

# “Testing of the international capital asset pricing model with Markov switching model in emerging markets”

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<b>ARTICLE INFO</b>	Turhan Korkmaz, Emrah Ismail Çevik and Serhan Gürkan (2010). Testing of the international capital asset pricing model with Markov switching model in emerging markets. <i>Investment Management and Financial Innovations</i> , 7(1)
<b>RELEASED ON</b>	Thursday, 18 March 2010
<b>JOURNAL</b>	"Investment Management and Financial Innovations"
<b>FOUNDER</b>	LLC “Consulting Publishing Company “Business Perspectives”



NUMBER OF REFERENCES

0



NUMBER OF FIGURES

0



NUMBER OF TABLES

0

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## Testing of the international capital asset pricing model with Markov switching model in emerging markets

### Abstract

The purpose of this article is to examine the relationship between emerging markets and world index and to evaluate the risk of these countries. For this purpose, Markov switching model (MS) is used to test ICAPM. The data range of 23 emerging markets under study is between January 1995 and April 2009. Empirical results obtained by using likelihood ratio (LR) test shows that MS-ICAPM is preferable to the linear model. The estimated beta coefficients ( $\beta$ ) from linear model are between the estimated beta coefficients ( $\beta_0$  and  $\beta_1$ ) from MS-ICAPM. These findings suggest that risk can be varying according to the current regime. With this perspective, it is clear that the empirical results in this study would be extremely useful for investors who invest in different countries' stock markets.

**Keywords:** international CAPM, Markov switching model, emerging markets.

**JEL Classification:** G12, D53, C32.

### Introduction

The international capital asset pricing model (ICAPM) that takes countries as stock portfolios in global market is established on capital asset pricing model (CAPM). The variation in the systematic risks of countries might explain the variation in excess returns.

The knowledge about the relationship between markets and the level of systematic risk of markets is very important to international portfolio investors. In finance literature, the different expected return is gained by taking the different risk levels. However, it is more complicated for the international capital markets. The starting point of international investments is that the stock prices are affected by domestic or local events so that systematic risk of portfolio could be decreased without decline in expected return by investing different capital markets. In other words, domestic systematic risk can be diversified away by investing internationally without paying a price in terms of lower returns. With this perspective, it is clear that the consequences obtained by ICAPM are so useful to diversify portfolio for international portfolio investors. If cross-sectional variation in expected returns can be explained by the ICAPM, the results can be used to evaluate capital market integration.

The flow of portfolio investments to emerging markets has increased since they opened up their capital markets to foreign investors in 1990s. The main reasons of this interest are high expected returns due to their high volatility compared to more developed markets and their low correlation with developed markets. At this stage, high volatility is important for expected return and low correlation is important for portfolio diversification.

Concordantly, the purpose of this article is to examine the relationship between investable emerging markets and world index and to evaluate the risk of these countries. Some findings in finance literature point out that the relationship between return and risk is not linear at any time. Depending on whether the capital markets are under high or low volatility regime, the beta coefficients might be time-variant. Thus, we test ICAPM with Markov switching model which is one of the non-linear time-series analysis methods to determine the systematic risks of emerging markets.

Our study contains several contributions. In comparison with earlier studies on ICAPM, we present simultaneous analysis of most of the investible emerging markets (23 emerging markets). In addition to this, we establish that beta coefficients are time-varying and non-linear models are superior to linear model to determine the systematic risk.

### 1. Literature review: ICAPM

The idea of ICAPM is based on CAPM which was firstly introduced by Sharpe (1964) and Lintner (1965). The starting point of ICAPM is that the structure of the theory of international finance largely mirrors that of domestic financial theory (Adler and Dumas, 1983). In parallel with this thought, the basic international version of CAPM can be obtained by integrating index returns of each country, world index return and global risk free rate into domestic CAPM. In other words, ICAPM generally takes account of world market portfolio instead of domestic market portfolio. CAPM is frequently used in finance literature to explain the differences in risk premiums across assets. These differences are results of variations in riskiness of the returns on assets (Chen and Huang, 2007). The model predicts that expected return on any traded asset is proportional to the systematic risk of the asset, as measured by its covariance with a market-wide portfolio return (De Santis and Gerard, 1997).

Agmon (1972), Solnik (1974), Lessard (1974) and Adler and Dumas (1983) might be shown as the first theoretical studies about ICAPM. In the ensuing years, the number of studies which contributed to the model has increased. The main works of second stream studies are Harvey (1991), Bekaert and Harvey (1995), Dumas and Solnik (1995), De Santis and İmrohoroğlu (1997), De Santis and Gerard (1997) and Ramchand and Susmel (1998). The focal points of recently published studies are identification of contradictions between data and models' assumptions and model regulations to rule out these contradictions. Furthermore, depending on the increase of comparable data and liberalization of emerging markets, studies over the last two decades have started to use more complex models and found more realistic results.

When papers on ICAPM are examined, it is observed that they differ in methods. Although there are differences among these methods, they all seek to capture the conditionality of betas as well as that of the risk factors. Some articles on ICAPM (Adler and Dumas, 1983; Dumas and Solnik, 1995; Phylaktis and Ravazzolo, 2004; Wu, 2008) in addition to market risk, take currency risk and/or inflation risk into consideration by using multi-factor models; but most of the articles on ICAPM (Lessard, 1974; Bekaert and Harvey, 1995; De Santis and Gerard, 1997; Ramchand and Susmel, 1998) take only market risk into consideration by using single-factor models. There are many studies, as Korajczyk and Viallet (1989), which find that multi-factor models tend to outperform single-factor models in both domestic and international forms. Solnik (1974) also indicates that complex models which take into account both national and international factors should be used to explain the international relations. It might be shown as a limitation of single-factor forms of ICAPM. However, in Solnik's subsequent study (1977) he points out the importance of simplifying assumptions such as the existence of real risk-free assets for the conclusions which are simple enough to be tested. He also suggests that it mustn't be forgotten that more complex models of international world are interesting for the theoretician but lose empirical tractability. More importantly, in the same study, he mentioned that *exchange rate and inflation uncertainty is very small compared to stock market risk so that they could be ignored to simplify the computation* (Solnik, 1977). Consistent with Solnik (1977) and most of the literature on ICAPM, we test ICAPM under assumption that there is no exchange rate risk and local inflation is zero to simplify the model.

