spillover across countries. Of particular interest is why some of the crises, which begin as country specific events, quickly spread over countries and regions like Latin America. This type of codependence has been named, at least within the financial econometrics community, *contagion.*

The empirical literature for testing whether contagion exists is extensive, as it is the various ways it has been defined. Among the available strategies to evaluate contagion only two will mentioned in this paper. The most common strategy contrasts the correlation in returns between two markets during a stable period with the same correlation after the occurrence of some shock. The other approach is due to using GARCH models to make inference about the variance-covariance transmission mechanism across countries. Forbes and Rigobon (2000) and Edward and Susmel (2000) are central to understand those alternatives classes of models. Particularly in the latter, interest rate volatility for a group of Latin American countries were examined based on weekly data from 1994 up to 1999. Both conclude that the results are not overly supportive of contagion stories. An alternative approach was proposed by Agénon, Aizenman and Hoffmaister (1998) in studying the effects of contagion on bank lending spreads and output fluctuations in Argentina. The effects of a positive historical shock in the external interest rate spread were analyzed using generalized impulse response functions in the context of a VAR model relating the *ex ante* bank lending spread, the cyclical component of output , real bank lending rate and external interest rate spread.

In this article we apply factor models (Bartholomew, 1995), to characterize covariance structures in certain classes of multivariate stochastic volatility models, or more specifically, factor stochastic volatility models (FSV), with a particular view to applications in economics and finance. Stochastic volatility models are basically a class of time-series models that allow the time-series variances and covariances to evolve with time as stochastic functionals of past variances, covariances and possibly other information available. Further details about univariate stochastic volatility models, as well as comparisons with the well-known class of autoregressive conditionally heterokedastic (ARCH) models, can be found in Shephard (1996) and Kim, Shephard and Chib (1998). Although generalizations to multivariate situations are theoretically and conceptually simple, academics and practitioners experienced computational problems with the statistical inference. Many attempts have been made to overcome dimensionality problems and factor models opened the possibility to solve the problems for the same reasons stressed above. Diebold and Nerlove (1989) introduce the latent factor ARCH models, which is further explored and compared with other variance models in Sentana (1998) and Giakoumatos, Dellaportas and Politis (1999). The former studied the differences between Diebold and Nerlove's latent factor ARCH models and Engle's (1987) factor ARCH models, while the latter compared a latent one-factor ARCH model with Shephard's unobserved ARCH model. The works of Harvey, Ruiz and Shephard (1994) followed by Jacquier, Polson and Rossi (1995) and Kim et al (1998), and more recently by Lopes, Aguilar and West (2000), Aguilar and West (2000) and Pitt and Shephard (1999) , form the basis for the model developments we consider here. They basically model the levels of a set of time-series by a factor model where both the common factor variances and the specific (or idiosyncratic) variances follow multivariate and univariate first order stochastic volatility structures respectively.

From a more methodological viewpoint, we build on these works in some theoretical and practical directions by allowing the factor loadings to evolve in time. The rationale behind these extensions is that by allowing the factor loadings to change over time we maintain the factor scores interpretability virtually the same across time and give more flexibility to the model. In other words, our model incorporates the idea that the weight that some factors have on a particular time series might change with time, mimicking real financial/economic scenarios. A simple example is when a country (or countries) enter/leave a particular market, and when such a market is been represented by a group of stable latent factors. Moreover, in a more general framework and with the current global market integration, financial and economic indicators tend to be driven by latent factors which importance is constantly changing. This is clearly the case in most Latin American stock markets.

The rest of the article is organized as follows. Section 2 sets up the model which has two major components. In the first component, a factor model is used to represent the level of time series dependence structure where we allow the loadings matrix to change overtime by specifying a stochastic evolution process. In the second component, we follow previous work on multivariate stochastic volatility models by specifying multiple time series models for the log volatilities of the common factors. In this section, we also setup the environment for Bayesian inference and we lay down the prior distributions for the model's parameters.

When analyzing the five-dimensional time series vector containing the rate of return for four Latin American countries plus the U.S. DOW JONES index, in Section 3, we start with traditional static factor analysis to gain some intuition about the time series covariance structure and their potential dynamic components (Section 3.2). Univariate stochastic volatility models for each of the five series are also presented to motivate the factor stochastic structure. We then implement the factor stochastic volatility models through Bayesian simulation to sample from the posterior distribution of model parameters including our new time-varying structure on the loadings of the factor model. Finally we close the paper, in Section 4, by highlighting the benefits of including time-varying structure to the loadings matrix and give comments regarding the real-time application of these models focusing on benefits in the predictive area.

