When Markets Fall Down: Are Emerging Markets All The Same?

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Abstract

This paper studies the dynamics of stock market regimes in emerging markets. Using a mixture version of the standard regime-switching model, we find that the 18 analyzed emerging markets can be clustered into three groups. Whereas each of these three groups is characterized by the same two regimes – a bull state with positive returns and low volatility and a bear state with negative returns and high volatility – they clearly differ with respect to their regime-switching dynamics. The first group contains stock markets which swing frequently between the two regimes, the second group shows more regime persistence, and the third group consists of stock markets that are less likely than the others to move to a bear regime period. Standard practice among stock market analysts is to group emerging markets by geographical region. The fact that our model-based clustering is only weakly related to such a regional classification demonstrates the limited validity of the latter. Moreover, a detailed analysis of regime synchronicities across the 18 studied emerging markets shows that there is evidence of regime synchronicity for certain pairs of markets, but this does not rule out that two synchronized markets have different regime dynamics and thus belong to different regime-switching clusters. Hence, our results show that it is incorrect to treat the studied emerging markets as a single homogeneous group because there is strong evidence for substantial differences in their regime-switching dynamics.

JEL classification: C22, G15

Key words: emerging markets; bull; bear; heterogeneity; switching-regime model.

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1 Introduction

It is well known that financial markets present upward and downward trends.¹ For portfolio and risk management it is of great importance to be able to characterize market regimes as well as to time the transition of assets among regimes. For example, it is rather common that investors implement long-short strategies according to their expectation of the market state. In addition, portfolio risk reduction might be achieved by procedures that take into account the synchronization of market regimes. Therefore, methods that provide a sound analysis of the swings, durations and synchronization of regimes are of great help to investors who wish to optimize the timing of portfolio strategies and reduce risk.

Timing the transitions among stock market states is especially relevant in emerging markets because these markets have been recognized as the main responsible for international diversification of gains in the recent years (Goetzmann et al., 2005). However, the frequent occurrence of episodes of price disruptions are an hindrance to international investment in those markets. Investors concerns might be magnified by the fact that it is common to treat emerging markets as a single homogeneous financial asset class. Emerging markets tend to share all the same cliché of “high return and high risk”, regardless of substantial differences on international capital mobility regulation, political regimes, and exchange rates regimes.

Rather than treating emerging markets as a single homogeneous group, we pro-

¹ A common terminology is to classify stock markets in “bull” and “bear” markets according to market expectations. Bull markets correspond to a generalized upward trend (positive returns) and bear markets correspond to periods of a generalized downward trend (negative returns).
pose taking into account the differences between the various emerging markets. This is achieved using a new heterogeneous switching-regime model (HRSM) which takes into account unobserved heterogeneity by a model-based clustering of the markets.\textsuperscript{2} Regime-switching models (RSM) have been introduced by Hamilton (1989) and have been extensively used to model economic and financial time series. Our extension of common RSMs will allow to distinguish 18 emerging stock market indexes with respect to their likelihood of switching between bear and bull markets. It will expand existing methods that do not seem to provide a way to differentiate the behavior of stock market cycles in emerging markets. Also, the proposed methodology accounts for the problem of non-normality in financial returns. It is well documented that emerging markets’ returns are not normally distributed (see for instance Harvey (1995) or Susmel (2001)). As indicated above, the proposed heterogeneous regime-switching model (HRSM) allows taking into account both stock markets heterogeneity and hidden regimes within time series. Moreover, the flexible modeling of observed returns using a mixture of normal distributions makes it straightforward to capture almost any departure from the normality (see, for example, McLachlan and Peel (2000) and Dias and Wedel (2004) on the use of mixture models to address unobserved heterogeneity).

This paper contributes to the literature being the first to address simultaneously the issue of heterogeneity between emerging markets as well as the existence of regimes. Up to now, research has focused on the features and synchronization of stock market cycles. Chen et al. (2002) analyze the dynamic interdependence of six Latin America countries. Edwards et al. (2003) ana-

\textsuperscript{2} As Heckman emphasized in his Nobel lecture (Heckman, 2001), one of the most important discoveries in microeconometrics is the pervasiveness of heterogeneity and diversity in economic life.
lyze stock market cycles in four Latin countries and two Asian countries to see whether they have similar features. They find that cycles in emerging markets tend to have shorter duration and larger amplitude and volatility than in developed countries, and that synchronization of cycles have increased for those countries under analysis. Candelon et al. (2008) measure and analyze the evolution of synchronization of cycles of five emerging Asian countries. Our model accounts for unobserved heterogeneity between emerging markets by identifying groups of markets that differ in certain aspects, e.g., the propensity to switch between regimes. This makes possible to test whether the common practice of the financial industry to cluster emerging markets regionally is suitable. A striking result obtained with the new model is that stock markets that are similar with rather synchrone regimes may differ substantially in terms of dynamics; that is, in the likelihood of jumping from one regime to the other. This is something that the traditional RSM model fails to recognize by assuming the same change pattern applies to all 18 stock markets. Finally, we investigate stock market synchronization. An interesting conclusion of our analysis is that the association with other emerging markets regimes does not preclude countries from having different regime-switching dynamics; that is, to belong to different clusters.

The paper is organized as follows. Section 2 describes the 18 country financial time series data set that is used throughout this paper. Section 3 presents the heterogeneous regime switching model (HRSM) for the analysis of financial time series from multiple markets, as well as discusses shortly parameter estimation by maximum likelihood and model selection issues. Section 4 reports the results obtained for the data set at hand. The paper concludes with a summary of the main findings and a description of their implications.
Emerging stock markets are often viewed as a financial asset class since they tend to present high returns, high volatility, and high diversification benefits because of low correlation with stock market indices of developed markets. However, one can question whether emerging markets should be treated as single homogeneous group since large differences exist between them in aspects such as regulation regarding international capital mobility, market size, liquidity, political institutions, and exchange rates regime.

