Conditional autocorrelation and stock market integration in the Asia-Pacific

Conditional Autocorrelation and Integration of Emerging Stock Markets

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Abstract

This paper considers the relationship between stock market autocorrelation and i) the presence of international investors which is proxied by the level of capital market integration, and ii) stock market volatility. Drawing from a sample of stock indices for a range of emerging or newly emerged markets, significant evidence of a relationship between the presence of international investors and the level of stock market autocorrelation is found. This evidence is consistent with the view that international investors are positive feedback traders. Robustness testing of this model suggests that the trading strategy of international investors changed as a result of the Asian currency crisis. The evidence for the role of volatility in explaining autocorrelation is, however, is generally weak and varies across the sample countries.

JEL: G15, F36

Keywords: market integration, conditional autocorrelation, Markov models, stock markets.

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Abstract

This paper considers the relationship between stock market autocorrelation and i) the presence of international investors which is proxied by the level of capital market integration, and ii) stock market volatility. Drawing from a sample of stock indices for a range of emerging or newly emerged markets, significant evidence of a relationship between the presence of international investors and the level of stock market autocorrelation is found. This evidence is consistent with the view that international investors are positive feedback traders. Robustness testing of this model suggests that the trading strategy of international investors changed as a result of the Asian currency crisis. The evidence for the role of volatility in explaining autocorrelation is, however, is generally weak and varies across the sample countries.

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I. Introduction

The capital flows of international investors have been subject of a great deal of interest in the academic literature. The primary issues revolve around how international investors behave and their impact on the capital markets in which they invest. A brief survey of the literature reveals an interesting divergence of opinion. On the one hand, international investors are perceived as a respectable group who provide capital to countries which have a range of investment opportunities but only limited means. They possess a superior set of information when compared to local investors and their portfolio allocation decisions are based on a sophisticated set of investment strategies which focus on the fundamentals (see Froot and Ramadorai (2001) and Seasholes (2004)). On the other hand, a competing view casts international investors as the scourge of the global economy. Under this view, international investors are thought to pursue positive feedback trading strategies which exacerbate trends causing overshooting, excess volatility and increased market vulnerability (see Dornbusch and Park (1995), Choe Kho and Stulz (1999), Kim and Wei (2002), Grinblatt and Keloharju (2000), Froot, O'Connell and Seasholes (2001)). In the extreme, international investors have been blamed for a number of financial market disasters, such as the 1997 Asian currency crisis (Radalet and Sachs (1998)).

In general terms, investors may pursue either 'information' or 'feedback' trading strategies. The trading behavior of this latter group has been linked to autocorrelation in asset prices (see Sentana and Wadhwani (1992)). A feedback trader bases the decision to buy, sell or hold on past price movements. Two types of feedback trader can be characterized: 'positive' ('negative') feedback traders systematically follow the strategy of buying (selling) after price rises and selling (buying) after price falls. Thus, positive feedback traders reinforce price movements such that prices will continually overshoot the levels suggested by current publicly available information. As the market corrects for this over-reaction in the following trading period, prices tend to move in the opposite direction and so negative autocorrelation is induced. The converse situation is true for negative feedback traders who are thought to induce positive autocorrelation.

Recognizing the existence of both types of traders, it can be argued that the sign and strength of any observed return autocorrelation may well reflect the relative market dominance of one group of feedback traders over another. Positive (negative) stock return autocorrelation would tend to suggest negative (positive) feedback traders are the dominant trading group for that particular asset. This autocorrelation may vary over time as different trading strategies come into, and go out of, favor with investors (see Farmer (2000)). Information traders are benign in this context however, as they do not follow market trends and so, do not contribute to market momentum.

Säfvenblad (2000) shows that the return autocorrelation of individual stocks is an important determinant of stock index autocorrelation. Thus, the market will exhibit a given level of autocorrelation which reflects the amount and type of feedback trading by investors in individual stocks. If we begin by assuming the market is closed to foreigners, then the level of autocorrelation observed in the market will reflect the trading strategies employed by local investors. If foreign traders are granted access to the market, then types of trading strategy employed by this group may impact on the observed level of autocorrelation. If international investors pursue feedback trading strategies, ceteris paribus, the collective presence of feedback traders in the market as a whole will have increased. This has implications for the level of autocorrelation exhibited by the market. For example, if international investors are positive feedback traders, then their trading activity will serve to further exacerbate the momentum of market trends causing an even greater reversal the following day. In this case, lower and possibly even negative autocorrelation will result. On the other hand, if international investors are negative feedback traders, then their presence in the local market will add to the negative feedback trading of locals. Greater profit taking in a rising market means an increased likelihood of a price continuation the following day and so heightened autocorrelation will be observed. Where international investors pursue information based strategies, the level of feedback trading will not change. In this case, the presence of international investors in the local market should have no impact on autocorrelation.[1]