2 Methodology

As is traditional in the factor analysis context, we assume that $\boldsymbol{y}_t$ is a m-dimensional vector of time series, whose levels follow a k-factor model,

$$(\boldsymbol{y}_t|\boldsymbol{f}_t, \boldsymbol{\gamma}_t, \boldsymbol{\beta}_t, \boldsymbol{\Sigma}_t) \sim N(\boldsymbol{\gamma}_t + \boldsymbol{\beta}_t \boldsymbol{f}_t; \boldsymbol{\Sigma}_t) \tag{2.1}$$

where, again, $\boldsymbol{\gamma}_t$ is the m-dimensional mean level vector, $\boldsymbol{\beta}_t$ is the $m \times k$ factor loading matrix, $\boldsymbol{f}_t$ is the $k \times 1$ vector of common factors and $\boldsymbol{\Sigma}_t$ is the $m \times m$ diagonal matrix with the specific or idiosyncratic variances. The main departures from standard factor analysis lie in the time structure of the parameters in $\boldsymbol{\gamma}, \boldsymbol{\beta}, \boldsymbol{\Sigma}$ and the variances of $\boldsymbol{f}$. We assume that the mean level, $\boldsymbol{\gamma}_t$ follows a simple multivariate random walk process of the following form,

$$(\boldsymbol{\gamma}_t|\boldsymbol{\gamma}_{t-1}, \boldsymbol{W}_t^\gamma) \sim N(\boldsymbol{\gamma}_{t-1}, \boldsymbol{W}_t^\gamma) \tag{2.2}$$

to capture constant local (myopic) levels in the series. We will further assume that the evolution matrices $\boldsymbol{W}_t^\gamma$ are completely specified by a single and known discount factor $\delta_\gamma \in (0, 1)$, see West and Harrison (1997) for further details. We also assume the common factors are independent and normally distributed over time, conditional on $\boldsymbol{H}_t$,

$$(\boldsymbol{f}_t|\boldsymbol{H}_t) \sim N(\boldsymbol{0}; \boldsymbol{H}_t) \tag{2.3}$$

with $\boldsymbol{H}_t = diag(h_{1t}, \ldots, h_{kt})$. Following Aguilar and West (2000) model, the log-volatilities $\lambda_{it} = log(h_{it})$, can be described by a multivariate first-order autoregressive (VAR) model with correlated innovations,

$$(\boldsymbol{\lambda}_t|\boldsymbol{\lambda}_{t-1}, \boldsymbol{\alpha}, \boldsymbol{\phi}, \boldsymbol{U}) \sim N(\boldsymbol{\alpha} + \boldsymbol{\phi}(\boldsymbol{\lambda}_{t-1} - \boldsymbol{\alpha}); \boldsymbol{U}) \tag{2.4}$$

for $\boldsymbol{\lambda}_t = (\lambda_{1t}, \ldots, \lambda_{kt})'$, $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_k)'$, and $\boldsymbol{\phi} = diag(\phi_1, \ldots, \phi_k)$.

As is traditional in the stochastic volatility literature, the persistence parameters are such that $0 < \phi_i < 1$ for $i = 1, \ldots, k$, to guarantee non-explosive behavior in the final time series variances and covariances and representing real life volatility clusters. Moreover, by allowing correlated innovations in the time series model we are capturing the potential high levels of correlations observed in periods of high financial stress and volatility peaks, Aguilar and West (2000). Under such assumptions, it is easy to see that $\boldsymbol{\lambda}_1 \sim N(\boldsymbol{\mu}, \boldsymbol{W})$, where $\boldsymbol{W}$ satisfies $\boldsymbol{W} = \boldsymbol{\phi}\boldsymbol{W}\boldsymbol{\phi} + \boldsymbol{U}$.

On the other hand, univariate stochastic volatility structures are assumed for the non-zero elements of $\boldsymbol{\Sigma}_t = diag(\sigma^2_{1t}, \ldots, \sigma^2_{mt})$ in the same fashion as in Jacquier et al (1995), Pitt and Shephard (1999) and Aguilar and West (2000). More specifically, the idiosyncratic log-volatilities, $\eta_{it} = log(\sigma^2_{it})$ follow standard first-order autoregressive models,

$$(\boldsymbol{\eta}_t|\boldsymbol{\eta}_{t-1}, \tilde{\boldsymbol{\alpha}}, \boldsymbol{\rho}, \boldsymbol{S}) \sim N(\tilde{\boldsymbol{\alpha}} + \boldsymbol{\rho}(\boldsymbol{\eta}_{t-1} - \tilde{\boldsymbol{\alpha}}); \boldsymbol{S}) \tag{2.5}$$

for $\boldsymbol{\eta}_t = (\eta_{1t}, \ldots, \eta_{mt})'$, $\tilde{\boldsymbol{\alpha}} = (\tilde{\alpha}_1, \ldots, \tilde{\alpha}_m)$, $\boldsymbol{\rho} = (\rho_1, \ldots, \rho_m)$ and $\boldsymbol{S} = diag(s_1, \ldots, s_m)$. As for the common factor variance equations, we assume that $0 < \rho_i < 1$ for $i = 1, \ldots, m$.