Typically, emerging markets are grouped by geographical areas. An example of this practice in the financial industry can be seen in the MSCI sub-indices on emerging markets which are clustered regionally because of the presumption that neighbor countries share certain important features. This idea is based on the fact that neighbor countries have more intense trade and, as a result, “cycles” related to one neighbor are likely to affect the other neighbor country. For example, when a country experiences a crisis marked by a currency depreciation, its major partners are negatively affected both through loss of competitiveness and through the fall in demand in the crisis country. Therefore, we will investigated whether it is indeed the case that neighbor countries have similar regime-switching propensities.

For our study, we selected 18 emerging markets that belong to the MSCI Emerging Market Index as of June 2006, as these represent the most active markets. The investigated countries are: Argentina (AR), Brazil (BR), Chile

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3 For a review of emerging markets literature, see Errunza (1997) and Bekaert and Harvey (2003).
4 These are the MSCI Emerging Markets (EM) Latin America Index and the MSCI EM Europe, Middle East and Africa Index.
(CL), China (CH), Czech Republic (CZ), Hungary (HN), India (IN), Israel (IS), Malaysia (MY), Mexico (MX), Pakistan (PK), Peru (PE), Philippines (PH), Poland (PO), Russia (RS), South Africa (SA), Taiwan (TA) and Thailand (TH).

As noted by Goetzmann and Jorion (1999), many of the so-called “emerging markets” are “re-emerging markets”, markets whose stock markets have started a long time ago, but whose development was interrupted. More specifically, they indicated that many countries\(^5\) that already had active equity markets in the 1920’s experienced trading interruptions due to events such as wars, expropriations, hyperinflation, and political changes. As a result of this, a common problem in studying financial time series of emerging markets is the availability of long time series. Although we collected data starting from 1985, for some countries complete data is only available from a later starting year. Hence, the data set used in this article are daily closing prices from 4 July 1994 to 31 July 2007 for the above emerging stock market indexes drawn from Datastream.\(^6\) The series are denominated in U.S. dollars. In total, we have 3412 end-of-the-day observations per country. Let \(P_{it}\) be the observed daily closing price of market \(i\) on day \(t\), \(i = 1, \ldots, n\) and \(t = 0, \ldots, T\). The daily rates of return are defined as the percentage rate of return by \(y_{it} = 100 \times \log(P_{it}/P_{i,t-1}),\) \(t = 1, \ldots, T\), with \(T = 3411\). This definition which is commonly used in the literature is justified by the fact that for expected small increases (decreases) of value, say \(r\), \(\log(1 + r) \simeq r\).

The 18 stock markets in our sample are listed in Table 1, which also provides

\(^5\) For instance, China, Malaysia, India, Egypt, Poland, Romania, Czechoslovakia, Colombia, Uruguay, Chile, Venezuela and Mexico.

\(^6\) Data on countries such as Egypt, Indonesia, Jordan, Korea and Morocco was not available or presented some problems.
relevant descriptive statistics for the stock-return time series. Figure 1 depicts
the full time series.

[Table 1 about here.]

[Fig. 1 about here.]

The period analyzed can be characterized as of market instability. Although
financial crises do not happen exclusively in emerging markets (see Sachs et
al. (1996)), they are more frequent in emerging markets than in developed
markets, and they usually have a larger negative impact. Moreover, crises
in emerging markets tend to last longer than in developed markets (Patel
and Sankar, 1998), and tend to spread to the other emerging markets in the
same region. The sample period includes the Mexican crisis of 1994, the East
Asian Crisis of 1997, the Russian crisis of 1998, the 1999 Brazilian crisis, the
Argentina crises in 2001-2002, as well as the global stock market downturn of
the 2001 Internet bubble.

The descriptive statistics in Table 1 show that the mean return rates are all
positive, except for Thailand. Central and Eastern European stock markets,
such as Russian Federation, Hungary and Czech Republic, tend to have larger
positive mean return rates than the other countries. Based on the median, one
would however conclude that non-European stocks such as Mexico, Brazil and
South Africa have the highest returns.

The analyzed markets show very diverse patterns of dispersion, where the
largest standard deviation is found in Russia (43.11%) and the lowest in Chile
with a standard deviation of 16.42%. These differences in volatility are smaller
than the ones found by Harvey (1995), who reports a difference of 86% between
the lowest and the largest standard deviation of returns in his emerging market
sample, while in our data set the difference between the highest and the lowest standard deviation is around 35%. The smaller gap could be explained by the fact that, as shown in some studies (e.g., Bekaert and Harvey (2000)), volatility decreases after liberalization reforms.

Most of these stock market distributions of return rates are negatively skewed, which can be explained by the series of market recessions in the studied period. Exceptions with positive skewness are Philippines, Russia, Thailand and Peru. Moreover, the excess kurtosis (which equals 0 for normal distributions) shows values above 0, indicating heavier tails and more peakness than the normal distribution. The Jarque-Bera test rejects the null hypothesis of normality for each of the 18 stock markets. The non-normality of equity returns for stock markets has already been documented by Harvey (1995) and Susmel (2001).

3 The heterogeneous regime-switching model (HRSM)

Two different types of statistical methods have been proposed in the literature for identifying cycles or regimes in economic variables. The first type involves specifying a parametric model for the data generating process, where it is assumed that there is a switching between two regimes. While applications were initially in the analysis of business cycles (e.g., Goodwin (1993)), this approach has been widely used to model financial times series such as equity returns of developed markets (e.g., Ang and Bekaert (2002) and Maheu and McCurdy (2000)), interest rates (e.g., Garcia and Perron (1996) and Kanas (2008)) and exchange rates (e.g., Kanas (2005)). The other alternative type of method is nonparametric: rather than specifying a statistical model that generates the data, it involves a search in the original time series for periods of
generalized upward and downward trends, as well as for turning points, peaks and troughs. Applications of this nonparametric approach in stock market analysis are reported by Pagan and Sossounov (2003), Edwards et al. (2003) and Candelon et al. (2008). The HRSM for financial time series analysis that we describe next belongs to the first class of parametric methods.