In this paper, we have a dual aim of investigating the impact of international investors on local stock market dynamics and the relationship between market volatility and conditional autocorrelation in a number of emerging stock markets. Our research findings will be of interest to investors, economists, market regulators and government policy makers alike. For example, Stiglitz (1998) called for regulation of international capital flows arguing that developing countries are extremely vulnerable to fluctuations in international capital flows. We argue that the presence of international investors will influence the observed level of autocorrelation if they pursue feedback trading strategies. The nature of the relationship will reflect the type of feedback trading strategy employed. An important issue with this type of

[1] The use of feedback trading strategies by international investors does not imply irrationality. Choe, Kho and Stulz (1999) argue that where informational asymmetries exist, the trades of local investors reveal their informational advantage to foreigners who will then trade based on this information embodied in price changes. Thus, upward price movements suggest good news which causes foreigners to trade in what may be incorrectly interpreted as irrational positive momentum trading.

research relates to how to measure the presence of foreigners in the local market. The previous literature has analysed datasets which directly capture information on the trading activity of foreigners and residents. Such datasets are typically highly specialised and not readily available for a wide selection of countries. In this paper, we adopt a different tact by using a measure of capital market integration to proxy for the presence of foreign investors. An important part of the process of capital market integration involves the removal of capital market restrictions on the participation of foreigners in domestic stock markets.[2] As such, increased levels of trading by foreigners will accompany higher levels of integration. According to our hypothesis, higher levels of integration should significantly impact on the observed level of autocorrelation and the direction of this relationship will be a function of the type of trading strategy employed by international investors.

As for the role of volatility in determining autocorrelations, we argue that the presence or lack of feedback traders would have an implication. As autocorrelation is argued to reflect the activity of feedback traders (see Sentana and Wadhwani (1992) and Black (1988, 1989)) changes in volatility therefore have implications for the level of autocorrelation. Where negative return autocorrelation exists, volatility increases should serve to heighten the observed level of autocorrelation. On the other hand, where positive autocorrelation is evident, a rise in volatility should lessen the level of return autocorrelation. In support of this theory, a negative relationship between volatility and autocorrelation has been found in the literature (see *inter alia* Sentana and Wadhwani, 1992, Koutmos, 1997, and McKenzie and Faff, 2003) for individual

[2] Albuquerque, Loayza and Servén (2003) argue that, "the process of integration starts with the removal of capital market restrictions, most notably the liberalization of foreign investors' participation in domestic stock markets, the listing of domestic firms in foreign markets, and the privatization of state-owned companies".

stocks. In testing the nature of the relationship between volatility and autocorrelation, the previous literature has failed to recognize that heightened volatility may result from either an increase or a decrease in prices. In this paper, we argue this to be an important distinction and investigate the disaggregated influence of heightened volatility with either positive or negative returns on conditional autocorrelations.

To test our hypotheses, we specify a conditional measure of autocorrelation which is generated using a multivariate generalised ARCH (M-GARCH) model. The autocorrelation term of the covariance equation in this model has been augmented to include a measure of market integration and measures of market volatility as well as other determinants found to be of importance in the literature such as daily periodicity, large returns, etc. This issue of integration is an important one and a substantial volume of literature has been devoted to considering the question of whether capital markets are integrated, in particular for emerging economies (for a survey see Bekaert and Harvey (2002, 2003)). The evidence suggests that capital markets are imperfectly integrated and that the level of integration changes over time. As such, we specify a time-varying integration parameter adopted from Bekaert and Harvey (1995) in our analyses. This model is to be applied to a wide range of emerging market data. Harvey (1995) reports that emerging markets typically exhibit higher levels of autocorrelation compared to developed markets. To provide a control sample for the analysis a number of developed markets are also tested in this framework. The value and volume of transactions in these markets is substantial and the trading strategies employed by incumbent investors span the full spectrum of information and momentum based trading strategies. The presence of foreigners is not expected to alter the playing field in any significant way and as such, no relationship between autocorrelation and the presence of foreigners is hypothesised for these developed markets.