Finally, the loading matrices, $\boldsymbol{\beta}_t$, are block lower triangular, i.e. $\beta_{ij,t} = 0$ for all $j > i$ and ones in the main diagonal. The unconstrained elements of $\boldsymbol{\beta}$ are assumed to follow simple random walk processes with evolution driven by a single and known discount factor $\delta_\beta \in (0, 1)$. See West and Hassion (1997) for further details and Lopes, Aguilar and West (2000) for a related application. In order to complete the requisites for the Bayesian analysis, prior distributions must be defined and we will restrict our analysis to conditionally conjugate prior distributions to facilitate the already complicated posterior analysis. To begin with, the prior distribution for the time series mean level at time $t = 1$ is $\boldsymbol{\gamma}_1 \sim N(\boldsymbol{\gamma}_0, \boldsymbol{\Sigma}_0)$, for $\boldsymbol{\gamma}_0$ and $\boldsymbol{\Sigma}_0$ known hyperparameters. Analogously, the prior distribution for the unconstrained loadings at time $t = 1$ is $\tilde{\boldsymbol{\beta}}_0 \sim N(\boldsymbol{m}_0, \boldsymbol{C}_0)$, with $\boldsymbol{m}_0$ and $\boldsymbol{C}_0$ known hyperparameters. The prior distributions for components of $\boldsymbol{\zeta}$ and the nonzero components $\boldsymbol{\Delta}$ are $\zeta_j \sim N(\zeta_{0j}, C_{0j})$ and $\delta_j \sim N(\delta_{0j}, V_{0j})$, respectively, for $j = 1, \ldots, d$.

For the parameters that define both the factors's log-volatility equations, $\boldsymbol{\alpha}, \boldsymbol{\phi}, \boldsymbol{U}$, and the idiosyncratic factors's log-volatility,$\tilde{\boldsymbol{\alpha}}, \boldsymbol{\rho}, \boldsymbol{s}$, we follow Aguilar and West (2000) suggestions. They assume independent normal priors for the univariate terms of $\boldsymbol{\alpha}$ and $\tilde{\boldsymbol{\alpha}}$ and independent truncated normal priors for the terms in $\boldsymbol{\phi}$ and $\boldsymbol{\rho}$. Inverted Wishart and inverted gamma distributions are assigned to $\boldsymbol{U}$ and to the diagonal elements of $\boldsymbol{S}$, respectively. More specifically, $\boldsymbol{U} \sim IW(r_0, r_0\boldsymbol{R}_0)$ and $\boldsymbol{s}_i \sim IG(\nu_{0i}/2, \nu_{0i}s_{0i}^2/2)$, para $i = 1, \ldots, m$ with $r_0, \boldsymbol{R}_0, \nu_{0i}$ and s_{0i}^2 given hyperparameters.

Posterior analysis is attained by applying an hybrid Markov chain Monte Carlo sampler that was tailored for the model presented. The sampler combines methodology developed by various authors that dealt with similar models. See Aguilar and West (2000), Pitt and Shephard (1999) and Lopes (2000) for technical details and further references.

In the next section we apply the techniques developed above to analyze the financial time series presented in the introduction.

3 Contagion Latin America's stock markets

In this section we apply our methodology to study the relationship amongst four Latin American stock market indexes and the north American index. In our application the vector $\boldsymbol{y}_t$ is composed by log transformation of rates of returns for the following five American indexes: the north American Dow Jones Industrial Average index (DOW JONES), the Brazilian Índice Bovespa (IBOVESPA), the mexican Indice de Precios y Cotaziones (MEXBOL), the argentinean Indice Merval (MERVAL), and the chilean

Indice de Precios Selectivos de Acciones (IPSA). However, let us first introduce the definition of contagion we will adopt in this empirical section and outline general arguments in its favour.

3.1 Defining contagion

In this paper we will adopt the definition provide by Forbes and Rigobon (2000). A significant increase in cross-market linkages after a shock to an individual country will be called *contagion*. This means that if two markets are strongly correlated after a shock, this is not necessarily contagion. Different forms of measurement include the correlation in asset return, the probability of a speculative attack, the transmission of shocks or volatilities. Although this definition is not universally accepted, Forbes and Rigobon (2000) pointed out many advantages associated to it. The shift contagion is empirically useful, extremely valuable in drawing policy conclusions, among others.