Let \( y_{it} \) represent the response of observation (stock market) \( i \) at time point \( t \), where \( i \in 1, \ldots, n \), \( t \in 1, \ldots, T \). We model simultaneously the time series of \( n \) stock markets. In addition to the observed “response” variable \( y_{it} \), the HRSM contains two different latent variables: a time-constant discrete latent variable and a time-varying discrete latent variable. The former, which is denoted by \( w \in \{1, \ldots, S\} \), is used to capture the unobserved heterogeneity across stock markets; that is, stock markets are clustered based on differences in their dynamics. We will refer to a model with \( S \) clusters as HRSM-S. The two-state time-varying latent variable is denoted by \( z_t \in \{1, 2\} \). Changes between the two states or regimes between adjacent time points are assumed to be in agreement with a first-order Markov or first-order autocorrelation structure.

Let \( f(y_i; \varphi) \) be the (probability) density function associated with the index return rates of stock market \( i \). The HRSM-S defines the following parametric model for this density:

\[
f(y_i; \varphi) = \sum_{w=1}^{S} \sum_{z_1=1}^{2} \sum_{z_2=1}^{2} \cdots \sum_{z_T=1}^{2} f(w, z_1, \ldots, z_T) f(y_i | w, z_1, \ldots, z_T). \tag{1}
\]

The right-hand side of this equation shows that we are dealing with a mixture model containing the time-constant latent variable \( w \) and \( T \) realizations of the time-varying latent variable \( z_t \). The total number of mixture components equals \( S \cdot 2^T \), which is the product of the number of categories of
and \( z_t \) for \( t = 1, 2, ..., T \). As in any mixture model, the observed data density \( f(y_i; \varphi) \) is obtained by marginalizing over the latent variables. Because in our model these are discrete variables, this simply involves the computation of a weighted average of class-specific probability densities – here \( f(y_i|w, z_1, \ldots, z_T) \) – where the (prior) class membership probabilities or mixture proportions – here \( f(w, z_1, \ldots, z_T) \) – serve as weights (McLachlan and Peel, 2000).

Using the factoring \( f(w, z_1, \ldots, z_T) = f(w)f(z_1, \ldots, z_T|w) \) and the assumption that within cluster \( w \) the sequence \( \{z_1, \ldots, z_T\} \) is in agreement with a first-order Markov chain, we can simplify the form of \( f(w, z_1, \ldots, z_T) \) as follows:

\[
f(w, z_1, \ldots, z_T) = f(w)f(z_1|w) \prod_{t=2}^{T} f(z_t|z_{t-1}, w), \tag{2}
\]

where

- \( f(w) \) is the probability of belonging to a particular latent class or cluster \( w \) with multinomial parameter \( \pi_w = P(W = w) \);
- \( f(z_1|w) \) is the initial-regime probability; that is, the probability of having a particular initial regime conditional on belonging to latent class \( w \) with Bernoulli parameter \( \lambda_{kw} = P(Z_1 = k|W = w) \);
- \( f(z_t|z_{t-1}, w) \) is a latent transition probability; that is, the probability of being in a particular regime at time point \( t \) conditional on the regime at time point \( t - 1 \) and class membership; assuming a time-homogeneous transition process, we have \( p_{jkw} = P(Z_t = k|Z_{t-1} = j, W = w) \) as the relevant Bernoulli parameter. In other words, within cluster \( w \) one has the transition
probability matrix

\[ P_w = \begin{pmatrix} p_{11w} & p_{12w} \\ p_{21w} & p_{22w} \end{pmatrix}, \]

with \( p_{12w} = 1 - p_{11w} \) and \( p_{22w} = 1 - p_{21w} \). Note that the HRSM-S allows that each cluster has its specific transition or regime-switching dynamics, whereas in a standard RSM it is assumed that all cases have the same transition probabilities.

The other term in Equation (1) is the observed data density conditional on the latent variables, \( f(y_t|w, z_1, \ldots, z_T) \). As is typical in the literature on regime switching, we assume that the observed return at a particular time point depends only on the regime at this time point; i.e., conditionally on the latent state \( z_t \), the response \( y_{it} \) is independent of returns at other time points, which is often referred to as the local independence assumption, and, moreover, independent of the latent states occupied at other time points. These assumptions can be formulated as follows:

\[ f(y_t|w, z_1, \ldots, z_T) = \prod_{t=1}^{T} f(y_{it}|z_t). \quad (3) \]

The probability density of having a particular observed stock return in index \( i \) at time point \( t \) conditional on the regime occupied at time point \( t \), \( f(y_{it}|z_t) \), is assumed to have the form of a univariate normal (or Gaussian) density function. This distribution is characterized by the parameter vector \( \theta_k = (\mu_k, \sigma^2_k) \) containing the mean \( (\mu_k) \) and variance \( (\sigma^2_k) \) for regime \( k \). Note that these parameters are assumed to be equal across clusters, an assumption that may, however, be relaxed. Since \( f(y_i; \varphi) \), defined by Equation (1), is a mixture of densities across clusters \( w \) and regimes, it defines a flexible Gaussian mixture
model that can accommodate deviations of normality in terms of skewness and kurtosis (see, e.g., Dias and Wedel (2004) and Pennings and Garcia (2004)).

As far as the first-order Markov assumption for the latent regime switching conditional on cluster membership \( w \) is concerned, it is important to note that this assumption is not as restrictive as one may initially think. It does clearly not imply a first-order Markov structure for the responses \( y_{it} \). In fact, after marginalizing over \( w \), the process for the sequence \( z_t \) is not even Markovian.