The results of our analyses find important evidence of a significant relationship between the presence of international investors and the level of stock market autocorrelation. Specifically, lower levels of conditional autocorrelation in returns are associated with the increased presence of international investors. This result is consistent with the view the international investors are positive feedback traders and is consistent with previous research. The nature of the relationship however, may change over time. For example, analysis of our model for post-1997 Asian currency crisis data suggests that the extent to which positive feedback trading is a feature of the market has diminished and foreign investors either withdrew from the market or modified their trading strategies to suit the new regime. As for the impact of market volatility on the autocorrelations, we find that volatility is not as significant a determinant of autocorrelation as has previously been found in the individual stock setting. The limited evidence of a relationship in our sample is more mixed compared to the past literature where higher levels of volatility are typically associated with lower levels of autocorrelation.

The remainder of the paper is organized as follows. In the next section we outline our empirical approach as well as the Markov regime switching models used to generate proxies for market volatility and integration. Section III presents the data used in the analysis and discusses the results. Robustness testing of our results to the 1997 Asian currency crisis is also undertaken. Finally, section IV presents some concluding comments.

II. Bivariate GARCH Model Estimates of Conditional Autocorrelation

Empirical estimates reveal that stock return autocorrelation is sample dependent and may exhibit sign reversals (see Chan (1993), and Knif, Pynnönen and Luoma, (1996)) which suggests that it is appropriate to model autocorrelation as a time-varying process. To this end, Sentana and Wadhwani (1992), Koutmos (1997) and Booth and Koutmos (1998) generated conditional autocorrelation estimates whose temporal variation was driven solely by changes to the variance. One weakness of this model is the assumption of a constant covariance which potentially suppresses an important source of variation in autocorrelation. In this paper, conditional autocorrelation estimates are generated using an M-GARCH model in which both the variance and covariance equations are time-varying. Estimates of conditional autocorrelation may be generated where this M-GARCH model is fitted to that returns series (R_{1t}) as well as its lagged values (R_{2t}).

Specifically, the mean equation for each series is specified with a constant as well as day-of-the-week dummies, ie.:

$$\begin{aligned} R_{1,t} &= \alpha_{1,c} + \alpha_{1,Lag} \cdot R_{1t-1} + \alpha_{1,WRTN} \cdot WRTN_{t-1} + \sum_{i=MON}^{THU} \alpha_{1,i,} \cdot DayDum_{i,t} + e_{1,t} \\ R_{2,t} &= \alpha_{2,c} + \alpha_{2,Lag} \cdot R_{2t-1} + \alpha_{2,WRTN} \cdot WRTN_{t-2} + \sum_{i=MON}^{THU} \alpha_{1,i,} \cdot DayDum_{i,t-1} + e_{2,t} \end{aligned} \tag{1}$$

where R is the continuously compounding return on an index, calculated as log price relative $\times 100$, $WRTN$ is the return to a world market index and $DayDum_{it}$ is the dummy variable capturing daily periodicity where i = Mon, Tue, Wed and Thu. The error terms (e_{1t}, e_{2t}) are assumed to be normally distributed with a mean of zero and a conditional variance which is modeled as a GARCH process, which has been modified to include a threshold term and day of the week dummy variables, ie.:

$$h_{R1t} = \beta_{1c} + \beta_{1h} \cdot h_{1,t-1} + \beta_{e11} \cdot e_{1,t-1}^2 + \beta_{e12} \cdot e_{1,t-1}^2 \cdot I_{1t} + \beta_{1WVLT} \cdot WVLT_{t-1} + \sum_{i=Mon}^{Thu} \beta_{1i} \cdot DayDum_{it}$$
$$h_{R2t} = \beta_{2c} + \beta_{2h} \cdot h_{2,t-1} + \beta_{e21} \cdot e_{2,t-1}^2 + \beta_{e22} \cdot e_{2,t-1}^2 \cdot I_{2t} + \beta_{2WVLT} \cdot WVLT_{t-2} + \sum_{i=Mon}^{Thu} \beta_{2i} \cdot DayDum_{it-1} \quad (2)$$

where I_{1t} is an indicator variable that takes one where $e_{1t-1} < 0$, and zero otherwise. I_{2t} is similarly defined for e_{2t-1}.[3] The threshold term is designed to capture the asymmetric nature of volatility responses to positive and negative shocks to the market (see Bollerslev, Engle and Nelson, 1994). $WVLT_{t-1}$ is the conditional variance generated from a GARCH(1,1) model of the world index returns.

In addition to the variance equations, the covariance equation also needs to be specified and a conditional specification is adopted in which all elements are time-varying, ie.:

$$h_{R1,R2,t} = \rho_t \sqrt{h_{R1,t} \times h_{R2,t}} \quad (3)$$

where ρ_t is the conditional return autocorrelations of an Index which is specified as:

$$\rho_t = d_0 + d_1 \cdot \rho_{t-1} + d_2 \cdot (e_{1.t-1} \cdot e_{2,t-1}) / \sqrt{h_{R1,t-1} \times h_{R2,t-1}} \quad (4)$$

The focus of this paper is on identifying the determinants of autocorrelation and as such, equation (4) may be augmented to include a number of determinant variables, ie.