The transmition of international shocks can be empirically assessed in many different ways. Rigobon (1999) provides an excellent review of the literature and offer an alternative identification assumption avoiding the problems of heteroscedasticity, omitted variable and the presence of endogenous variables. To discuss the main limitations of the standard measures of contagion he proposed a very simple model. Assuming that there are only two countries and denoting their stocks returns by x_t and y_t the following simple model is proposed:

$$\begin{aligned} y_t &= \beta x_t + \gamma z_t + \epsilon_t \\ x_t &= \alpha y_t + z_t + \eta_t \end{aligned}$$

where z_t is an non-observable aggregate shock (normalized), ϵ_t and η_t are country specific shocks assumed to be independent but not necessarily identically distributed. The common shocks described by z_t include international interest rate, international demand, market attitude toward risk, liquidity shocks etc. It quite simple to see that Rigobon's parameterization is a particular case of our factor stochastic volatility model where the factor loadings, of the reduced form, are functions of α, β and γ.

Therefore, using the methodology introduced above the smoothed posterior mean for the time varying correlation matrix of the observations is given by $\frac{1}{M}\sum_{i=1}^{M}\left[\boldsymbol{\beta}_t^{(i)}\boldsymbol{H}_t^{(i)}\boldsymbol{\beta}_t^{(i)'} + \boldsymbol{\Sigma}_t^{(i)}\right]$, where M is the number of draws taken from the joint posterior distribution of all model's parameters and states. Those correlation will be graphically examined through time and the mean value of those correlation in the tranquil period before each crisis can be compared with its values just after the crisis.

We strongly believe that the methodology introduced in this paper to test for changes in the transmission channel do not suffer from the criticisms extensively discussed in Rigobon (1999). The classical tests used to evaluate contagion, although straightforward to evaluate are biased in the presence of heteroscedasticity and omitted variable and endogeneity. Both the individuals time varying level and the common factors could respond for the omitted variables and the stochastic volatility model of course contemplate the heteroscedasticity involved in the data. The propagation is evaluated by the correlation between stock markets. Those correlation are easily derived from the factor model and its distribution could be assessed from the MCMC procedure. More details can be found in Section 3.3 and in our conclusions (Section 4).

3.2 Exploratory data analysis

The series are observed daily from August, 1st 1994 to February, 14th 2001, comprising a total of 1484 observations. Figure 1 present the logarithm transformation of the five stock-price indexes and the same transformation for their first differences. This figure reveals some interesting facts. Firstly, the middle part of the data, that goes from August, 2nd 1995 to August, 1st 1997, exhibit growth trends with low variability for all countries, with exception of the Chilean index that seems to fluctuate around a stationary level. Secondly and related to the first point, the other two thirds of the data, before 8/2/95 and after 8/1/97 to 1/18/99, both present clustered periods of high volatility (this can be better seen through the figure's right column that represents the log rate returns transformation). Thirdly, the Brazilian's IBOVESPA and the Mexican's MEXBOL indexes exhibit quite similar movements, the same appearing between the Argentinian's MERVAL and the Chilean's IPSA. These kinds of co-movements suggest that one or two common factors might be a reasonable choice for describing the five-dimensional vector of stock returns. Finally, the raw estimates of $E(y_{ti}y_{t-k,j})$ for all series i, j and k lags (graphs not presented here) indicate the presence of time dependence among the squared series. Later on, we will use this motivation to introduce multivariate stochastic volatility models to jointly analyze these dataset. It needs to be pointed out that January, 19th 1999 and December, 23rd 1999 were excluded from the analysis when considering rate of returns.

In order to learn more about the data we started our exploratory analysis by fitting static factor models by maximum likelihood. Based on both the one-factor and the two-factor models (estimates available with the first author upon request) one can argue that the first common factor is virtually the same whether one fits a one-factor or a two-factor model to the whole dataset. The results are similar when focusing on the three subsets. The importance of each of the common factors are accessed by asymptotic tests. Table 1.1 present the p-values associated to each fitted model and sample period. It is noteworthy that there is no strong evidence to reject the one-factor model, the usual 1% significance level and considering the three divisions of the dataset. However, at a level of 5% an extra factor seems to be needed for exactly the periods where the data appears to be more volatile (first and third thirds of the sample period). In fact, all five series exhibit similar volatility behavior in the middle of the sample period indicating that just one latent factor needed to explain most of their variability. Prior and posterior to this more tranquil period the series are more volatile and show related but not highly synchronized movements.

Period	# of factors	χ^2 test	dof	p-value
8/2/94-8/4/95	K=1	12.20	5	0.032
	K=2	1.85	1	0.174
8/7/95-8/25/97	K=1	6.53	5	0.258
	K=2	1.09	1	0.297
8/26/97-2/13/01	K=1	11.42	5	0.044
	K=2	0.56	1	0.452

TABLE 1.1. Number of common factors in the static factor analyzes. Here dof corresponds to the number of degrees of freedom for the χ^2 tests.