The standard regime-switching or hidden-Markov model (Baum et al., 1970; Hamilton, 1989) is the special case of the HRSM-S that is obtained by eliminating the time-constant latent variable \( w \) from the model, that is, by assuming that there is no unobserved heterogeneity. This model can be obtained without modifying the formulae, but by simply specifying that \( S = 1 \) yielding HRSM-1; that is, by assuming that all stock markets have homogeneous dynamics and belong to the same latent class. Whereas a general two-state HRSM-S has \( 4S + 3 \) free parameters to be estimated, including \( S - 1 \) class sizes, \( S \) initial-regime probabilities, \( 2S \) transition probabilities, \( 2 \) conditional means, and \( 2 \) variances, the two-state HRSM-1 has seven parameters: one initial regime probability, two transition probabilities, two means and two variances.

Maximum likelihood (ML) estimation of the parameters of the HRSM-S involves maximizing the log-likelihood function:

\[
\ell(\varphi; y) = \sum_{i=1}^{n} \log f(y_{i}; \varphi),
\]

a problem that can be solved by means of the Expectation-Maximization (EM) algorithm (Dempster et al., 1977). In the E step, we compute

\[
f(w, z_1, \ldots, z_T|y_i) = f(w, z_1, \ldots, z_T, y_i)/f(y_i),
\]

which is the joint conditional distribution of the \( T + 1 \) latent variables given the data and the current provisional estimates of the model parameters. In the M step, standard complete data ML methods
are used to update the unknown model parameters using an expanded data matrix with \( f(w, z_1, \ldots, z_T|y_i) \) as weights. Since the EM algorithm requires us to compute and store the \( S \cdot 2^T \) entries of \( f(w, z_1, \ldots, z_T|y_i) \) for each stock market, computation time and computer storage increases exponentially with the number of time points, which makes this algorithm impractical or even impossible to apply with more than a few time points. However, for regime-switching or hidden-Markov models, a special variant of the EM algorithm has been proposed that is usually referred to as the forward-backward or Baum-Welch algorithm (Baum et al., 1970; Hamilton, 1989). This special algorithm is needed here because the model for our data set contains a huge number of entries in the joint posterior latent distribution \( f(w, z_1, \ldots, z_T|y_i) \). Recall that in our application \( T = 3411 \). This means that even for \( S = 2 \), the number of entries in the joint posterior distribution is too large to process and store for all \( n \) stock markets as has to be done within a standard EM algorithm. The Baum-Welch algorithm circumvents the computation of this joint posterior distribution making use of the conditional independencies implied by the model.\(^7\).

An important modeling issue is the selection of the value of \( S \), the number of clusters needed to capture the unobserved heterogeneity across stock markets. The standard approach within a maximum likelihood framework would be to set up a likelihood ratio testing a more restricted \( S - 1 \) cluster model against a less restricted \( S \) cluster model. However, this yields a test in which the null hypothesis is defined on the boundary of the parameter space of the alternative hypothesis and as a result the asymptotic properties of the maximum

\(^7\) An extension of the Baum-Welch algorithm that includes the time-constant variable \( w \) is implemented in the Latent GOLD 4.5 software (Vermunt and Magidson, 2008).
likelihood estimates are no longer valid. That is the reason why in mixture models, the selection of $S$ is typically based on information statistics such as the Bayesian Information Criterion (BIC) of Schwarz (Schwarz, 1978) and the Akaike Information Criterion (AIC) of Akaike (Akaike, 1974). Because simulation studies have shown that in mixture modeling AIC tends to overestimate the number of clusters (see, for example, Dias (2006)), in our application we will select $S$ that minimizes the BIC value. This measure is defined as follows:

\[
BIC_S = -2\ell_S(\hat{\phi}; y) + N_S \log n,
\]

where $N_S$ is the number of free parameters of the model concerned and $n$ is the sample size.

4 Results

4.1 Regimes and clusters

This section reports the results obtained when applying the HRSM-S described in the previous section to the 18 emerging markets. We estimated models using different values for $S$ ($S = 1, \ldots, 8$), where 1000 different sets of starting values were used to avoid local maxima. A solution with three latent classes ($S = 3$) yielded the lowest BIC value (log-likelihood = -109177.894; number of free parameters = 15, and BIC = 218399.144). This model will therefore be treated as the final model (HRSM-3). We also provide results for the HRSM-1 for comparison purposes.

Table 2 summarizes the results related to the distribution of stock market
across latent classes which gives the size of each cluster. The estimated prior class membership probability or cluster size is somewhat larger for Class 1 (0.442) and Class 2 (0.383) than for Class 3 (0.175). One way to interpret the nature of the obtained clustering of emerging markets is by looking at the posterior class membership probabilities, the probability of belonging to each of the clusters conditional on the observed data (Table 2). As can be seen, eight countries are assigned to Class 1, seven countries to Class 2 and the remaining three to Class 3. Based on this classification one clearly has to reject the hypothesis that stock markets cluster regionally. Each of the three groups has countries from different regions. The first group includes Argentina, Brazil, China, Pakistan, Poland, Russia, Taiwan and Thailand. The second group includes Czech Republic, Hungary, India, Israel, Mexico, Philippines, and South Africa, and the third and smaller group includes Chile, Peru and strikingly Malaysia. Except for Argentina and Hungary, the class assignments are always with probability one, indicating very little overlap between the classes which reveals very low classification uncertainty. Note that also for Argentina the misclassification probability is very low, assuming that we assign each stock market to the most likely latent class (modal class).

By combining the classification information with the descriptive statistics in Table 1, it can be seen that Class 1 is rather heterogeneous with regard to the mean returns. Thailand has a negative annual return of 2.72%, while Russia rewards 29.41% annually during the observational period. However, the eight stock markets share a high volatility of around 30%, with Russia having the highest value around 40%. The second latent class is more homogeneous with respect to both the mean and the volatility. All countries show positive returns
in the period, the average is 9.61% per year, and Hungary has the highest value of 15.36%. The average yearly volatility is around 25%, with values ranging from 21% to 28%. Class 3 seems to be rather heterogeneous in the sense that it contains two neighbor countries – Chile and Peru – with the lowest volatility of the 18 studied markets (16.42% and 18.25%), as well as Malaysia that has a much higher volatility of around 29%. However, Figure 1 shows that, apart from the Asian crisis period, Malaysia’s stock market has the same low volatility as Chile and Peru.