[3] EGARCH specifications were also tested and the results (available on request) are qualitatively unchanged to those obtained using the GJR models reported in this paper.

$$\rho_t = d_0 + d_1 \cdot \rho_{t-1} + d_2 \cdot (e_{1.t-1} \cdot e_{2,t-1}) / \sqrt{h_{R1,t-1} \times h_{R2,t-1}}$$
$$+ c_1 \cdot MRP3_{t-1} + c_{12} \cdot MRP4_{t-1} + c_2 \cdot AAP_{t-1} + c_3 \cdot AAN_{t-1} \quad (5)$$
$$+ c_4 \cdot MarkovInt_{t-1} + \sum_{i=Mon}^{Thu} c_i \cdot DayDum_{i,t}$$

where $MRP3_{t-1}$ ($MRP4_{t-1}$) is the time series of filtered Markov regime probabilities of return regime 3 (4) which corresponds to a negative (positive) return and high return volatility. These terms and their derivation are explained more fully in section II.A. A change in autocorrelation from a given rise in volatility however, is argued to be less where the underlying cause for the change in volatility is falling prices. Recognizing this potential asymmetry in the context of the model, suggests that the coefficient associated with the high volatility/falling market scenario will be less than the coefficient estimated for the high volatility/rising market scenario, ie. $|c_1| < |c_{12}|$. AAP_{t-1} (AAN_{t-1}) is a dummy variable that takes the value of one if an above average positive (negative) return is observed. $DayDum_{i,t}$ is defined as in (1) and (2).

$MarkovInt_{t-1}$ is the time-varying probability of integration which is generated using the approach of Bekaert and Harvey (1995). Section II.B provides a detailed explanation of its derivation. We use it as a proxy for the presence of foreign investors in the individual stock markets, and hypothesize that a negative coefficient suggests a presence of positive feedback trading in the market. Dominance of foreigners with predominantly positive feedback trading strategies would imply a lower and possibly a negative conditional autocorrelation. As we focus on a selection of emerging stock markets that have recently liberalized, investigating the extent to which foreigners dominate the market movements, as proxied by the integration probabilities, would shed light on the nature of trading patterns of these foreign investors.

By augmenting the autocorrelation equation in this way, this paper avoids the two-step estimation procedure which has been previously used in the literature, with resulting gains in estimation efficiency. Further, the use of Markov probabilities to proxy volatility avoids the issue of endogeneity that occurs when the proxy and the autocorrelation series are not independent.[4]

II.A. Markov Regime Shifting Models of Index Return Volatility

The observed volatility clustering in high frequency return series may be explained by the existence of different regimes with different variances present in the data generating process. These regimes can be modelled as a pure Markov switching variance process (see Turner, Starz and Nelson, 1989, and Kim, Nelson and Starz, 1998). We use the Markov model of Bollen, Gray and Whaley (2000) to generate the regime probabilities which are interpreted as a proxy for volatility in that series. The return R in period t is defined as:

$$\mathrm{R}_t = \mu_{\mathrm{MSP1},t} + \mathrm{e}_t \quad , \quad e_t \sim N(0, \sigma^2_{MSP2,t}) \tag{6}$$

where, MSP1 is the first order, two state Markov switching process that drives the return and has the transition probability of :

[4] McKenzie and Faff (2003) generated conditional autocorrelation estimates using an M-GARCH model and subsequently tested the relationship between autocorrelation and its determinants in a SUR framework. The conditional variance from this GARCH model was used to proxy volatility and also appeared as the denominator in the autocorrelation estimate.

$$\Pi_{\mu} \equiv \begin{bmatrix} p_{\mu} & 1-p_{\mu} \\ 1-q_{\mu} & q_{\mu} \end{bmatrix} \tag{7}$$

Depending on the state governed by MSP1 the mean return could be either $\mu_1(\text{State}=1)$ or $\mu_2(\text{State}=2)$, where $\mu_1 < \mu_2$. The variance of the error term, e_t, is driven by another first order, two state independent Markov switching process, MSP2 whose transition probability is:

$$\Pi_{\sigma} \equiv \begin{bmatrix} p_{\sigma} & 1-p_{\sigma} \\ 1-q_{\sigma} & q_{\sigma} \end{bmatrix} \tag{8}$$