Earlier literature on ICAPM has tended to focus on developed markets (Agmon, 1972; Solnik, 1974; Adler and Dumas, 1983; Korajczyk and Viallet,

1989; Engel and Rodrigues, 1989; Ramchand and Susmel, 1998). On the contrary, more and more studies have focused on emerging markets over the last two decades (De Santis and İmrohoroğlu, 1997; Jan, Chou and Hung, 2000; Gerard, Thanyalakpark and Batten, 2003; Phylaktis and Ravazzolo, 2004; Chi, Li and Young, 2006; Chen and Huang, 2007; Jacobsen and Liu, 2008; Tai, 2007). This evaluation could be explained by increase of flow of portfolio investments to emerging markets since they opened up their capital markets to foreign investors in 1990s. Indeed, emerging market index has been on increase from 2000; in parallel with index, the number of studies which focus on emerging markets has also increased.

Recently, finance literature started to argue whether beta is time-varying or not, contrary to the common belief that the relationship between expected return and systematic risk is linear. Although CAPM suggests that relationship between return and risk are linear, there is increasing evidence documenting time varying relationship. For example, Blume (1971), Levy (1971), Fabozzi and Francis (1978), Chen (1981), Ferson and Harvey (1991, 1993), and Ferson and Korajczyk (1995) show that estimated beta in linear CAPM tends to be volatile over time (Huang, 2003).

After literature on ICAPM had noticed the importance of time-varying volatility, Autoregressive Conditional Heteroscedasticity (ARCH) model proposed by Engle (1982) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model proposed by Bollerslev (1986) started to be employed in ICAPM. Even though ARCH models are very popular in finance, several papers point out that they are very sensitive to changes in regimes, that is, the results estimated by ARCH models might not be reliable during periods of low/high volatility because of betas that are significantly different across low and high variance states (Ramchand and Susmel, 1998).

The level of stock markets co-movement is different under high and low volatility regime. While stock markets show low level of co-movement during periods of stability due to geographical position, structure of markets etc., they move more closely during unstable periods (Bekaert, Harvey and Ng, 2005; Edwards and Susmel, 2001; Forbes and Rigobon, 2002). Therefore, it is expected that beta coefficients used for measuring systematic risk are regime-switching due to the volatility. For this reason, more realistic results could be acquired employing Markov regime-switching model suggested by Hamilton (1989) or switching ARCH model suggested by Susmel (1999) and Ramchand and Susmel (1998).

Also, there have been several financial crisis in emerging countries since 1990's such as Asian crises in 1996, Russia and Brazil crises in 1998, Turkey crises in 1994, 2000 and 2001, and Argentina crises in 2001. These crises affected the countries' stock market volatility and led to increase volatility. Therefore, regime changes in the stock market of emerging countries might be due to financial crises. Recently, Huang (2000, 2001, and 2003) and Chen and Huang (2007) consider regime changes in the stock market using Markov switching CAPM (MSCAPM) to allow beta to come from low and high volatile regime.

## 2. The empirical models and data

International capital asset pricing model (ICAPM) in which currency risk is ignored is written as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + \varepsilon_{it}, \quad (1)$$

where  $i = 1, 2, \dots, n$ ,  $t = 1, 2, \dots, T$  and  $\varepsilon_{it} \sim \text{iid } N(0, \sigma^2)$ . In Equation (1),  $R_{it}$ ,  $R_{mt}$  and  $R_{ft}$  indicate index return of country  $i$ , world index return as a market return and risk free rate, respectively. In ICAPM,  $\beta$  is affected by three factors: (i) correlations among the country and world index return, (ii) volatility of country index return, and (iii) volatility of world index return.

In this study, we use two different empirical models to determine systematic risk of emerging markets. First of all, we consider linear ICAPM in which alpha and beta are not time varying. Conventional ICAPM is written as follows:

$$\text{Model I: } r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it}, \quad (2)$$

where  $r_{it} = R_{it} - R_{ft}$  and  $r_{mt} = R_{mt} - R_{ft}$  denote excess returns on country  $i$  and world portfolio, respectively. According to the Sharpe-Lintner CAPM, the following relationship between expected returns and systematic risk must hold:

$$E(r_{it}) = \beta_i E(r_{mt}). \quad (3)$$

It implies that an asset's risk premium is equal to the market risk premium times the systematic risk,  $\beta$ . In other words, if the data are consistent with the Sharpe-Lintner CAPM, the intercept terms in Equation (2) must be zero.

However, in the literature, it has been reported that beta is not constant and it is switching according to low and high volatility regime. Huang (2000) suggests MSCAPM to estimate  $\beta$  coming from two different regimes, namely, a high-risk and a low-risk regime. Also, he finds that the two-regime assumption is accepted and CAPM is consistent with the data in the low-risk state but is inconsistent with the

data in the high-risk state. Thus, we consider that two-state Markov regime switching ICAPM (MS-ICAPM) allows alpha and beta to come from low and high volatility regime following by:

$$\text{Model II: } r_{it} = \alpha_{s_t} + \beta_{s_t} r_{mt} + \varepsilon_{it}, \quad (4)$$

where  $\varepsilon_{it} \sim \text{iid } N(0, \sigma_{s_t}^2)$  and the unobserved state variable,  $s_t$ , evolves according to the first order Markov-switching process described in Hamilton (1994):

$$\begin{aligned} P[s_t = 1 | s_{t-1} = 1] &= p, \\ P[s_t = 0 | s_{t-1} = 1] &= 1 - p, \\ P[s_t = 0 | s_{t-1} = 0] &= q, \\ P[s_t = 1 | s_{t-1} = 0] &= 1 - q, \\ 0 < p < 1 \quad 0 < q < 1, \end{aligned} \quad (5)$$

where  $p$  and  $q$  are the fixed transition probabilities of being in low or high volatility regime, respectively. In Equation (4),  $\sigma_{s_t}^2$  is assumed to change according to regimes.