Table 3 provides information on the two regimes that were identified; that is, the average proportion of markets in regime \( k \) over time and the mean and variance of the return in regime \( k \). The reported means show that one of the regimes is associated with negative returns, around -37% annually, and the other with positive returns, around 23% annually. This corresponds to the typical distinction between bear and bull regimes. The probability of being in the bear and bull regimes is 0.237 and 0.763, respectively. We would also like to emphasize that these results are consistent with the common acknowledgment of asymmetry of the volatility in financial markets. Volatility is likely to be higher when markets fall than when markets rise. The results are similar to the ones of Ang and Bekaert (2002) who find two similar regimes for developed markets: a normal regime with positive returns and low volatility and bear regime with negative returns and high volatility. To gain more insight into the effect of applying the HRSM methodology, Table 3 also shows the regimes encountered with a standard RSM or HRSM-1; i.e., assuming homogeneity across all 18 emerging stock markets. The estimated regime-specific means and volatilities turn out to be similar irrespective of whether we assume
homogeneity of transitions or not. The annual returns in the bear and bull regimes is again around -37% and 23%, respectively.

[Table 4 about here.]

Table 4 reports the estimated probabilities of being in a regime for each latent class, i.e., a estimate of $P(z_t|w = s)$. The probability of being in the bear regime is smaller than the probability of being in the bull regime for all classes. Notwithstanding Class 1 has the largest probability of being in this regime and Class 3 the smallest. This means that countries like Argentina, Brazil, China, Pakistan, Taiwan, Thailand, Poland and Russia show a higher propensity to be in a bear regime than Mexico, India, Philippines, Czech Republic, Hungary, Israel and South Africa, which in turn have higher propensities than Chile, Peru and Malaysia. Note that Class 1 contains countries like Argentina, Brazil, Thailand or Russia that were severely affected by crises.

[Table 5 about here.]

Table 5 provides the key result of our analysis. It gives the transition probabilities between the two regimes for each of the three latent classes. First, notice that all classes show regime persistence. Once a stock market jumps to a regime it is likely to stay within the same regime for some period of time. Second, Class 3 shows the lowest propensity to move from a bull regime to a bear regime. This propensity is higher for Class 2 and even higher for Class 1. Third, Class 2 shows the highest probability of jumping from a bear to a bull regime. We would like to highlight that the traditional RSM (or HRSM-1) does not account for these important differences in the dynamics of switching regimes. Instead, by forcing the pattern of change to be the same in all 18 stock markets, one obtains a kind of average of the three sets of transition
probabilities we find with the HRSM-3.

4.2 Stock markets dynamics and synchronization

In this subsection we look at the synchronization of the regimes across markets. In order to hedge portfolio positions, a risk averse investor has interest in knowing whether regime switches tend to coincide across emerging stock markets or whether they are more or less independent. Figures 2, 3, and 4 show the regime-switching dynamics of the countries within each of our three latent classes. These figures depict the posterior probability of being in bull regime at period $t$ (and blue colored whenever probability of being in bull regime is below 0.5, i.e., higher probability of being in a bear regime).

[Fig. 2 about here.]

These figures show that the three clusters of countries have rather different patterns of regime switching. Emerging stock markets in Class 1 are extremely dynamic and tend to move very fast between regimes. Stock markets belonging to Class 2 are more regime persistent. Class 2 contains markets with short duration crises that did not turn out to be endemic during the period of analysis. For concreteness, let us have a closer look at the cases of Poland and Hungary. As can be seen from Table 1, Poland has a mean return of 11.4% and a volatility of 30% and Hungary of 15.5% and 28%. These stock markets are thus very similar in terms of mean return and volatility, but are nevertheless assigned to different classes. A clear explanation for this can be found in Figure 2 which shows that Poland has a much higher propensity than Hungary to fall in a bear regime, mainly in the beginning of the observational period.
Finally, comparison of the profiles of the Class 3 stock markets shows why Malaysia belongs to this class. It turns out to have a dynamic pattern which is rather similar to that of Chile and Peru apart from the period of the Asian crisis in 1997. Similarly to Chile and Peru, after that period Malaysia shows no propensity to switch to a bear regime.

Table 6 provides summary information on the bear and bull markets regime durations; that is, for each of the 18 emerging markets, it reports the mean, first quartile, median, third quartile, and inter-quartile range of the number of days that the market concerned stayed in a given regime before switching into the other regime. From the fact that the means are much higher than the medians, one can conclude that both for bull and for bear markets, the duration distributions are asymmetric. For example, Argentina has an average bear market duration of 10.4, while the median equals 6. This implies the existence of episodic periods of bear regimes. As far as the length of the bear regime period is concerned, the investigated countries seem to be rather similar: the median duration varies between 5 and 7 days and the third quartile varies between 9 and 16 days. Strikingly, the mean value of Malaysia is much larger than for the other countries, which can however be attributed to a single very long bear-market episode.

Contrary to the bear market durations, large country differences are encountered in the bull market duration. The median bull-market duration ranges from 11 days for China, Poland and Russia to 134 for Chile. This heterogeneity
is picked up very well by our HRSM. The countries with the lowest medians are the countries that belong to Class 1, while the countries with the largest medians are classified into Class 3. This duration information complements what we have learned using the HRSM methodology: the first latent class is characterized by short regime durations, both on bull and bear regimes, the second class shows more regime persistence, with a larger regime persistence in bull markets, and Class 3 has the longest duration for bull regimes.