Thus, the variance could be either $\sigma_1^2(\text{State}=1)$ or $\sigma_2^2(\text{State}=2)$, depending on the state. We have $\sigma_1^2 < \sigma_2^2$. It is clear from (6) that the model for the return generating process is conditionally normal and the parameters of the distribution depend on the state under consideration. But the nature of the two independent Markov switching processes suggests that we have four different state combinations to consider. These are. $\{MSP1, MSP2\} = \{(\mu_1, \sigma_1^2), (\mu_2, \sigma_1^2), (\mu_1, \sigma_2^2), (\mu_2, \sigma_2^2)\}$. That is, there are four separate regimes that need to be considered: Regime 1 = low mean (negative return) state and low volatility state; Regime 2 = high mean (positive return) and low volatility; Regime 3 = low mean (negative return) and high volatility; and Regime 4 = high mean (positive return) and high volatility. Using equations (7) and (8), the overall transition probability of the combined process can be written as:

$$\begin{bmatrix} \Pi_{\mu}.p_{\sigma} & \Pi_{\mu}.(1-p_{\sigma}) \\ \Pi_{\mu}.(1-q_{\sigma}) & \Pi_{\mu}.q_{\sigma} \end{bmatrix} \tag{9}$$

Since the return generating process is conditionally normal, it is straightforward to write the conditional density function of the joint process given a state pair (a regime). We multiply the conditional densities for different states by the corresponding probabilities of the states and sum them to obtain the likelihood function. Next, we maximize the weighted likelihood function numerically with respect to the parameters of the model, which are $\Theta \equiv \left(\mu_1, \sigma_1^2, \mu_2, \sigma_2^2, p_\mu, q_\mu, p_\sigma, q_\sigma\right)$. This algorithm generates the filtered probabilities of each state, i.e. the probability of a particular state occurring given the information up to that point in time. These are the time series of return/volatility regime probabilities that represent the market participants' view of the state of return/volatility in the individual country. In this paper, the time series of the resulting regime probabilities are used to explain the time varying nature of conditional return autocorrelations. As the regime 1 and 2 probabilities will contain the same information (with opposite sign) as the high volatility regime probabilities (regimes 3 and 4), our model only formally considers the latter as exogenous variables in equation (5).

II.B. Conditional Stock Market Integration

Bekaert and Harvey (1995) specify two regimes of market integration; 1) complete integration to world market where individual market returns are a function of the covariance between the individual market return and the world index returns, scaled by a world covariance risk factor; and 2) complete segmentation where the individual market return is determined in isolation and by own variance scaled by a representative investor's relative risk aversion. We adopt their model and generate the time varying integration probabilities. The completely integrated market return for country *i* is given by

$$r_t^i = \alpha_1 + \beta_1 \cdot r_{t-1}^i + \lambda_t \cdot COV(r_t^i, r_t^w) + \varepsilon_{1,t}^i \tag{10}$$

Where r_t^i is a daily index return for country *i*, COV(.) is the conditional covariance between the country *i*'s index return and the world index return, λ_t is time varying world price of covariance risk, and $\varepsilon_{1,t}^i$ is *iid* with (μ_1^i, σ_1^i).

On the other hand, in completely segmented markets, the index returns are determined as

$$r_t^i = \alpha_2 + \beta_2 \cdot r_{t-1}^i + \lambda_t^i \cdot VAR(r_t^i) + \varepsilon_{2,t}^i \tag{11}$$

Where VAR(.) is the conditional variance of country *i*'s index return, and λ_t^i is country *i*'s time varying price of risk, and $\varepsilon_{2,t}^i$ is *iid* with (μ_2^i, σ_2^i) [5].

The standard Hamilton (1989, 1990) model of two state Markov regime switching with constant transition probabilities is adopted where the two transition probabilities are shown as below:

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[5] The time varying price of risk for each country is generated in a similar fashion to Bekaert and Harvey (1995, p417, 419). It is a time varying coefficient, λ_t^i, attached to the conditional variance (ARCH-M term) included in the conditional mean equation of the ARCH-M model of the index returns. It is conditioned on each country market's dividend yield and exchange rate volatility. The price of world covariance risk, λ_t, is similarly generated. It is a time varying coefficient on the conditional variance term in the mean equation of the ARCH-M model of the daily return of the world index. It is conditioned by world market dividend yield in access of the 30 day Eurodollar rate, the spread between the US 10 year bond and 3-month rates, and the change in the 30-day Eurodollar rate.

$$P = \text{prob}[S_t = 1 \mid S_{t-1} = 1], \quad Q = \text{prob}[S_t = 2 \mid S_{t-1} = 2] \tag{12}$$

Using equations (10), (11) and (12), we generate the time series of the smoothed probabilities, p_t^*, of individual countries being in the integration state ($S_t = 1$)[6], and this is used as the time varying probability of integration $MarkovInt_t$ in equation (5).

