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Research Article

Regime Transitions in Emerging Markets under the Weak Dollar Period: An Empirical Analysis with Two-State Time-Varying Regime Switching Model

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Abstract

This empirical research paper examines the structural changes in Brazilian, Mexican, Korean, Turkish, South African and the US financial markets in a comparative perspective. Using daily returns of stock markets, exchange rates and CDS spreads, the transition probabilities and regime properties in the selected developing markets are estimated and compared using Hamilton's regime switching model. Empirical evidence shows that degrees of transition probabilities vary depending on the economy under investigation besides the markets. A comparison of the results with those from the US markets underlines the fact that creating portfolio diversification in international markets requires extensive volatility analysis among the economies and financial instruments.

Keywords: Emerging markets, Regime switching, CDS spreads, Dollar Trade Weighted Index.

JEL codes: E32, F36, F21, G15

1. Motivations and Literature Review

Developing markets display relatively high and instant volatility in the stock returns because of their specific characteristics, such as, low trade volume, high political and economic stability, thin trading, non-persistent portfolio investments and sudden regulatory changes. Investors should analyze the probabilities of regime switches and duration of the volatility in the financial markets to insight the risk in their investments.

The weak dollar since 2004 has caused the international portfolio investments to flow into the developing markets. Though money flows have increased the trade volume and lead those markets to bull; high volatility being sensitive to the global liquidity and the value of the US dollar has been observed, as well. Since hot money is sensitive to liquidity and carry-trade, that development results in a contagion risk in the global economy.

In this research paper, we aim at determining the structural changes in developing financial markets using Hamilton's Markov switching model. Employing daily data from equity, exchange rate and CDS markets; we estimate and compare the regime transition probabilities in developing markets. The results are compared to those from the US markets to see if there is a parallel shift in the regimes between the US markets and the developing markets. In that sense, the paper also examines volatility spillovers among the markets.

As the aim of the paper is empirical rather than methodological, a popular and flexible model, namely two state Markov switching regime model, is selected for the analysis. Examining if the prices contain occasional jumps, probability of existence and persistence of the high volatile regime is estimated by Hamilton's [1] regime switching algorithm. In the model, an ergodic Markov chain defined by the transition probabilities generates the unobservable regime variable [2]. The model combines model parameters into one system, and which set of parameters are applied varies on the regime the system is likely in at the time period. In that sense, a Markov switching model enables the economy to be in one of n different regimes. The transition probability from state x at time t to state y at time t+1 is only affected by the state at time t and not by any previous state [3].

Switching regressions date back to Quandt [4], Goldfeld and Quandt [5], Barber, Robertson and Scott [6] and Lindgren [7] proposing a Markov switching model, where the latent state variable is serially dependent. By deriving the methodology from Ball and Torous [8] and extending the Markov switching model into the case of dependent data, Hamilton [1] creates a two-state regime-switching model.

Hamilton's model has been empirically used under different conditions with various financial data. Early works with the model concentrate on the macroeconomic regime switches. For example, the model is applied to examination of business cycle asymmetry [1], government expenditure [9], labor market recruitment [10], the influences of oil prices on the U.S. GDP growth [11]. The early version of the

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Markov regime-switching model has been employed for other areas apart from finance and economics such as for speech recognition [12], DNA composition [13] and ion channels [14].

In the hidden Markov model, the Markov variable is unobservable volatility [15]. The hidden Markov model has been used for estimating equity returns, exchange rates and interest rates [16-25].

In recent literature, the model has been used for return estimations with various alterations. Huang [26] models beta as a first-order Markov chain and display the fact that the data from the low-risk state is consistent with the CAPM whereas the data from the high-risk state is not. Hess [27] compares competing Markov regime-switching model specifications and reported that for the Swiss security market index monthly returns, the market movement is optimally tracked by time-varying first and second moments, including a memory effect. Constantinou et al. [28] use two-state Markov switching model combined with artificial neural networks to predict returns in Cyprus stock markets. Alvarez-Plata and Schrooten [29] analyze the currency crisis in Argentina in 2002 using Markov switching model. They conclude that the crisis, although associated with weak fundamentals, cannot be explained by the macroeconomic factors alone. Estimating a Markov-switching model shows that shifts in agents' beliefs also play a crucial role.