The last important question we would like to address is whether there is evidence for synchronization of the stock market regimes. In order to measure synchronization and co-movement between the 18 emerging stock markets, we compute the association between markets based on the posterior probability of being in a given regime. Let $\hat{\alpha}_{it}$ be the estimated probability of market $i$ at period $t$ being in bull regime. To obtain a number in the full range of real numbers, this probability is transformed using the logit transformation:

$$\text{logit}_{it} = \log\left(\frac{\hat{\alpha}_{it}}{1 - \hat{\alpha}_{it}}\right).$$

Synchronicity is quantified using the product-moment correlation between the logits for two countries. Measurement of synchronization of stock markets using cross correlations of returns is rather popular. However, Edwards et al. (2003) demonstrated the limitation of this approach resulting from the fact that crises periods may yield very large “outliers in the returns” which introduces so much noise that the concordance between markets is fully distorted. Our logit-based measure does not have this problem because it filters out extreme observations on returns.
Figure 5 depicts the encountered associations between stock markets using our new measure. We represent the absolute value of the correlation (the most negative value is -0.0115), i.e., the absolute correlation between $\text{logit}_{it}$ and $\text{logit}_{jt}$. The minimum and maximum correlation values (0 and 1) are colored with white and black, respectively, and the gray colors for values in between are obtained by a linear grading of colors between white and black. We find one cluster of countries with high correlations on the logit of the probability being in the bull regime: Argentina, Brazil, Chile, Mexico and Peru. Also the correlation between China, Malaysia, Philippines and Thailand is strong. Moreover, we find a regime similarity between Poland and Hungary, and Hungary and Russia. Interestingly is the alignment between South Africa and Czech Republic, Hungary and Mexico. Countries that do not show any coincidence with other regimes are India, Israel and Pakistan. The matrix shows that Chile, despite of being in another cluster, is strongly associated with Argentina and Brazil. Therefore, irrespective of having a different speed in dynamics through the period, there is a large co-movement with its neighbors. Indeed, when the Chilean market is in a bear regime, its neighbors are in that regime as well. Interestingly, these results for Chile are in line with the results reported by Edwards et al. (2003). These authors found that the Chilean economy is highly concordant with its close neighbors, Argentina and Brazil, but “at the same time it is somehow insured against contagion from crises that affect neighbors (p. 944)”. A similar thing can be observed in the comparison between Malaysia and Thailand: there is regime association but they nevertheless belong to different classes because of different regime-switching dynamics.
This paper investigates the dynamics and synchronization of 18 stock markets regimes in emerging markets. For this purpose we expand the methodology of Hamilton (1989) by introducing a discrete latent variable capturing unobserved heterogeneity in RSMs. The time-series data from 18 emerging stock markets could be well described using a model with two regimes; that is, a bear regime, characterized by negative returns and high volatility, and a bull regime with positive returns and low volatility. Two similar return/volatility patterns were found by Ang and Bekaert (2002) using data from the U.S., the U.K. and Germany.

We also investigated whether the common practice of the financial industry to cluster emerging markets regionally is suitable. A striking feature captured by the new model is that stock markets that are similar with respect to their regimes may differ substantially in their dynamics; that is, in the likelihood of jumping from one regime to another. Based on our results the hypothesis of a regional clustering should be rejected. It turns out that the sample of countries can be divided into three classes with different regime-switching dynamics. Whereas all groups show a certain amount of regime persistency, one group of emerging markets is more likely to switch into bear regimes. In another class, we find countries with a lower propensity to switch to this regime. The third class contains the emerging stock markets that are more dynamic, moving faster between regimes. The traditional RSM model fails to recognize the different regime-switching dynamics by assuming the same change pattern in all 18 stock markets.

Finally, we investigate stock market synchronization using various types of
measures. Countries such as Chile, Czech Republic, Peru, Philippines and South Africa show a high level of general synchronicity with other emerging markets. On the other extreme, we find countries such as India, Israel and Pakistan that show a low level of coincidence with other emerging markets regime. An interesting result of our analysis is that despite of being associated, markets may have different regime-switching dynamics; that is, may belong to different clusters. A good illustration is the case of Chile, which shows a large co-movement with its neighbors, Argentina and Brazil: when the Chilean market is in a bear regime, the above neighbors are in that regime as well. However, Chile belongs to a different cluster because it jumps faster to bull market than its neighbors.

Our paper has important implications for international portfolio management. Identifying and recognizing differences on regimes and on the dynamics of the swings can be very useful in the field of portfolio management as an investor would typically like to relate trading rules that explore Markov RSM\(^8\) to market time stock markets or enter into country rotation strategies.

We would like to stress that we did not study the occurrence of contagion and financial crises. Similar to various other studies dealing with stock market cycles (Ang and Bekaert (2002) and Edwards et al. (2003)), we are not able to link bear regime periods to crises or infer contagion based on the fact that markets share the same regime. Regime sharing can be the result of either similar macroeconomic situations or contagion. In future research, we would like to focus on the study of the macroeconomic and financial explanations of the observed differences in dynamics between emerging stock markets.

\(^8\) See, e.g., Engel and Hamilton (1990), Brooks and Persand (2001), Dewachter (2001) and Dueker and Neely (2007).
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1 Time series of index return rates. Countries are Argentina (AR), Brazil (BR), Chile (CL), China (CH), Czech Republic (CZ), Hungary (HN), India (IN), Israel (IS), Malaysia (MY), Mexico (MX), Pakistan (PK), Peru (PE), Philippines (PH), Poland (PO), Russia (RS), South Africa (SA), Taiwan (TA) and Thailand (TH).

2 Estimated posterior bull regime probability and modal regime within Class 1. Countries are Argentina (AR), Brazil (BR), China (CH), Pakistan (PK), Poland (PO), Russia (RS), Taiwan (TA) and Thailand (TH).

3 Estimated posterior bull regime probability and modal regime within Class 2. Countries are Czech Republic (CZ), Hungary (HN), India (IN), Israel (IS), Mexico (MX), Philippines (PH) and South Africa (SA).

4 Estimated posterior bull regime probability and modal regime within Class 3. Countries are Chile (CL), China (CH), Malaysia (MY), and Peru (PE).