III. Data and Results

The analysis of this paper focuses on Datastream national stock market index prices for emerging markets or markets which up until recently were classified as emerging.[7] Although data for a wide range of countries is available, only those series which provided a sufficiently long sample period for analysis were included in this study. A total of 15 stock market indices were sampled at a daily frequency[8], eleven countries over the period January 1988 to May 2005 giving

[6] Bekaert and Harvey (1995) provides detailed discussions on the modeling issues and interested readers are referred to their paper for further discussions on the issue.

[7] This distinction is necessary as Singapore, Hong Kong and Greece are no longer classified as emerging countries according to the International Finance Corporation.

[8] A relevant issue given our choice of daily data is whether, as assumed by the theoretical model developed earlier, investors undertake shifts in risk bearing activities on a daily basis. The following comments justify our stance. First, the majority of the technical trading literature focuses on daily decisions made by investors which implicitly assumes that they do modify (or at least act as if they modify) their risk bearing activities to reflect changing conditions in the market on a daily basis. Second, not all investors must update their portfolios every day. Where only a subset of investors update at any point in time, say weekly, and imperfect correlation exists between the trading activities of each subset (such that their trading is spatially distinct), we will be able to observe shifts in risk

a total of 4266 observations, and four countries with varying start dates - Brazil (start date July 1994), Chile (July 1989), China (July 1993) and Indonesia (April 1990). The continuously compounding returns data were computed from these index data and descriptive statistics are provided in Panel A of Table 1. Descriptive statistics for the US and Japanese stock market returns are included in Panel B of Table 1.[9] These markets provide a control benchmark against which the estimation results for the developed markets may be compared.

The average annualized return across these markets is high by developed market standards with Argentina, Chile, Greece, Hong Kong and Mexico all providing estimates in excess of the US annualized return of 9.20 percent. Japan's long suffering economy is mirrored in the poor performance of its stock market which recorded an average of –1.25 percent. The only emerging market to generate a negative average return was Indonesia (-10.85) which was largely driven by the ongoing effects of the 1997 currency crisis. Consistent with the previous literature, the volatility of these markets is substantially higher than developed markets. All of our sample generated higher annualised standard deviation estimates compared to the US and in the case of Argentina, this figure was four times higher. The distribution of these returns is skewed and also feature excess kurtosis. The daily maximum rise in the value of the index

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bearing activities on a continual basis. Third, the bulk of previous literature in this area has also used daily data and for reasons of consistency, the same interval is chosen for analysis in this paper.

[9] Eighteen developed markets were included as a control sample and the results are qualitatively consistent across all markets. To limit the presentation of our results to a manageable level, we chose to focus on Japan and the US only which are the two largest stock markets in the world (2003, World Federation of Exchanges data). Further regional indices of Asia ex-Japan, Latin America and a combined index across our entire sample were also constructed and tested. Full details of the estimation results for all developed markets and indices are available on request.

exceeds 20 percent for Argentina, Indonesia, Korea, Malaysia and Turkey. Similarly, daily price falls in excess of 20 percent were observed for these same countries plus Hong Kong and Mexico. This suggests that the potential for substantial capital gains as well as losses are more common in these markets.

III.A. Regime Switching Estimates of Volatility

The literature suggests that one of the primary determinants of autocorrelation is volatility. In this paper, volatility proxies are generated using Markov regime switching models as detailed in Section II.A. Table 2 reports the estimated parameters of the four-regime Markov models driven by the two independent Markov switching processes. The mean returns μ_1, μ_2 indicate negative and positive stock returns, respectively, with respect to the market indices analysed. The transition probabilities P_μ and Q_μ help us infer the persistence of these two different regimes. A high value of P_μ relative to Q_μ, indicates that the probability of encountering a negative return period is very high during the sample period. Similarly, the probability of encountering positive return period is quite low. The two estimated variance parameters suggest different levels of variances in the two regimes. The higher variance is bigger by a factor ranging from about seven to forty compared to the variance in the low-variance regime. This is similar to results reported in Bollen, Gray and Whaley (2000). The transition probabilities for the variance regimes suggest that in all cases indices have high propensity to stay in a particular variance regime once it is in that regime. Bollen, Gray and Whaley (2000) explores this particular finding in the context of currency option pricing.