In the paper, the empirical results are presented in a comparative perspective to show if the transition probablities coincide in the same time periods. In other words, the paper includes a volatility spillover and co-movements analysis for the markets since 2004. The volatility spillover and co-movements in the international markets have been examined with different methodology and financial data in the literature. Dissimilarities among the financial markets can be used as a natural hedging technique in international portfolio investments. For example, Butler and Joaquin [30] empirically show how the change in co-movement of financial markets influences the performance of a diversified portfolio without dynamic rebalancing. The empirical works, in general, are based on the international asset pricing model of Solnik [31] underlying the international factors in pricing risk stock markets [32-34].

Frankel and Roubini [35], Goeij and Marquering [36], Dailami, Masson and Padou [37] investigate the effects of the volatility in the US markets onto the emerging markets and conclude that there is an evidence of negative correlation between the US financial markets and developing markets implying opportunities and dynamics for enhanced return through diversification in global portfolio investments though Ozun et al. [38] empirically show that the world markets have started to show volatility spillovers recently by employing the cross-border and multi-markets analysis.

Previously, the empirical papers concentrated on cross country transmissions for a single financial asset group. For example, Cerra and Saxena [39] and Dungey and Martin [40] analyze the exchange rate markets, Forges and Rigobon [41] examine stock markets; and Favero and Giavazzi [42] and Dungey et al. [43] investigate the interest rate markets. Recently, different markets across borders have been examined emphasizing the crisis economies, i.e. Asian crisis [44-45]. In that sense, this research paper has its originality in presenting a multi market cross-country analysis of regime switching emphasizing the role of the weak dollar in those transitions in a comparative perspective.

2. The Two-State Time-Varying Regime Switching Model

The Hamilton MS–AR model of the US business cycle has been used as a proper methodology for characterizing macroeconomic fluctuations in empirical research [46]. The model is employed to model the "stable" and "volatile" regimes in the developing financial markets.

Markov switching models enable the influence of explanatory variables to be state-dependent. The model enhances traditional performance measures by allowing an assessment of the investment strategy to dynamic factor exposure through time. Within a two-regime model, the regimes can be expressed in Equation (1).

$$Y(t) = \begin{cases} = X(t) \times b_1, S(t) = 1, \\ = X(t) \times b_2, S(t) = 0. \end{cases} \tag{1}$$

In the equation, *S (t)* is the state variable, which changes through time and cannot be observed by market participants. The regime *0* means the markets are in stability with low volatility while the regime *1* underlines the fact that the markets are in turbulences under high volatility. *S (t)* is determined by Markov chain as displayed in Equation (2).

$$P(S_{t+1} = j \mid S_t = i) = p_{ji} \tag{2}$$

Taylor [15] describes the distribution for the volatility of σ for period *t* as in Equation (3).

$$\sigma = (\sigma_L \text{ with probability } p \,;\, \sigma_H \text{ with probability } p\text{-}1) \tag{3}$$

In the equation (3), *L* denotes stable regime with low volatility while *H* refers highly volatile state. Assuming time independent transition probabilities, the probability of a regime change only depends on the latest state when the volatility is a Markov process. We continue to follow Taylor [15] to explain the two-state model, in general.

$$P(\sigma_t = \sigma_H \mid \sigma_{t-1} = \sigma_L) \tag{4}$$

denotes the probability of volatile shifts (P_{LH}). On the other hand,

$$P(\sigma_t = \sigma_L \mid \sigma_{t-1} = \sigma_H)$$

does the probability of shift from volatility to stability

$$(P_{HL}). \tag{5}$$

The return for period t is expressed in Equation (6),

$$R_t = u + \sigma_t u_t \tag{6}$$

where *u* is a constant and u_t is independent and identically distributed as N (0,1). In the model, the processes { σ_t } and { u_t } are stochastically independent. Returns have distribution N (u, σ_L^2) under stable regime, and distribution N (u, σ_H^2) under volatile regime [47]. On the other hand, as the Markov chain is assumed to be unobservable, none can be sure about the regime [3]. Regimes set up in this way are crucial for estimating the probability of high volatility in the future [46].

3. Historical Figures on Financial Markets in Emerging Economies

In this part, we introduce the time series data used in the analysis and present descriptive statistics of those time series. Daily historical values of the log-returns of financial variables are used. Descriptive statistics of the financial time series are displayed on Table 1. The remarkable statistics are that the credit default spreads have relatively higher standard deviations, and skewness and kurtosis of the time series are high in general.