Table 1.2 presents each factor's effect, measured by the percentage of the explained variance, on each one of the five time series under study for the whole dataset and for the three disjoint subsets and fitting a two-factor model. Notice that the first common factor explains at least 41% of the variability of four of the five series under study when considering the whole period. Of course there still is a great deal of variability that is due primarily to the series and is not capture by the latent factors. For instance, at least one quarter of IBOVESPA's variability is due to its own idiosyncrasies, the remainder being heavily explained by the first common factor by itself. Overall, the first factor seems to capture the comovements across all five time series. Another interesting fact is that the second common factor becomes less important during the middle and final periods of the dataset for all but the Brazilian index. We believe that the main reason for this factor to have its impact diminished is related to the calmer period where volatilities seem to be under control, or at least, well explained by one common latent factor alone.

3.3 Bayesian analysis

Relatively vague prior were implemented for almost all model parameters. The prior for $\tilde{\alpha}_i, \rho_i$ are relatively vague, while for s_i an inverse gamma with mean 0.0004 and 25 degrees of freedom is assigned. The hyperparameters for the time series mean level, $\boldsymbol{\gamma}_i$, are $\boldsymbol{\gamma}_{0i} = 0$ and $\boldsymbol{\Sigma}_0 = 100,000\boldsymbol{I}_6$, describing quite vaguely the information about the time series locations. The unconstrained elements of $\boldsymbol{\beta}_0$ are normally distributed with zero mean and unit variance. Finally, the prior for the stochastic volatility regression pa-

1st subset		2nd subset		3rd subset	
F1	F2	F1	F2	F1	F2
10	0	33	0	64	0
55	8	26	27	63	18
51	49	40	0	74	1
58	3	52	3	75	8
56	11	11	2	42	2

TABLE 1.2. Percentage of the variance, in the static factor models, explained by the two common factors (F1 and F2).

rameters, α_i, ϕ_i are $N(0, 25)$ and $2Be(20; 1.5) - 1$, respectively. For $\boldsymbol{U}$ we chose $\boldsymbol{R}_0 = 0.001\boldsymbol{I}_2$ and $r_0 = 10$, in Aguilar and West's notation. Other combinations of $\boldsymbol{R}_0$ and r_0 where tested resulting in most of the parameters being unaffected. This behavior was also found when analyzing currency markets (Lopes, 2000) or assets series (Aguilar and West, 2000). The discount factors δ_β and δ_γ were set to 0.99 and 0.975 representing locally constant series levels and factor loadings. Similar results were achieved when $\delta_\beta = 0.975$ even though the results were, as expected, less smooth. The MCMC was run for 20,000 iterations and for the next 10,000 draws every other one was stored, performing a total of 5,000 draws used for posterior and predictive summaries.

Univariate and one-factor stochastic volatility models

Univariate stochastic volatility models can be estimated under our methodology by simply assuming that $k = 0$. Therefore, it is quite natural to begin with individual analysis for each particular country's returns series. We have used the same hyperparameter specifications (when needed) and simulation directives. It was found that all series present highly persistent volatilities with the ρ's close to unity. Also, the series seem to have similar behavior with quite overlapping periods of high volatility, this being particularly emphasized by the Brazilian, Mexican and Argentinian indexes after August, 1997. In what follows we have applied our methodology to both one and two-factor stochastic volatility models.

Following previous findings, we have fitted a one-factor stochastic volatility model to the whole dataset. It is noticable that the posterior means and standard deviations for the parameters defining the stochastic volatility equation for both common and specific factors are fairly similar to those obtained for the first common factor in the two factor stochastic volatility model (see below), the main difference being that the persistence of the factor's volatility is smaller when just one common factor is fitted to the data. The factor loadings' posterior means in the one-factor model is virtually the same as those obtained in the two-factor model (not presented here for the sake of space). This empirical evidence supports the argument that the first factor reflects the overall dependence of the time series through time. All other comparisons are similarly conclusive and suggest that the one-factor model fits well the dataset. Despite this fact, a two-factor stochastic volatility model has been fitted to the data in order to identify possible subtleties overlooked by the one-factor model.

Two-factor stochastic volatility model

Inference for the parameters defining the stochastic volatility equations for both the common factor variances and for the idiosyncratic variances are summarized in table 1.3. There seems to exist high degrees of persistence in both volatility structures, common and specific, for all the indexes under consideration. The results are virtually the same when setting $R_0 = 0.001$.