To provide a feel for these regime probabilities, Figure 1 presents a representative plot of these four regime states for the Argentinean stock market which is the first country in our sample. Note that regime 1 = negative returns and low volatility, regime 2 = positive return and low volatility, regime 3 = negative returns and high volatility, and regime 4 = positive returns and high volatility. These probability plots are typical of the Markov model results for all of the countries included in the sample. These coefficients reveal that the probability of the market being in one of the two low volatility states is high a majority of the time. Quite sharp and sudden reversals of these probabilities can be seen however, suggesting that these tranquil periods are interspersed with a number of high volatility episodes, which is consistent with the volatility clustering phenomena. For these Argentinean probabilities, the correlation between regime 1 and regime 3 (4) is –0.1856 (-0.2352) while the correlation between regime 2 and regime 3 (4) is –0.8187 (–0.8082). The two high volatility regimes exhibit a positive association with a correlation between regime 3 and 4 of 0.7499.

III.B. Regime Switching Estimates of Integration

In this paper, we investigate the impact of the presence of foreign investors on emerging stock market autocorrelation, where the Bekaert and Harvey (1995) time-varying measure of capital market integration is used to proxy for the presence of foreign investors. As such, equations (10), (11) and (12) are estimated for the 15 national stock market indices which comprise our sample and the integration probabilities, p_t*, are presented in Figure 2. Table 3 reports the Markov model estimations. It is noticeable that both P and Q are fairly high for all countries, suggesting that once a market enters a state it tends to stay in that state. The coefficients for the lagged returns, β_1 and β_2, measure the extent of autocorrelation in return in each state, and the average of the two is essentially the same as the relevant ρ_i for each country. They are, in essence, disaggregated ρ_i in Table 1. In 7 out of 15 emerging countries the autocorrelation is higher in the integrated state, so there is no general pattern of significant difference in autocorrelation coefficient between the two states. Another interesting result of note is that the standard deviation of returns in the integrated state is significantly higher than that of the non-integrated state in all cases except for the Philippines. This suggests that once a country moves to the integrated state, it is exposed to the vagaries of world market forces with a commensurate increase in the level of market volatility.

Bekaert and Harvey (1995) found that shifts in the indicated level of integration could be traced back to political and economic events which impacted on either the willingness or the ability of international investors to access the local stock market. A qualitative assessment of the probabilities estimated in this paper produces similar evidence.[10] For example, Argentina in the early part of the sample period exhibited quite high levels of integration which is to be expected as most papers date liberalization of the market during either the late 80s or early 90s.[11] Concerns over the economy lead to a devaluation in December, 1994 and a subsequent mass withdrawal of foreign investors from not only Argentina, but also Latin America. The integration parameter has been consistently low since that time, with some brief exceptions such as the shift in the parameter associated with the period of high economic growth and subsequent

[10] A detailed account of financial, political and economic events for a wide range of emerging and developing markets can be found at www.duke.edu/~charvey/Country_risk/couindex.htm.

[11] Bekaert, Harvey and Lumsdaine (2002) and Kim and Singal (2000) both estimate the date of liberalisation as November 1989, while Buckberg (1995) estimates the date of Argentinean liberalisation as October 1991.

recession in the late 90s. At a more general level, it is interesting to note the impact of the 1997 currency crisis on the integration parameter for the Asian markets. A clear increase in integration is evident for Hong Kong, Indonesia, Korea, Malaysia, Singapore and Thailand which were at the center of the speculative attacks. This change reflects the dominance of the global information set over the local one in local asset pricing. Except for the Philippines, there is a clear and interesting trend of a steady decline of the integration parameter starting mid- to late-1998. One possible explanation is that the increased dominance of foreign investors in these markets shortly after the breakout of the crisis was to take advantage of the emerging profitable opportunities, which have started to dissipate as these markets began the process of recovery from around 1998. As the markets started to recover, the local information began to dominate the local asset pricing once again. This suggests that the bouts of heightened integration in the countries were only temporary.

III.C. Conditional and Unconditional Autocorrelation

Unconditional autocorrelation estimates (ρ_i) may be estimated for each of our indices, i, and the results are presented in Table 1. Except for Indonesian, all of the data series exhibit significant positive first order autocorrelation. The highest observed level of autocorrelation is 0.18 for China and the lowest significant level of autocorrelation is 0.07 for Turkey. To investigate this further time-varying autocorrelation estimates are generated using the M-GARCH model specified in equations (1) – (4). The estimated model coefficients and diagnostic properties of the residuals are not presented to conserve space and are available on request.