Maximum likelihood (ML) estimation of the Equation (4) is based on the Expectation-Maximization (EM) algorithm discussed in Hamilton (1994) and Krolzig (1997). Iterative estimation technique obtains estimates of parameters and the transition probabilities governing the Markov chain of unobserved states. Denote this parameter vector by  $\lambda$ , so that for the Equation (4)  $\lambda = (\alpha_{s_t}, \beta_{s_t}, \sigma_{s_t}^2, p, q)$ .  $\lambda$  is chosen to maximize the likelihood for given observations of  $r_{it}$  and  $r_{mt}$ .

Each iteration of the EM algorithm consists of two steps. The expectation step involves a pass through the filtering and smoothing algorithms, using the estimated parameter vector  $\lambda^{(j-1)}$  of the last maximization step in place of the unknown true parameter vector. This delivers an estimate of the smoothed probabilities  $\Pr(S|Y, \lambda^{(j-1)})$  (where  $Y$  is observed variables such as  $r_{it}$  and  $r_{mt}$ ) of the unobserved states  $s_t$  (where  $S$  records the history of the Markov chain). In the maximization step, an estimate of the parameter vector  $\lambda$  is derived as a solution  $\tilde{\lambda}$  of the first-order conditions associated with the likelihood function, where the conditional regime probabilities  $\Pr(S|Y, \lambda)$  are replaced with the smoothed probabilities  $\Pr(S|Y, \lambda^{(j-1)})$  derived in the last expectation step. Equipped with the new parameter vector  $\lambda$  the filtered and smoothed probabilities are updated

in the next expectation step and so on, guaranteeing an increase in the value of likelihood function (Clements and Krolzig, 1998).

As there are many studies in literature that deal with the procedures that use Markov switching model in estimation, we prefer not to give more detailed information about this. Hamilton's (1994), Krolzig's (1997), Susmel (1999) and Shami and Galagedera's (2004) studies are being considered as good references for Markov switching model.

We consider two different empirical models in this study and we use likelihood ratio (LR) test to select the most appropriate model. The Likelihood Ratio (LR) test can be based on the statistic (Krolzig, 1997):

$$LR = 2[\ln L(\lambda) - \ln L(\lambda_r)], \quad (6)$$

where  $\lambda$  denotes the unconstrained maximum likelihood estimator and  $\lambda_r$  – the restricted maximum likelihood estimator. Because the LR test is nonstandard we use the approach proposed in Davies (1987) to test null hypothesis of no regime switching in the CAPM against alternative of regime switching CAPM<sup>1</sup>.

In this study, systematic risk of 23 emerging markets is examined with ICAPM. For this purpose, the monthly index return series of Argentina, Brazil, Czech Republic, China, Indonesia, Morocco, Philippines, South

Africa, South Korea, India, Israel, Colombia, Hungary, Malaysia, Mexico, Egypt, Peru, Poland, Russia, Chile, Thailand, Taiwan and Turkey covering the period of January 1995 to April 2009 are used. As market values, world index return and as risk-free interest rate, monthly government bonds' interest rates are used as variables. The data on the index returns of the emerging countries and world index return are taken from MSCI-Barra's official web-site<sup>2</sup> and the monthly US T-Bill rate is taken from Kenneth W. French's official web-site<sup>3</sup>.

### 3. Empirical results

Descriptive statistics of world/emerging markets index return are presented in Table 1. As shown in the table, highest average monthly return is gained in Egypt stock market, and vice versa lowest average monthly return is gained in Thailand stock market for given period. Russian (Morocco) stock market has highest (lowest) volatility according to standard deviation value (see Table 1). Kurtosis statistics indicate that the stock market return series tend to fatter tail distribution than a normal distribution. According to the Jarque-Bera normality test statistics, all of the return series of emerging markets exhibit significant deviation from normality except for Taiwan.

Table 1. Summary statistics (January 1995-April 2009)

Countries	n	Mean	Std. deviation	Skewness	Kurtosis	J-B	Q (10)	Q <sub>s</sub> (10)
World Index	172	0.213	4.579	-1.165	5.716	91.754*	14.338	30.761*
Argentina	172	0.026	11.966	-0.768	6.136	87.395*	7.724	11.694
Brazil	172	0.632	11.990	-1.015	5.380	70.112*	2.201	13.285
Czech Republic	172	0.879	8.905	-0.750	5.007	44.987*	9.557	16.013
China	172	-0.251	10.972	0.024	4.297	12.074*	18.364**	73.895*
Indonesia	172	-0.128	14.775	-0.543	5.076	39.322*	20.263**	90.687*
Morocco	172	0.867	5.765	-0.038	4.331	12.735*	12.154	11.007
Philippines	172	-0.688	9.434	-0.143	5.094	32.002*	13.235	38.141*
South Africa	172	0.228	8.573	-1.032	5.254	66.936*	6.804	24.174
South Korea	172	0.138	12.197	0.244	5.393	42.734*	4.991	62.938*
India	172	0.371	9.093	-0.488	3.264	7.336*	5.214	17.242
Israel	172	0.564	7.185	-0.482	3.983	13.570*	5.910	25.454
Colombia	172	0.653	9.899	-0.437	3.858	10.742*	12.324	16.874
Hungary	172	0.777	11.334	-1.196	8.431	252.392*	11.389	4.801
Malaysia	172	-0.150	9.354	-0.118	7.053	118.112*	32.883*	144.676*
Mexico	172	0.613	9.167	-1.297	6.428	132.407*	6.201	7.820
Egypt	172	1.061	9.581	0.036	5.021	29.311*	34.832*	10.577
Peru	172	0.841	9.399	-1.063	7.683	189.584*	8.481	8.480
Poland	172	0.234	11.157	-0.513	4.860	32.330*	6.866	15.347
Russia	172	0.947	17.548	-1.018	7.639	183.901*	15.918	37.996*
Chile	172	0.206	7.011	-1.186	7.231	168.604*	10.519	10.872
Thailand	172	-0.776	12.554	-0.392	4.773	26.953*	12.358	74.773*

<sup>1</sup> This test does not have the usual limiting chi-squared distribution because the transition probabilities are unidentified under null.