Table 1. Descriptive Statistics of the Financial Time Series

	Mean	Std. Error	Median	Std. Dev	Variance	Kurtosis	Skewness	Range	Max	Min	Sum	Count
ISE	-0,00047	0,00025	-0,00071	0,00755	0,00006	1,12662	0,34873	0,06243	-0,02477	0,03766	-0,43375	931
TRY	-0,00005	0,00012	-0,00016	0,00377	0,00001	6,41202	0,82031	0,04719	-0,02149	0,02570	-0,04226	931
TR CDS	-0,00026	0,00045	-0,00133	0,01383	0,00019	4,38324	1,09763	0,12269	-0,04249	0,08020	-0,24218	931
BOVESPA	-0,00041	0,00023	-0,00025	0,00703	0,00005	1,09314	0,24864	0,05513	-0,02536	0,02978	-0,37827	931
BRL	-0,00020	0,00012	-0,00038	0,00360	0,00001	9,49913	1,13165	0,05159	-0,02257	0,02902	-0,18287	931
BR CDS	-0,00062	0,00052	-0,00092	0,01589	0,00025	10,39791	0,58877	0,22071	-0,10538	0,11534	-0,57260	931
BOLSA	-0,00056	0,00017	-0,00082	0,00515	0,00003	2,66288	0,24119	0,05423	-0,02827	0,02596	-0,52341	931
MXN	0,00001	0,00006	-0,00011	0,00180	0,00000	2,03220	0,52647	0,01666	-0,00818	0,00847	0,00707	931
MEX CDS	-0,00029	0,00047	-0,00083	0,01448	0,00021	8,90021	0,93679	0,19501	-0,07898	0,11603	-0,26643	931
KOSPI	-0,00039	0,00018	-0,00052	0,00547	0,00003	2,80234	0,65430	0,05520	-0,02403	0,03117	-0,36335	931
KRW	-0,00011	0,00006	-0,00005	0,00172	0,00000	4,09674	-0,17788	0,01772	-0,01069	0,00703	-0,10578	931
KR CDS	-0,00020	0,00044	-0,00060	0,01347	0,00018	16,09511	1,74823	0,19870	-0,07643	0,12227	-0,18639	931
JSE	-0,00048	0,00016	-0,00064	0,00478	0,00002	3,52872	0,48031	0,05045	-0,02136	0,02910	-0,44907	931
ZAR	0,00003	0,00014	-0,00009	0,00442	0,00002	1,38021	0,40990	0,03210	-0,01333	0,01877	0,03156	931
SA CDS	-0,00034	0,00046	-0,00089	0,01416	0,00020	13,05130	1,20317	0,20933	-0,09452	0,11480	-0,31362	931
DOLLAR TWI	-0,00004	0,00007	-0,00010	0,00203	0,00000	0,66891	0,00188	0,01359	-0,00667	0,00692	-0,04180	931
DJIA	-0,00015	0,00010	-0,00020	0,00301	0,00001	1,32285	0,30369	0,02530	-0,01075	0,01454	-0,14221	931

Abbreviations in Table 1 as follows:

ISE: Istanbul Stock Exchange National 100 Index, TRY: Turkish currency against US dollar, TR CDS: 5 years CDS of Turkey, BOVESPA: Bovespa Brazilian Stock Exchange Index, BRL: Brazilian currency against US dollar, BR CDS: 5 years CDS of Brazil, BOLSA: Mexican Stock Exchange Index, MXN: Mexican currency against US dollar, MEX CDS: 5 years CDS of Mexica KOSPI: Korean Stock Exchange Index, KRW: Korean currency against US dollar, KR CDS: 5 years CDS of Korea, JSE: FTSE/JSE South African Stock Index, ZAR: South African currency against US dollar, SA CDS: 5 years CDS of South Africa, DOLLAR TWI: Dollar Trade Weight Index DJIA: Dow Jones Industrial Average.

4. Empirical Discussions

In the empirical analysis, the main idea has been to display the regime properties and transition probabilities of the sub-markets within the selected emerging economies and also compare time of the transitions among the markets. The US dollar index and Dow Jones Industrial Average are used as a benchmark to compare the regime properties and transitions between the emerging and the US economies. It is assumed to have an impact on the emerging market countries in times of jumps in volatility.

In order to check if there is a concurrency between a jump in the US stock exchange, Dollar trade weighted index and the emerging markets a Markov chain analysis is carried out and the correlation between jumps is calculated afterwards.