Factor	α	ϕ	$\boldsymbol{u}$
1st	-10.201(0.416)	0.987(0.007)	0.064(0.019)
2nd	-8.340(3.802)	0.997(0.002)	0.346(0.106)
Index	$\tilde{\alpha}$	ρ	s
DOWJONES	-0.833(0.337)	0.988(0.006)	0.013(0.005)
IBOVESPA	-1.533(0.227)	0.968(0.011)	0.058(0.022)
MEXBOL	-1.125(0.285)	0.989(0.005)	0.009(0.003)
MERVAL	-1.625(0.148)	0.911(0.027)	0.147(0.049)
IPSA	-1.440(0.098)	0.896(0.033)	0.108(0.040)

TABLE 1.3. Two-factor model: retrospective posterior means and standard deviations (in parenthesis) for the stochastic volatility parameters defining the common and the specific variances.

The posterior mean and standard deviation of u_{21} are 0.143 and 0.037, respectively. Additionally, the posterior mean of the correlation of the two factors' volatilties is 0.972. Graphical summaries are presented in Figures 2 to 3. Figure 2 shows the posterior means for the factor loadings through time and shows that there is little variation on the weights attributed to the factors across time. It can be argued that the first common factor is virtually the stochastic component underlying the North American index, the Dow Jones. Analogously, the second common factor shows a behavior similar to those experienced by all four Latin American indexes. This latter factor, for instance, captures the highly volatile period that extends from earlier 1994 to late 1995. Figure 3 presents the factorization of the returns' volatilities among the three factors: two common factor and the specific factor. Finally, Figure 4 shows the posterior means of the time series correlations. As it can be seen, the series seem to experience abrupt changes in the correlation structures during periods of crisis, which are: (i) the Tequila Effect in December, 1994, (ii) the East Asian Flue with the collapse of Thai Baht and Hong Kong dollar attack by speculators in October and November, 1997, (iii) the Siberian Cold that took place in Russia in early August, 1998, and finally (iv) the Brazilian Fever in January, 1999. This results corroborates with our earlier arguments about contagion. More specifically, there seems to exist contagion amongst Latin American countries.

It is worthwhile to mention that both one and two-factor models are able to capture the overall level of the time series volatilities, while their univariate counterparts are more erratic, reflecting their struggle to locate and estimate the series' stochastic volatility's levels (graph not presented).

4 Final thoughts

In this article we have combined factor models with multivariate stochastic volatility models in order to learn and analyze the comovements amongst several Latin American stock price indexes. We have arguably shown that the time varying covariance structure could be modeled by one or two common factors and that some sort of contagion, as measured by abrupt changes in the time series correlations, was present in most of the series during periods of economical instability. Using our methodology and the Bayesian approach it is fairly straightforward to compute predictives, $p(\boldsymbol{y}_{t+h}|\boldsymbol{y}_t) = \int p(\boldsymbol{y}_{t+h}|\boldsymbol{\theta}_{t+h})p(\boldsymbol{\theta}_{t+h}|\boldsymbol{y}_t)d\boldsymbol{\theta}_{t+h}$ with $p(\boldsymbol{\theta}_{t+h}|\boldsymbol{y}_t)$ accurately represented by the MCMC draws. Interesting by-product quantities are $E(y_{t+h,i}|y_{t+h,j}, \boldsymbol{y}_t)$ and $V(y_{t+h,i}|y_{t+h,j}, \boldsymbol{y}_t)$ which assess the future (average) behaviour of a certain market, y_i, to shocks received by another market, y_j at a certain period of time.

However, several interesting questions remain unanswered either because statistical methodology is not available for meaningful and practical answers or because they need further and careful thought. Several of those questions are the following: (i) How to incorporate pre-specified structural changes (such as Markov switching regimes, for instance), in the series mean levels and variances? (ii) Are there alternative ways of stochastically pinpointing periods of time where possible shifts have happened in the time series levels and/or volatilities without appealing for pre-specified structures? (iii) Can both previous questions be answered or touched from a multivariate viewpoint? In other words, can we monitor the changes in sets of time series? And how?