<sup>2</sup> <http://www.msibarra.com/products/indices/stdindex/performance.html> (Access Date: 20.05.2009).

<sup>3</sup> [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) (Access Date: 20.05.2009).

Table 1 (cont.). Summary statistics (January 1995-April 2009)

Countries	n	Mean	Std. deviation	Skewness	Kurtosis	J-B	Q (10)	Q <sub>s</sub> (10)
Taiwan	172	-0.310	8.862	0.012	3.274	0.543	17.409	16.476
Turkey	172	0.599	16.360	-0.277	4.201	12.539*	8.151	4.870

Note: n denotes number of observations, J-B denotes Jarque-Bera normality test, Q(10) and Q<sub>s</sub>(10) stands for Box-Pierce serial correlation test for return and squared return series, respectively. \* and \*\* indicate significance at 1% and 5% levels, respectively.

The table of cross-country correlation of emerging market stock returns is presented in Appendix 1. The findings of Appendix 1 indicate that the whole coefficients of correlation between the country and other emerging markets are significant, except for Morocco. The index return of Morocco is only correlated with index return of South Africa, Egypt and India. However, all of the emerging markets have significant and positive correlation with world index.

In ICAPM, the excess return series of countries should be acquired to calculate the systematic risk of these countries. For this purpose, we subtract risk-free rate

from index return of countries; in a similar way, risk-free rate is subtracted from world index return and we get excess return series of countries and world index that we use in formula of ICAPM. The existence of the unit-root is investigated by ADF which is developed by Dickey and Fuller (1979), PP test by Phillips and Peron (1988) and KPSS test by Kwiatkowski, Phillips, Schmidt and Shin (1992) to avoid the spurious regression problem. The unit root tests of ADF, PP and KPSS are applied with constant-term model and the results are presented in Table 2. As shown in Table 2, we find that whole excess return series are stationary.

Table 2. Results of unit root test

	ADF	PP	KPSS		ADF	PP	KPSS
World Index	-10.587*	-10.668*	0.248*	Colombia	-10.894*	-10.915*	0.460*
Argentina	-12.153*	-12.190*	0.105*	Hungary	-11.864*	-11.833*	0.188*
Brazil	-12.418*	-12.422*	0.132*	Malaysia	-6.417*	-10.233*	0.119*
Czech Republic	-11.448*	-11.396*	0.267*	Mexico	-12.726*	-12.737*	0.087*
China	-11.895*	-11.875*	0.242*	Egypt	-9.373*	-9.842*	0.123*
Indonesia	-10.320*	-10.208*	0.210*	Peru	-12.821*	-12.830*	0.189*
Morocco	-11.792*	-11.926*	0.169*	Poland	-13.187*	-13.193*	0.100*
Philippines	-10.638*	-10.646*	0.327*	Russia	-10.827*	-10.812*	0.059*
South Africa	-12.435*	-12.423*	0.148*	Chile	-11.921*	-11.955*	0.252*
South Korea	-11.855*	-11.855*	0.140*	Thailand	-13.135*	-13.148*	0.326*
India	-11.529*	-11.596*	0.167*	Taiwan	-12.029*	-12.024*	0.052*
Israel	-12.078*	-12.078*	0.052*	Turkey	-13.158*	-13.161*	0.052*

Note: The lag length is determined by Schwarz information criteria in ADF test. Newey-West band-width selection is used for PP and KPSS tests. \* indicates stationarity at 1% level.

At first, systematic risks of emerging markets are calculated with linear ICAPM – Model I – and results are presented in Table 3. We examine the accuracy of the model specifications, using heteroskedasticity and serial correlation tests.

We determine that heteroskedasticity problem for Chile, Czech Republic, Hungary and Peru and then we solve this problem using covariance matrix proposed by White (1980). In addition to this, we determine both serial correlation and heteroskedasticity

problem for Indonesia and Malaysia and these problems are solved using covariance matrix suggested by Newey and West (1987). For other countries, serial correlation and heteroskedasticity problem are not determined at 1% significance level. The results in Table 3 suggest that expected values of  $\alpha$  parameter are not statistically significant for all countries; however expected values of  $\beta$  parameter are statistically significant at 1% level for all countries.

Table 3. The results of linear ICAPM

Countries	$\alpha$	$\beta$	$\sigma$	LogL	Countries	$\alpha$	$\beta$	$\sigma$	LogL
Argentina	-0.155 (0.779)	1.346* (0.230)	10.292	-644.05	Hungary	0.620 (0.649)	1.624* (0.207)	8.593	-613.02
Brazil	0.491 (0.673)	1.783* (0.147)	8.825	-617.60	Malaysia	-0.376 (0.842)	0.861* (0.155)	8.522	-611.60
Czech Rep.	0.664 (0.585)	0.986* (0.172)	7.724	-594.67	Mexico	0.438 (0.496)	1.417* (0.108)	6.505	-565.13
China	-0.444 (0.724)	1.212* (0.159)	9.504	-630.36	Egypt	0.838 (0.663)	0.901* (0.145)	8.694	-615.02
Indonesia	-0.290 (1.134)	1.560* (0.244)	13.000	-684.23	Peru	0.626 (0.625)	0.999* (0.221)	8.248	-605.97