From Table 2, number of observations, probability, and duration of each regime since 2004 is observed. First of all, we can argue that the US dollar has a volatile characteristic as compared to that of the US stock markets. Among the emerging markets, on the other hand, it might not be misleading to argue that Turkish markets including both stock market (the ISE), FX market (TRY) and credit markets (CDS) are relatively stable which might be due to the fact that the foreign money flows into the economy has been relatively high in this period. In fact, Turkish economy has benefited from the hot money inflows due to its high real yields for five years as a result of recovery after 2001 crisis. Furthermore, the official candidateship of Turkey into the EU in December 2004 has been created a stability and progress in the economy in general.

Table 2. Regime Properties of the Markets

Regime Properties											
ISE	nObs	Prob.	Duration	**BOLSA**	nObs	Prob.	Duration	**JSE**	nObs	Prob.	Duration
Regime 1	859.2	0.9240	22.19	Regime 1	535.7	0.5758	3.88	Regime 1	550.8	0.5917	4.13
Regime 2	70.8	0.0760	1.83	Regime 2	394.3	0.4242	2.86	Regime 2	379.2	0.4083	2.85
TRY	nObs	Prob.	Duration	**MXN**	nObs	Prob.	Duration	**ZAR**	nObs	Prob.	Duration
Regime 1	889.6	0.9564	29.18	Regime 1	912.6	0.9812	52.11	Regime 1	899.7	0.9675	40.21
Regime 2	40.4	0.0436	1.33	Regime 2	17.4	0.0188	1.00	Regime 2	30.3	0.0325	1.35
TR CDS	nObs	Prob.	Duration	**MEX CDS**	nObs	Prob.	Duration	**SA CDS**	nObs	Prob.	Duration
Regime 1	891.3	0.9584	34.42	Regime 1	510.3	0.5484	4.42	Regime 1	913.7	0.9827	83.95
Regime 2	38.7	0.0416	1.49	Regime 2	419.7	0.4516	3.64	Regime 2	16.3	0.0173	1.48
BOVESPA	nObs	Prob.	Duration	**KOSPI**	nObs	Prob.	Duration	**DOLLAR TWI**	nObs	Prob.	Duration
Regime 1	864.8	0.9297	21.59	Regime 1	548.6	0.5893	4.18	Regime 1	519.0	0.5577	3.58
Regime 2	65.2	0.0703	1.63	Regime 2	381.4	0.4107	2.92	Regime 2	411.0	0.4423	2.84
BRL	nObs	Prob.	Duration	**KRW**	nObs	Prob.	Duration	**DJIA**	nObs	Prob.	Duration
Regime 1	917.4	0.9864	76.02	Regime 1	435.7	0.4686	3.33	Regime 1	885.8	0.9523	25.95
Regime 2	12.6	0.0136	1.05	Regime 2	494.3	0.5314	3.77	Regime 2	44.2	0.0477	1.30
BR CDS	nObs	Prob.	Duration	**KR CDS**	nObs	Prob.	Duration				
Regime 1	533.0	0.5723	4.75	Regime 1	920.5	0.9899	108.94				
Regime 2	397.0	0.4277	3.55	Regime 2	9.5	0.0101	1.12				

On the other hand, Brazilian and Mexican markets follow similar patterns in general. However, Brazil CDS market is volatile compared to others. From the evidence it is possible to conclude that the CDS markets in Latin American economies are volatile while the currency and equity markets are relatively more stable. On the contrary, duration of the Korean CDS market in regime 1 is higher than all the emerging markets suggesting the market is more stable and liquid. However, the discrepancy between the Korean CDS market and stock exchange and the currency is evident as those markets seem to be highly volatile. In the South Africa it is shown that the stock market is generally turbulent as well.

Table 3 presents matrix of regime transition probabilities in the financial markets. In parallel to regime probabilities in the markets, the most stable economy seems to be Turkey. Mexico and Brazil follow similar patterns as usual. The probability of transition from stable to volatile regime is relatively high in Korean currency markets, Mexican and Brazilian CDS markets and South African equity markets.

From the empirical results, we can argue that during the increasing volatility and weakening US dollar periods, the world stock markets, except for the South Africa, are stable. In theory, it is conceivable that the weak dollar creates an upward trend on the stock markets as the supply of dollars into other markets result in inflows in those markets.