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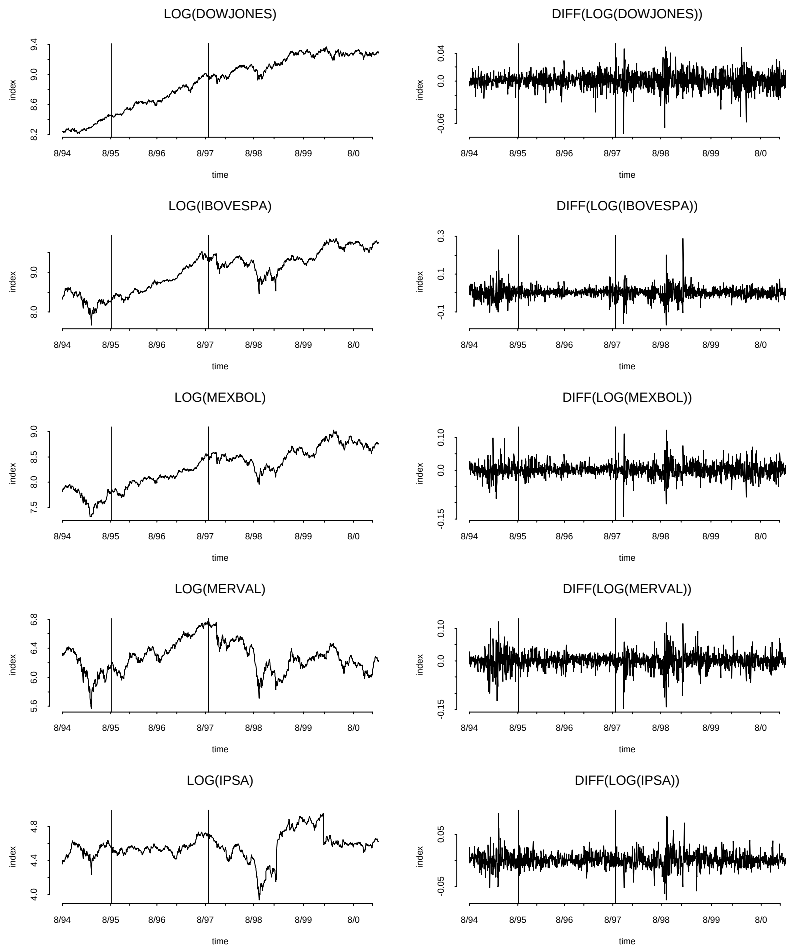

FIGURE 1. Returns from August, 1st 1994 to February, 14th 2001 (1484 observations).

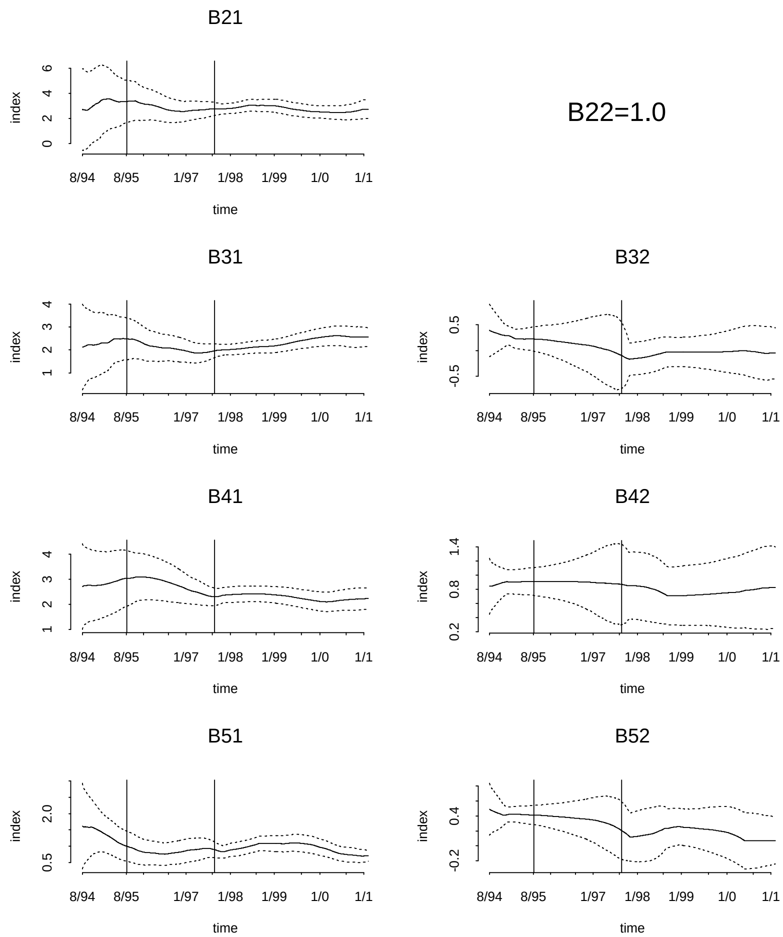

FIGURE 2. Factor loadings (posterior means).