5 Absolute correlation between posterior probabilities of being in bull regime. The linear grading denotes the intensity of the association. White color means zero correlation and black color means correlation equal to one. Countries are Argentina (AR), Brazil (BR), Chile (CL), China (CH), Czech Republic (CZ), Hungary (HN), India (IN), Israel (IS), Malaysia (MY), Mexico (MX), Pakistan (PK), Peru (PE), Philippines (PH), Poland (PO), Russia (RS), South Africa (SA), Taiwan (TA) and Thailand (TH).
Fig. 1. Time series of index return rates. Countries are Argentina (AR), Brazil (BR), Chile (CL), China (CH), Czech Republic (CZ), Hungary (HN), India (IN), Israel (IS), Malaysia (MY), Mexico (MX), Pakistan (PK), Peru (PE), Philippines (PH), Poland (PO), Russia (RS), South Africa (SA), Taiwan (TA) and Thailand (TH).
Fig. 2. Estimated posterior bull regime probability and modal regime within Class 1. Countries are Argentina (AR), Brazil (BR), China (CH), Pakistan (PK), Poland (PO), Russia (RS), Taiwan (TA) and Thailand (TH).
Fig. 3. Estimated posterior bull regime probability and modal regime within Class 2. Countries are Czech Republic (CZ), Hungary (HN), India (IN), Israel (IS), Mexico (MX), Philippines (PH) and South Africa (SA).
Fig. 4. Estimated posterior bull regime probability and modal regime within Class 3. Countries are Chile (CL), China (CH), Malaysia (MY), and Peru (PE).
Fig. 5. Absolute correlation between posterior probabilities of being in bull regime. The linear grading denotes the intensity of the association. White color means zero correlation and black color means correlation equal to one. Countries are Argentina (AR), Brazil (BR), Chile (CL), China (CH), Czech Republic (CZ), Hungary (HN), India (IN), Israel (IS), Malaysia (MY), Mexico (MX), Pakistan (PK), Peru (PE), Philippines (PH), Poland (PO), Russia (RS), South Africa (SA), Taiwan (TA) and Thailand (TH).
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| Stock Market       | Mean | Standard Deviation | Median | Skewness | Kurtosis | Jarque-Bera test p-value |
|-------------------|------|--------------------|--------|----------|----------|--------------------------|
| Argentina (AR)    | 0.6% | 31.3%              | 7.9%   | -1.8     | 35.2     | < 0.001                  |
| Brazil (BR)       | 13.4%| 31.5%              | 18.7%  | -0.2     | 5.1      | < 0.001                  |
| Chile (CL)        | 7.1% | 16.4%              | 0.0%   | -0.1     | 3.3      | < 0.001                  |
| China (CH)        | 11.4%| 29.8%              | 2.6%   | 0.0      | 5.2      | < 0.001                  |
| Czech Republic (CZ)| 12.8%| 21.3%              | 0.0%   | -0.2     | 2.4      | < 0.001                  |
| Hungary (HN)      | 15.4%| 27.8%              | 0.0%   | -0.7     | 10.0     | < 0.001                  |
| India (IN)        | 9.0% | 25.0%              | 0.0%   | -0.4     | 4.8      | < 0.001                  |
| Israel (IS)       | 11.4%| 22.2%              | 12.7%  | -0.5     | 4.8      | < 0.001                  |
| Malaysia (MY)     | 1.2% | 29.4%              | 0.0%   | -1.6     | 74.5     | < 0.001                  |
| Mexico (MX)       | 9.4% | 28.6%              | 20.8%  | -0.8     | 16.5     | < 0.001                  |
| Pakistan (PK)     | 2.8% | 30.3%              | 0.0%   | -0.4     | 6.5      | < 0.001                  |
| Peru (PE)         | 11.5%| 18.3%              | 8.0%   | 0.2      | 12.9     | < 0.001                  |
| Philippines (PH)  | 0.1% | 24.8%              | 0.0%   | 0.9      | 16.1     | < 0.001                  |
| Poland (PO)       | 11.4%| 29.9%              | 10.8%  | -0.1     | 3.2      | < 0.001                  |
| Russia (RS)       | 29.4%| 43.1%              | 12.0%  | 0.4      | 22.7     | < 0.001                  |
| South Africa (SA) | 9.1% | 23.8%              | 17.5%  | -0.8     | 6.9      | < 0.001                  |
| Taiwan (TA)       | 2.6% | 27.1%              | 0.0%   | -0.1     | 3.2      | < 0.001                  |
| Thailand (TH)     | -2.7%| 33.9%              | 0.0%   | 0.3      | 8.5      | < 0.001                  |
Table 2

Estimated prior probabilities ($P(W = w)$), posterior probabilities ($P(W = w|y_i)$) and modal classes for the HRSM-3.

| Stock market       | Latent Class 1 | Latent Class 2 | Latent Class 3 | Modal Class |
|--------------------|----------------|----------------|----------------|-------------|
| Prior probabilities| 0.442          | 0.383          | 0.175          | 1           |
| Posterior probabilities |              |                |                |             |
| Argentina (AR)     | 0.995          | 0.005          | 0.000          | 1           |
| Brazil (BR)        | 1.000          | 0.000          | 0.000          | 1           |
| Chile (CL)         | 0.000          | 0.000          | 1.000          | 3           |
| China (CH)         | 1.000          | 0.000          | 0.000          | 1           |
| Czech Republic (CZ)| 0.000          | 1.000          | 0.000          | 2           |
| Hungary (HN)       | 0.070          | 0.930          | 0.000          | 2           |
| India (IN)         | 0.000          | 1.000          | 0.000          | 2           |
| Israel (IS)        | 0.000          | 1.000          | 0.000          | 2           |
| Malaysia (MY)      | 0.000          | 0.000          | 1.000          | 3           |
| Mexico (MX)        | 0.000          | 1.000          | 0.000          | 2           |
| Pakistan (PK)      | 1.000          | 0.000          | 0.000          | 1           |
| Peru (PE)          | 0.000          | 0.000          | 1.000          | 3           |
| Philippines (PH)   | 0.000          | 1.000          | 0.000          | 2           |
| Poland (PO)        | 1.000          | 0.000          | 0.000          | 1           |
| Russia (RS)        | 1.000          | 0.000          | 0.000          | 1           |
| South Africa (SA)  | 0.000          | 1.000          | 0.000          | 2           |
| Taiwan (TA)        | 1.000          | 0.000          | 0.000          | 1           |
| Thailand (TH)      | 1.000          | 0.000          | 0.000          | 1           |
Table 3
Estimated marginal probabilities of the regimes and within Gaussian parameters.