Table 3. Matrix of Transition Probabilities

Matrix of Transition Probabilities								
ISE	Regime 1	Regime 2	**BOLSA**	Regime 1	Regime 2	**JSE**	Regime 1	Regime 2
Regime 1	0.9549	0.0451	Regime 1	0.7420	0.2580	Regime 1	0.7581	0.2419
Regime 2	0.5476	0.4524	Regime 2	0.3501	0.6499	Regime 2	0.3505	0.6495
TRY	Regime 1	Regime 2	**MXN**	Regime 1	Regime 2	**ZAR**	Regime 1	Regime 2
Regime 1	0.9657	0.0343	Regime 1	0.9808	0.01919	Regime 1	0.9751	0.0249
Regime 2	0.7526	0.2474	Regime 2	1.000	3,17E-02	Regime 2	0.7415	0.2585
TR CDS	Regime 1	Regime 2	**MEX CDS**	Regime 1	Regime 2	**SA CDS**	Regime 1	Regime 2
Regime 1	0.9709	0.0291	Regime 1	0.7739	0.2261	Regime 1	0.9881	0.0119
Regime 2	0.6694	0.3306	Regime 2	0.2746	0.7254	Regime 2	0.6761	0.3239
BOVESPA	Regime 1	Regime 2	**KOSPI**	Regime 1	Regime 2	**DOLLAR TWI**	Regime 1	Regime 2
Regime 1	0.9537	0.0463	Regime 1	0.7610	0.2390	Regime 1	0.7204	0.2796
Regime 2	0.6125	0.3875	Regime 2	0.3429	0.6571	Regime 2	0.3525	0.6475
BRL	Regime 1	Regime 2	**KRW**	Regime 1	Regime 2	**DJIA**	Regime 1	Regime 2
Regime 1	0.9868	0.0132	Regime 1	0.6995	0.3005	Regime 1	0.9615	0.0385
Regime 2	0.9520	0.0480	Regime 2	0.2650	0.7350	Regime 2	0.7693	0.2307
BR CDS	Regime 1	Regime 2	**KR CDS**	Regime 1	Regime 2			
Regime 1	0.7893	0.2107	Regime 1	0.9908	0.0092			
Regime 2	0.2819	0.7181	Regime 2	0.8953	0.1047			

One of the discussions to be raised here is that besides the regime properties, the probability of transition from one state to another. In that respect, we can observe that for the Turkish markets, including stock exchange, Turkish lira and

CDS markets, the probability of switching regime is relatively low. However, whenever a regime is changed the likelihood of staying in that regime is ranging from %24,76 to %45,24. For the Brazilian financial markets, the need to make a distinction appears. For the Brazilian CDS market, the regime transition probability is %21.07, which seems to be high compared to others. This might be occurring due to the fact that the investors use CDS as a hedge of other markets besides their proprietary CDS positions. Furthermore, whenever there is a regime switch, the probability of going to earlier state is quite low, which is around 28%. These findings are different than the currency and stock markets of Brazil; where the regime switching probabilities are low and the probability of going back to the earlier regime is high. The evidence for the Mexican markets suggest that transition probability is low in stock markets and currency and higher for CDS markets as in Brazil. However in Mexico case, for the stock exchange the probability of staying in regime 2 is higher which suggests that the volatilities are persistent rather than temporary in Bolsa. On the Korean market front, the CDS market is more stable. Kospi and Korean Won are more volatile and have a higher probability of regime switching. In South African markets, the stock markets seem to be more volatile and higher probability of staying in regime 2. Dollar trade weighted index has a higher transition probability compared to Dow Jones and seems to be more persistent. These observations seem to indicate that the transition probabilities differ according to countries and markets.

For the international portfolio management, the crucial empirical discussion is whether the regime switches coincide among different financial markets. In Table 4, we tried to elaborate if there is a relation between those jumps for those markets empirically.