Table 3 (cont.). The results of linear ICAPM

Countries	$\alpha$	$\beta$	$\sigma$	LogL	Countries	$\alpha$	$\beta$	$\sigma$	LogL
Morocco	0.585 (0.430)	0.265* (0.095)	5.647	-540.82	Poland	0.072 (0.655)	1.561* (0.143)	8.599	-613.13
Philippines	-0.906 (0.640)	0.955* (0.140)	8.391	-608.94	Russia	0.826 (1.145)	2.003* (0.251)	15.017	-709.03
S. Africa	0.038 (0.487)	1.257* (0.107)	6.394	-562.18	Chile	-0.013 (0.975)	0.939* (0.141)	5.582	-538.81
S. Korea	-0.024 (0.760)	1.549* (0.166)	9.973	-638.63	Thailand	-0.945 (0.812)	1.473* (0.178)	10.648	-649.89
India	0.159 (0.598)	1.019* (0.131)	7.841	-597.26	Taiwan	-0.513 (0.557)	1.107* (0.122)	7.310	-585.22
Israel	0.341 (0.449)	0.906* (0.098)	5.890	-548.06	Turkey	0.484 (1.023)	2.064* (0.224)	13.416	-689.65
Colombia	0.421 (0.705)	0.801* (0.154)	9.253	-625.75					

Note:  $\sigma$  denotes standard error of model and LogL represents the log likelihood function. The values in parentheses indicate the standard errors. \* denotes that coefficient is significant at 1% level.

As shown in Table 3,  $\beta$  coefficients are greater than one for Argentina, Brazil, China, Indonesia, South Africa, South Korea, India, Hungary, Mexico, Poland, Russia, Thailand, Taiwan and Turkey. It means that systematic risks of these countries' stock market are higher than the world average. In other words, it is expected that both the return and the systematic risk of investments in these stock mar-

kets are greater than world average. On the other hand,  $\beta$  coefficients of Czech Republic, Morocco, Philippines, Israel, Colombia, Malaysia, Egypt, Peru and Chile are lower than one. It indicates that these countries' systematic risks are lower than world average. It is expected that both the return and the systematic risk are lower than the world average for the investors who invest in these countries.

Table 4. The results of MS-ICAPM

Countries	Low volatility			High volatility			$p_1/q_1$	$p_2/q_2$	LogL
	$\alpha_L$	$\beta_L$	$\sigma_L$	$\alpha_H$	$\beta_H$	$\sigma_H$			
Argentina	0.461 (0.435)	1.190* (0.097)	5.445	-6.544 (4.243)	1.939* (0.647)	11.801	0.989	0.791	-550.902
Brazil	1.189 (0.898)	0.658* (0.238)	6.246	-1.304 (2.182)	1.991* (0.416)	13.565	0.841	0.734	-630.936
Czech Republic	1.591* (0.583)	1.602* (0.130)	6.408	-4.231 (2.680)	2.331* (0.498)	13.830	0.979	0.889	-599.671
China	0.456 (0.402)	0.855* (0.088)	4.844	-4.708** (2.248)	1.688* (0.403)	7.649	0.989	0.898	-529.871
Indonesia	0.726 (0.602)	1.240* (0.133)	6.543	-4.349 (2.638)	1.307** (0.545)	14.947	0.986	0.941	-607.753
Morocco	2.371* (0.783)	1.069* (0.173)	7.192	-3.029 (1.819)	0.303 (0.347)	10.966	0.986	0.958	-614.972
Philippines	1.564** (0.597)	1.720* (0.127)	4.520	0.080 (0.092)	0.291 (0.220)	8.242	0.951	0.956	-577.509
South Africa	-3.390** (1.759)	0.965* (0.240)	6.479	4.907* (1.634)	0.537 (0.400)	8.391	0.861	0.874	-608.460
South Korea	2.032** (1.020)	0.926* (0.211)	5.170	-0.503 (1.337)	2.136* (0.327)	10.442	0.773	0.724	-602.122
India	2.267* (0.623)	1.657* (0.131)	4.318	-1.156 (0.911)	0.540** (0.210)	8.538	0.917	0.941	-584.281
Israel	1.087 (0.692)	1.668* (0.166)	6.920	-2.546 (2.275)	1.376* (0.453)	18.489	0.987	0.980	-651.422
Colombia	1.332** (0.563)	0.872* (0.117)	3.362	-0.921 (1.339)	0.925* (0.217)	7.800	0.640	0.718	-539.418
Hungary	0.183 (0.613)	1.433* (0.125)	5.945	-0.636 (2.638)	1.827* (0.512)	16.317	0.990	0.973	-604.612
Malaysia	0.499 (0.409)	0.691* (0.091)	4.304	-2.329 (1.877)	1.210* (0.400)	13.268	0.987	0.962	-565.464
Mexico	1.163* (0.395)	1.319* (0.086)	4.497	-2.941 (2.111)	2.084* (0.435)	10.211	0.990	0.940	-540.036
Egypt	-0.121 (0.590)	0.496* (0.149)	3.777	1.790 (1.362)	-0.080 (0.284)	7.339	0.819	0.692	-533.151