|       | HRSM-1 |       | HRSM-3 |       |
|-------|--------|-------|--------|-------|
|       | Regime 1 | Regime 2 | Regime 1 | Regime 2 |
| P(Z)  | 0.239   | 0.761  | 0.237  | 0.763  |
|       | (0.008) | (0.008) | (0.024) | (0.008) |
| Return| -0.143  | 0.089  | -0.141 | 0.088  |
|       | (0.026) | (0.005) | (0.027) | (0.005) |
| Risk  | 9.295   | 1.057  | 9.357  | 1.037  |
|       | (0.154) | (0.012) | (0.154) | (0.012) |
| Regime 1 | Regime 2 | Regime 1 | Regime 2 | Regime 1 | Regime 2 |
|---------|---------|---------|---------|---------|---------|
| 0.239   | 0.761   | 0.342   | 0.658   | 0.184   | 0.816   |
| (0.008) | —       | (0.012) | —       | (0.816) | —       |
|         |         |         |         |         | (0.014) | —       |

Table 4
Estimated regime occupancies within each latent class.
Table 5
Estimated transition probabilities between regimes ($\hat{p}_{jkw}$).

| HRSM-1 |       |       | HRSM-3 |       |       |
|--------|-------|-------|--------|-------|-------|
|        | Latent class 1 |       | Latent class 2 |       | Latent class 3 |       |
|        | Regime 1 | Regime 2 | Regime 1 | Regime 2 | Regime 1 | Regime 2 | Regime 1 | Regime 2 |
| Regime 1 | 0.912   | 0.088   | 0.894   | 0.106   | 0.889   | 0.111   | 0.929   | 0.071   |
|         | (0.004) | —       | (0.006) | —       | (0.008) | —       | (0.011) | —       |
| Regime 2 | 0.027   | 0.973   | 0.055   | 0.945   | 0.025   | 0.975   | 0.007   | 0.993   |
|         | (0.001) | —       | (0.003) | —       | (0.002) | —       | (0.001) | —       |
| Countries         | Bear regime | Bull regime |
|-------------------|-------------|-------------|
|                   | Mean | Q1 | Median | Q3 | IQR | Mean | Q1 | Median | Q3 | IQR |
| Argentina (AR)    | 10.4 | 3.0 | 6.0 | 12.0 | 9.0 | 29.0 | 5.0 | 12.0 | 37.0 | 32.0 |
| Brazil (BR)       | 12.0 | 3.0 | 7.0 | 16.0 | 13.0 | 24.2 | 6.0 | 13.0 | 31.0 | 25.0 |
| Chile (CL)        | 8.0  | 2.5 | 5.0 | 9.0  | 6.5 | 255.0 | 46.5 | 134.0 | 344.5 | 298.0 |
| China (CH)        | 10.8 | 3.0 | 6.0 | 13.5 | 10.5 | 24.0 | 5.0 | 11.5 | 22.0 | 17.0 |
| Czech Republic (CZ)| 9.0  | 2.0 | 6.0 | 12.0 | 10.0 | 56.8 | 10.5 | 30.5 | 62.0 | 51.5 |
| Hungary (HN)      | 10.5 | 2.0 | 6.0 | 16.5 | 14.5 | 38.4 | 10.0 | 17.0 | 47.0 | 37.0 |
| India (IN)        | 11.0 | 3.0 | 7.0 | 13.0 | 10.0 | 53.1 | 12.0 | 31.0 | 71.0 | 59.0 |
| Israel (IS)       | 8.2  | 2.0 | 6.0 | 11.0 | 9.0 | 51.5 | 8.0 | 24.0 | 64.0 | 56.0 |
| Malaysia (MY)     | 28.3 | 3.0 | 7.0 | 14.5 | 11.5 | 152.7 | 22.0 | 43.0 | 99.0 | 77.0 |
| Mexico (MX)       | 13.4 | 2.0 | 7.0 | 15.0 | 13.0 | 55.0 | 9.0 | 21.0 | 45.0 | 36.0 |
| Pakistan (PK)     | 9.9  | 2.0 | 5.0 | 13.0 | 11.0 | 22.4 | 5.0 | 12.5 | 28.0 | 23.0 |
| Peru (PE)         | 10.3 | 2.0 | 4.5 | 16.0 | 14.0 | 138.5 | 33.0 | 68.0 | 192.0 | 159.0 |
| Philippines (PH)  | 9.5  | 2.0 | 5.0 | 11.5 | 9.5 | 54.9 | 7.5 | 18.0 | 57.5 | 50.0 |
| Poland (PO)       | 9.6  | 2.0 | 5.0 | 11.0 | 9.0 | 22.3 | 7.0 | 11.0 | 25.0 | 18.0 |
| Russia (RS)       | 15.1 | 3.0 | 7.0 | 15.5 | 12.5 | 20.1 | 6.0 | 11.0 | 22.0 | 16.0 |
| South Africa (SA) | 10.0 | 3.0 | 6.0 | 12.0 | 9.0 | 58.2 | 10.0 | 29.5 | 60.0 | 50.0 |
| Taiwan (TA)       | 10.1 | 2.0 | 6.0 | 15.0 | 13.0 | 26.1 | 7.0 | 13.5 | 27.0 | 20.0 |
| Thailand (TH)     | 12.7 | 2.0 | 7.0 | 13.0 | 11.0 | 23.7 | 5.5 | 12.0 | 27.0 | 21.5 |

*Regime duration is defined as the length in days in a given regime before switching into the opposite regime. In columns descriptive statistics for regime durations: mean, the first quartile, the median, the third quartile and the interquartile range.*