Table 4. Correlation in Timing of Regime Switches Among the Markets

	ISE	TRY	TR CDS	BOVESPA	BRL	BR CDS	BOLSA	MXN	MEX CDS	KOSPI	KRW	KR CDS	JSE	ZAR	SA CDS	DOLLAR TWI	DJIA
ISE	1,00																
TRY	0,26	1,00															
TR CDS	0,12	0,48	1,00														
BOVESPA	0,18	0,25	0,24	1,00													
BRL	0,31	0,28	0,27	0,09	1,00												
BR CDS	0,23	0,41	0,48	0,28	0,34	1,00											
BOLSA	0,15	0,27	0,23	0,36	0,08	0,32	1,00										
MXN	0,09	-0,02	0,03	0,03	-0,01	0,07	-0,03	1,00									
MEX CDS	0,20	0,31	0,37	0,16	0,20	0,55	0,23	-0,01	1,00								
KOSPI	0,13	0,14	0,19	0,12	0,06	0,15	0,19	0,03	0,23	1,00							
KRW	0,02	-0,01	0,00	0,03	0,03	0,05	0,01	-0,05	0,03	0,06	1,00						
KR CDS	-0,01	0,05	0,11	0,04	-0,01	0,14	0,06	-0,01	0,04	0,11	-0,02	1,00					
JSE	0,25	0,29	0,24	0,18	0,20	0,34	0,26	0,02	0,29	0,27	0,00	0,03	1,00				
ZAR	0,05	0,28	0,31	0,08	0,16	0,24	0,10	-0,02	0,16	0,05	-0,01	0,05	0,08	1,00			
SA CDS	0,08	0,22	0,36	0,11	0,14	0,21	0,12	-0,02	0,18	0,12	0,00	0,16	0,20	0,08	1,00		
DOLLAR TWI	-0,03	0,08	0,04	0,03	0,01	0,03	0,01	0,04	0,04	0,06	0,00	0,00	0,05	0,13	0,05	1,00	
DJIA	0,06	0,15	0,06	0,42	0,05	0,28	0,37	-0,02	0,14	0,07	-0,02	0,13	0,20	-0,03	0,09	-0,03	1,00

First of all, the regime switches in the US dollar do not coincide with the switches in other markets, which might be due to a lag effect due to portfolio readjustment periods. On the other hand, the timing of regime switches in DJIA matches with those in the Latin American equity markets. On that point, it is most probable that there is a lag between the US markets and the rest of the world except from the Latin America due to time differences in the world.

When the duration for regime 2 periods are compared, the jump likelihood is highest for Mexican stock market where it stays 2,86 days in regime 2 and 3,88 days in regime 1 only. For the Mexican CDS the regime 1 duration is 4,42 days and 3.64 days for regime 2. For the Korean stock exchange regime 1 duration is 4,18 days and 2,92 days and for the Korean Won regime 1 duration is 3,33 days and regime 2 duration is 3,77 days. For the Johannesburg stock exchange regime 1 duration is 4,13 days and regime 2 duration 2,85 days. Dollar trade weighted index stays 3,58 days in regime 1 and 2,84 days in regime 2, which also implies that the volatility is higher in the observed periods.

On the other hand, concurrencies of regime transitions among the emerging stock markets are worth pointing out. Besides the stock markets, there are parallel movements between the Latin American and Turkish CDS markets due to an integration of those markets and benchmarking matters. Also it should be underlined that there is a remarkable empirical finding about the Turkish markets in that Turkey has one of the volatile financial markets, however in the Latin American markets which are investment grade levels mostly coincide. Under the light of those empirical findings, due to increasing globalization, it can be argued that portfolio diversification in the international markets is not possible unless one invests in an economy with a special history, like Turkey.

5. Concluding Remarks

Globalization in the world economy has been created dependency in financial markets. In addition, the weak dollar since 2004 has had crucial effects in the financial markets, especially in the emerging markets. Carry trade opportunities have encouraged the global funds aiming at earning risky money to invest in the emerging markets. In the emerging markets, on the other hand, hot money flows, political and macroeconomic instability, changes in regulations might create sudden regime shifts with high volatility.

In this study, we aim at examining whether the jumps between different emerging markets are correlated and if they are observable; in addition, showing if there is a connection between those jumps and the US financial markets. The two-stage Markov switching model is used for the empirical analysis.

The research results show that the regime shifts in the financial market in emerging economies occur in mostly similar periods. Those periods coincide with the regime shifts with those in the US exchange rate and stock markets. Especially Turkish, Brazilian and Mexican stock markets display similar patterns in regime switches. Turkey is a special case in the analysis in that she is the less volatile market during the examined period. Due to probably her story about the European Union candidateship officially announced in December 2004, Turkish markets move in a growing and stable direction.

The empirical evidence underlines the important strategy in the global financial markets, which is that risk diversification in the international portfolio investments, is only possible if the investors can find special stories in the markets. Otherwise, the crises in the financial markets coincide in the same periods and risk diversification is not possible by just investing in different geographies. The next papers might concentrate on the time-scale of the regime switches in the markets by employing wavelets or Fourier analysis.

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