Table 4 (cont.). The results of MS-ICAPM

Countries	Low volatility			High volatility			$p_1/q_1$	$p_2/q_2$	LogL
	$\alpha_L$	$\beta_L$	$\sigma_L$	$\alpha_H$	$\beta_H$	$\sigma_H$			
Peru	1.009 (0.687)	0.361** (0.170)	5.597	0.388 (1.596)	1.608* (0.291)	10.486	0.936	0.879	-593.088
Poland	0.211 (0.675)	0.692* (0.135)	6.782	-5.030 (1.763)	1.918* (0.386)	9.957	0.987	0.955	-596.540
Russia	0.725 (0.691)	1.805* (0.162)	6.010	-0.450 (1.061)	1.301* (0.246)	10.092	1.000	0.989	-603.610
Chile	1.670** (0.799)	1.447* (0.162)	7.903	-1.442 (2.412)	3.329* (0.614)	20.128	1.000	0.986	-671.157
Thailand	-0.537 (0.559)	1.251* (0.113)	3.920	-0.476 (0.956)	1.004* (0.207)	9.018	0.913	0.932	-575.724
Taiwan	0.415 (0.649)	1.170* (0.138)	6.326	-3.138 (1.838)	1.958* (0.399)	14.493	0.987	0.977	-623.652
Turkey	-0.353 (1.509)	3.845* (0.677)	9.164	0.731 (1.410)	1.591* (0.320)	14.161	0.898	0.952	-684.193

Note: \* (\*\*) denotes coefficient is significant at 1% (5%) level. The values in parentheses indicate the standard errors.  $\sigma_L$  ( $\sigma_H$ ) is standard error of model under low (high) volatility regime.  $p_1/q_1$  ( $p_2/q_2$ ) indicates the probabilities of being in the low (high) volatility regime after the low (high) volatility regime. LogL represents the log likelihood function.

In the literature, it has been documented that relationship between market index and world index is not constant and it is switching according to low and high volatility regime. In this context, we examine whether systematic risks of stock markets are switching under the low and high volatility regime by using two state Markov regime switching ICAPM (MS-ICAPM). The periods of low and high volatility regime are determined by standard error of model. The low standard error of model is called as a low volatility regime and high standard error of model as a high volatility regime. Diagnostic tests (such as normality, serial correlation and heteroskedasticity) are applied for MS-ICAPM – Model II – and diagnostic problem is not detected.

The results in Table 4 indicate that while the entire expected values of beta parameter are found statistically significant for 23 emerging markets, the expected values of alpha parameter are different from zero for only Czech Republic, Morocco, Philippines, South Africa, South Korea, India, Colombia, Mexico and Chile under low volatility regime. The results of Model II show that systematic risks of Argentina, Czech Republic, Indonesia, Morocco, Philippines, Israel, Hungary, Mexico, Russia, Chile, Thailand, Taiwan and Turkey are higher than world average under low volatility regime. Hence, it is denoted that the investors who invest in these markets expect to gain more profit compared to average of world index return.

As shown in Table 4, alpha parameters are found statistically significant for only China and South Africa and beta parameters of Morocco, Philippines,

South Africa and Egypt are not found statistically significant under high volatility regime. The insignificant beta parameters mean that there is no relationship between these countries' market index and world index. Under high volatility regime, systematic risks of Argentina, Brazil, Czech Republic, China, Indonesia, South Korea, Israel, Hungary, Malaysia, Mexico, Peru, Poland, Chile, Thailand, Taiwan and Turkey are greater than one (world average); on the contrary, systematic risks of India and Colombia are lower than one (world average). In other words, while the investors who invest in Argentina, Brazil, Czech Republic, China, Indonesia, South Korea, Israel, Hungary, Malaysia, Mexico, Peru, Poland, Chile, Thailand, Taiwan and Turkey expect more return than average of world index return, the systematic risk level of their investments is high compared to world average under high volatility regime. On the other hand, it is expected that the investors who invest in India and Colombia are exposed to lower systematic risk and gain lower profit. Smoothed regime probabilities estimated by MS-ICAPM for high volatility regime are presented in Appendix 2. Smoothed regime probabilities suggest that the financial crisis in emerging markets causes the increase in volatility of these stock markets. Determining that emerging markets have high probabilities of being same regime supports the fact that there are strong asymmetries between regimes, in other words, coefficients of alpha and beta are time-varying under high and low volatility.

We test whether MS-ICAPM is superior to linear ICAPM by likelihood ratio test and present the results in Table 5.

Table 5. The results of likelihood ratio test

Countries	LR	p-value	Countries	LR	p-value
Argentina	26.227	[0.000]	Hungary	21.807	[0.000]

Table 5 (cont.). The results of likelihood ratio test

Countries	LR	p-value	Countries	LR	p-value
Brazil	35.873	[0.000]	Malaysia	92.272	[0.000]
Czech Rep.	34.337	[0.000]	Mexico	50.202	[0.000]
China	45.221	[0.000]	Egypt	13.131	[0.000]
Indonesia	65.624	[0.000]	Peru	25.763	[0.000]
Morocco	15.339	[0.001]	Poland	19.055	[0.000]
Philippines	24.801	[0.000]	Russia	75.754	[0.000]
S. Africa	22.555	[0.000]	Chile	17.888	[0.000]
S. Korea	68.047	[0.000]	Thailand	52.492	[0.000]
India	25.969	[0.000]	Taiwan	18.995	[0.000]
Israel	17.288	[0.000]	Turkey	10.919	[0.012]
Colombia	21.566	[0.000]			

The null hypothesis that the results of MS-ICAPM are similar to those of linear ICAPM is rejected at 5% level of significance for all countries. This finding suggests that

MS-ICAPM is superior to linear ICAPM and the estimates of alpha and beta coefficients are significantly different between low and high volatility regimes.