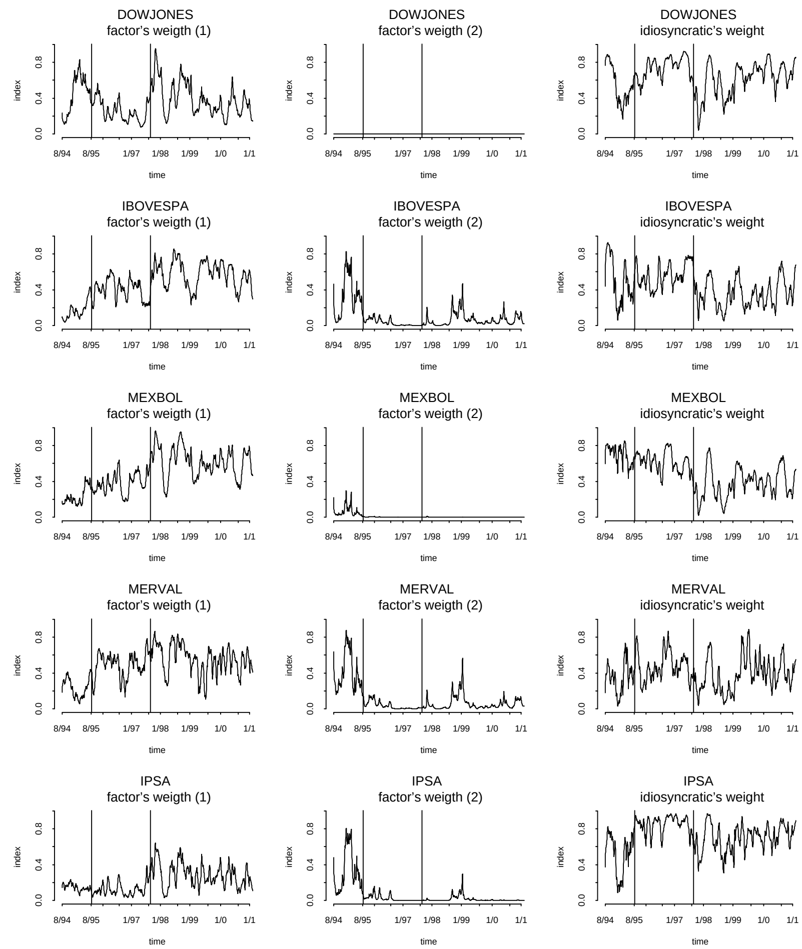

FIGURE 3. Separated factors' variances (posterior means).

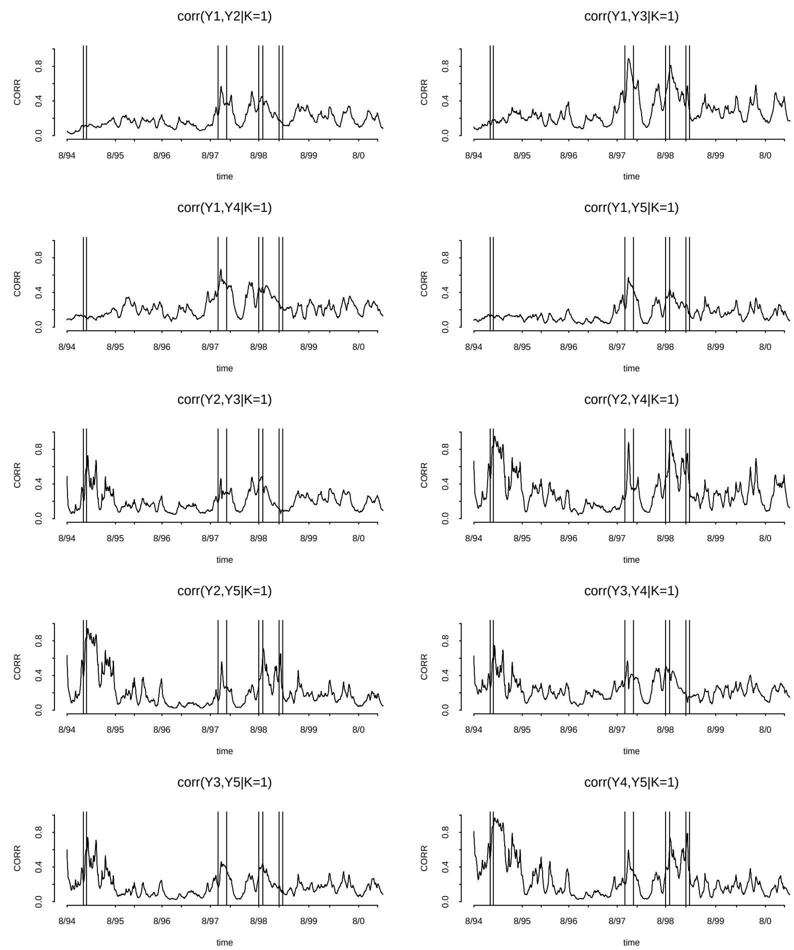

FIGURE 4. Posterior mean of time series correlations. Pairs of vertical lines represent the first and last business days of the following months: 12/94,10-11/97,8/98 and 01/99.