Table 6. The relationship between countries' index and world index under low and high volatility regimes

Countries	Low volatility			High volatility		
	Risky	Low-risk	Unrelated	Risky	Low-risk	Unrelated
Argentina	•			•		
Brazil		•		•		
Czech Rep.	•			•		
China		•		•		
Indonesia	•			•		
Morocco	•					•
Philippines	•					•
S. Africa		•				•
S. Korea		•		•		
India	•				•	
Israel	•			•		
Colombia		•			•	
Hungary	•			•		
Malaysia		•		•		
Mexico	•			•		
Egypt		•				•
Peru		•		•		
Poland		•		•		
Russia	•			•		
Chile	•			•		
Thailand	•			•		
Taiwan	•			•		
Turkey	•			•		

Table 6 classifies the countries according to the systematic risks estimated from MS-ICAPM. Table 6 illustrates that the systematic risks of Morocco and Philippines are high only under low volatility regime, otherwise systematic risks of Brazil, China, South Korea, Malaysia, Peru and Poland are high only under high volatility regime. Systematic risks of Argentina, Czech Republic, Indonesia, Israel, Hungary, Mexico, Russia, Chile, Thailand, Taiwan and Turkey are high under both low and high volatility regimes. Colombia is the only country whose systematic risk is low under both low and high volatility regimes.

**Conclusions**

The theory of International CAPM assumes that countries can be viewed as a stock portfolio in

global market. The starting point of international investments is that the stock prices are affected by domestic or local events so that domestic systematic risk can be diversified away by investing internationally without paying a price in terms of lower returns. The interest of investors has been increasing day by day due to emerging markets' high expected returns due to their high volatility compared to more developed markets, their low correlation with developed markets and attempt of liberalization.

The results derived by using ICAPM make commenting about risk and integration of capital markets possible. Considering information about markets' systematic risk is very important for the investors who want to diversify their portfolios internationally; we examine the relationship between 23 emerging markets and world index using ICAPM.

With this perspective, the empirical results in this study have interesting implications for these investors. Firstly, we try to determine the systematic risks of emerging markets using linear ICAPM. In linear model, systematic risks of Argentina, Brazil, China, Indonesia, South Africa, South Korea, India, Hungary, Mexico, Poland, Russia, Thailand, Taiwan and Turkey are found higher than the world average. On the other hand, systematic risks of Czech Republic, Morocco, Philippines, Israel, Colombia, Malaysia, Egypt, Peru and Chile are found lower than the world average.

Additionally, some findings in finance literature point out that the relationship between return and risk is not linear at any time. Depending on whether the capital markets are under high or low volatility regime, the beta coefficients might be time-variant. Thus, we test ICAPM with Markov switching model which is one of the non-linear time-series analysis methods for 23 emerging markets. We find that the estimated beta coefficients under low volatility regime are significantly different from estimated beta coefficients under high volatility regime. In other

words, our model generates a different beta for every state. For most of the countries, estimated beta coefficients acquired from Model I rank among the estimated  $\beta_0$  and  $\beta_1$  from MS-ICAPM. Moreover, results obtained by likelihood ratio test show that MS-ICAPM is superior to linear ICAPM.

When the results of likelihood ratio test are considered, it is possible to say that the beta coefficients estimated by linear ICAPM underestimate systematic risks for Argentina, Brazil, Czech Republic, China, South Korea, Israel, Colombia, Hungary, Malaysia, Mexico, Peru, Poland, Chile and Taiwan, but overestimate for Indonesia, India, Russia, Thailand and Turkey under the high volatility regime. On the contrary, beta coefficients estimated by linear ICAPM underestimate systematic risks for Czech Republic, Morocco, Philippines, India, Israel, Malaysia, Chile, Taiwan and Turkey under the low volatility regime but overestimate for other 14 markets.

Finally, while international investors diversify their portfolios, both this study and similar studies can provide useful information and be a guide for them.

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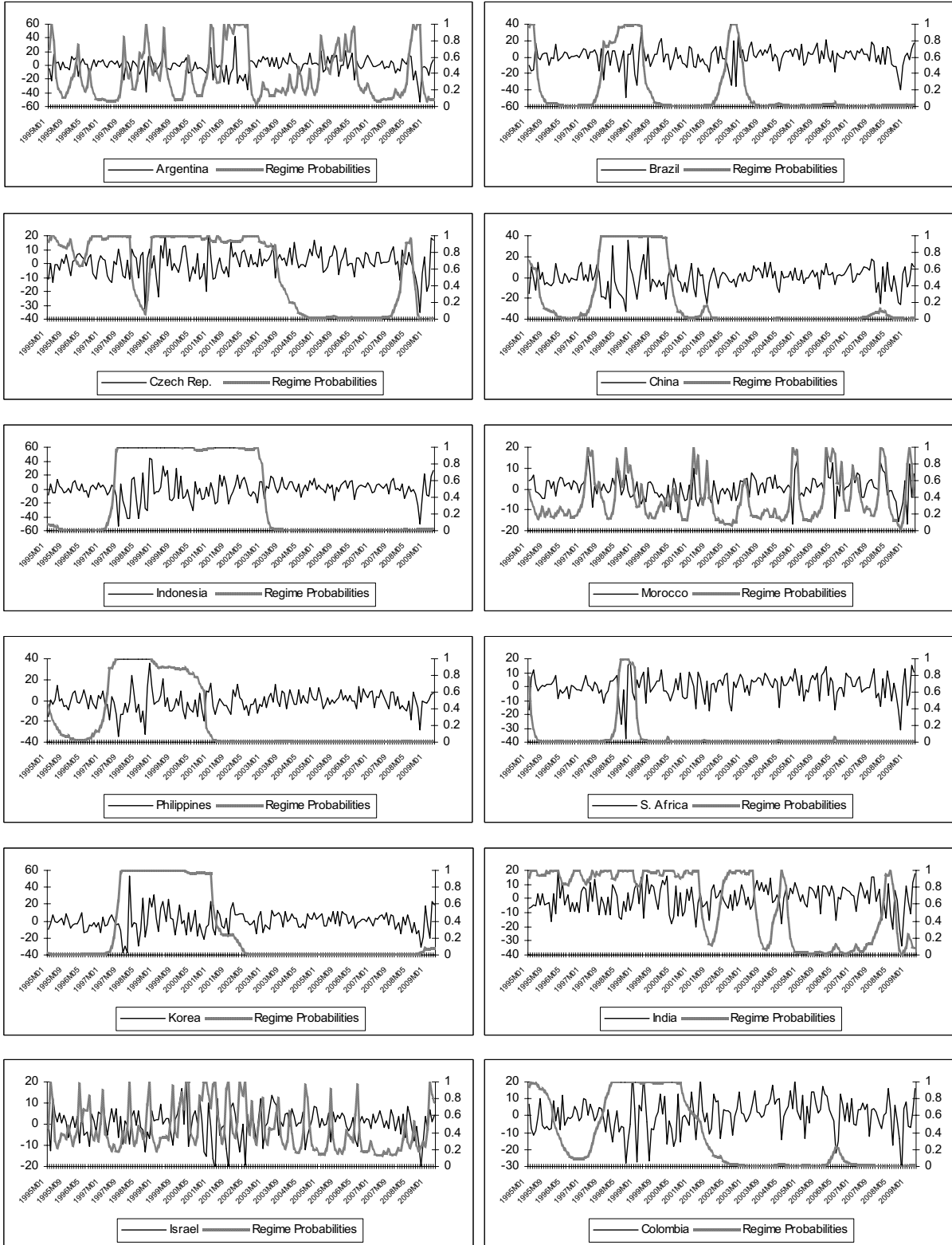
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Appendix 1. Coefficients of correlation (January 1995 – April 2009)

Countries	S. Africa	Argentina	Brazil	Chile	China	Colombia	Czech Rep.	Egypt	Hungary	India	Indonesia	Israel	S. Korea	Malaysia	Mexico	Morocco	Peru	Philippines	Poland	Russia	Taiwan	Thailand	Turkey	World Index
S. Africa	1.00																							
Argentina	0.49*	1.00																						
Brazil	0.61*	0.60*	1.00																					
Chile	0.59*	0.56*	0.69*	1.00																				
China	0.61*	0.40*	0.51*	0.51*	1.00																			
Colombia	0.37*	0.35*	0.42*	0.45*	0.28*	1.00																		
Czech Rep.	0.51*	0.45*	0.49*	0.45*	0.45*	0.37*	1.00																	
Egypt	0.43*	0.35*	0.32*	0.39*	0.29*	0.37*	0.39*	1.00																
Hungary	0.59*	0.50*	0.58*	0.53*	0.41*	0.40*	0.71*	0.43*	1.00															
India	0.50*	0.35*	0.46*	0.51*	0.41*	0.35*	0.48*	0.47*	0.45*	1.00														
Indonesia	0.46*	0.33*	0.42*	0.51*	0.39*	0.40*	0.38*	0.36*	0.43*	0.42*	1.00													
Israel	0.37*	0.41*	0.47*	0.43*	0.25	0.24*	0.33*	0.30*	0.39*	0.41*	0.25*	1.00												
S. Korea	0.53*	0.30*	0.39*	0.44*	0.37*	0.32*	0.38*	0.32*	0.37*	0.41*	0.46*	0.27*	1.00											
Malaysia	0.41*	0.32*	0.37*	0.50*	0.45*	0.31*	0.33*	0.26*	0.41*	0.39*	0.62*	0.22*	0.38*	1.00										
Mexico	0.64*	0.62*	0.70*	0.62*	0.45*	0.38*	0.49*	0.35*	0.64*	0.43*	0.43*	0.50*	0.41*	0.38*	1.00									
Morocco	0.25*	0.19	0.13	0.14	0.10	0.09	0.15	0.31*	0.11	0.21*	0.11	0.11	0.08	0.05	0.04	1.00								
Peru	0.63*	0.54*	0.64*	0.57*	0.43*	0.39*	0.48*	0.36*	0.56*	0.42*	0.42*	0.33*	0.33*	0.37*	0.60*	0.18	1.00							
Philippines	0.48*	0.35*	0.40*	0.52*	0.47*	0.29*	0.26*	0.32*	0.40*	0.33*	0.60*	0.25*	0.39*	0.57*	0.47*	0.01	0.36*	1.00						
Poland	0.64*	0.42*	0.55*	0.52*	0.42*	0.30*	0.66*	0.43*	0.76*	0.46*	0.36*	0.35*	0.48*	0.40*	0.62*	0.15	0.51*	0.39*	1.00					
Russia	0.52*	0.46*	0.57*	0.59*	0.41*	0.44*	0.44*	0.30*	0.56*	0.34*	0.55*	0.38*	0.32*	0.47*	0.60*	0.04	0.47*	0.42*	0.43*	1.00				
Taiwan	0.51*	0.48*	0.53*	0.58*	0.57*	0.32*	0.42*	0.36*	0.41*	0.46*	0.39*	0.35*	0.51*	0.53*	0.51*	0.21*	0.43*	0.42*	0.47*	0.52*	1.00			
Thailand	0.61*	0.39*	0.47*	0.50*	0.49*	0.30*	0.32*	0.32*	0.36*	0.36*	0.59*	0.19	0.64*	0.56*	0.47*	0.12	0.41*	0.65*	0.44*	0.40*	0.54*	1.00		
Turkey	0.47*	0.41*	0.49*	0.50*	0.31*	0.42*	0.41*	0.38*	0.54*	0.39*	0.26*	0.50*	0.33*	0.27*	0.49*	0.06	0.40*	0.27*	0.45*	0.49*	0.35*	0.27*	1.00	
World Index	0.67*	0.51*	0.68*	0.61*	0.50*	0.36*	0.50*	0.43*	0.65*	0.51*	0.48*	0.58*	0.58*	0.42*	0.71*	0.21*	0.48*	0.46*	0.64*	0.52*	0.57*	0.53*	0.57*	1.00

Note: \* denotes significant correlation at 1% level.

**Appendix 2. Return series of countries and smoothed regime probabilities<sup>1</sup>**



<sup>1</sup> Left axis is value of index return; right axis is regime probabilities.

Appendix 2 (cont.). Return series of countries and smoothed regime probabilities