The final three columns of Table 1 present a summary of the average conditional autocorrelation estimates as well as the maximum and minimum observed values. A comparison of the point estimates of autocorrelation to the average conditional autocorrelation estimate reveals that these two techniques provide a similar degree of information about the general level of observed autocorrelation which is consistent with previous research. The unconditional specification, however, omits important information about the variability of autocorrelation as evidence by the range of conditional estimates. Indonesia exhibits the greatest range of observations recording a maximum of 0.66 and a minimum value of –0.77 while Korea exhibits the smallest range of observations (0.09 to –0.06).

The conditional autocorrelation estimates exhibit a good deal of variation. To gain a fuller appreciation of the variability of this data, consider Figure 3 which presents a plot of the data for Argentina. The plot clearly highlights the variability of autocorrelation and a number of other interesting features can also be identified from the data. For example, the estimate is very low during the first part of the sample period whereas the mean and range of autocorrelation estimates increases noticeably post-1992. Previous research has found that such trends are mirrored in subperiod point estimates of autocorrelation and the same is true of our data. The unconditional autocorrelation estimate from 1998 to 1992 for Argentina is -0.03 whereas over the latter part of the sample period it is significant and positive (0.11). Indonesia provides another interesting example as the point autocorrelation estimate reported in Table 1 is negative and insignificant. Examination of the conditional values reveal that the early part of the data is characterised by high negative autocorrelation, while the latter part of the sample exhibits positive autocorrelation. Subperiod analysis using point estimates verifies this pattern as the autocorrelation from 1998 to 1992 for Indonesia is -0.43 whereas over the latter part of the sample period it takes a value of 0.12.

It is reassuring that these shifts in the conditional autocorrelation estimates are consistent with the unconditional values. The variability of the conditional autocorrelation estimates however, suggests that the use of points estimates may be potentially misleading. Further, it is an interesting empirical issue to consider the extent to which the observed variability in autocorrelation can be explained using economic factors and the remainder of this paper considers this issue.

III.D. Stock Market Autocorrelation and International Investors

To test the determinants of autocorrelation, the bivariate GARCH model summarized in equations (1) - (3) and (5) is fitted to the data where MRP3 and MRP4 are the volatility proxies which correspond to Markov Regime Probability (MRP) 3 and 4, respectively, and $MarkovInt_t$ is the time-varying probability of integration. In addition, above average return and the day-of-the-week dummies are also considered which have been found in the previous literature to be important. Tables 4a and 4b present the estimation results of the equations (1)-(3) and (5), respectively.

Conditional Mean and Volatility Estimation Results

We refrain from formally presenting the full model output to keep the presentation of our results to a manageable level. We present the results for the $R_{1,t}$ equation (the results for $R_{2,t}$ tend to mirror those of $R_{1,t}$ since the former is just the one period lagged values of the latter) in (1) and (2). Full results are available on request. For the mean equation, a number of significant day-of-the-week terms were estimated and they were almost exclusively negative suggesting the average market movement is typically higher on a Friday which is the assumed base case. This is especially so for the first two days of the week as 10 (9) countries generated significant and negative Monday (Tuesday) day-of-the-week coefficients, $\alpha_{1,Mon}$ ($\alpha_{1,Tue}$) Significant evidence of a relationship between the world market return and the local market return is in evidence as 15 coefficients are positive and 13 coefficients are positive and significant. Only Argentina and Mexico did not provide any evidence of a significant relationship.

In terms of the ARCH and GARCH coefficients, all of the estimates are significant at the 5% level except for the ARCH (β_{e11}) term in the model fitted to the Chinese return data which had a p-value of 0.15. The threshold terms (β_{e12}) capture the presence of asymmetry in the volatility response of shocks to the market. Ten of the countries generated threshold term which is significant, although the sign on the term was mixed as half were positive. In contrast to the mean equations, the day-of-the-week dummy variables in the variance equation exhibit a mix of positive and negative signs. Overall, there is certainly evidence of day-of-the-week effects in the volatility of these index returns series as 55 of the 60 coefficients were significant. Notably, Monday and Wednesday exhibit clear evidence of higher volatility compared to the base case of Friday with 14 and 11 positive and significant coefficients, respectively. While the world market return is generally found to be a significant factor in the mean equation, less evidence is found of a relationship between the variance of the world market return and local stock market volatility. Only nine countries generated a significant relationship and for six of those, higher global market volatility is associated with a heightened volatility response in the local market the subsequent trading day.

The last two columns of Table 4a present the Ljung Box test of white noise for the estimated standardized residuals, $z_t = e_t / \sqrt{h_t}$. There is evidence of remaining first moment serial correlation but the second moment dependencies are reduced in most cases. Attempts to address this imperfection led to the differing functional forms (especially with the lag structures of the B-GARCH models and the number of lagged dependent variables included in the mean equations) being relevant for the most of the 17 return series examined. This addressed the issue, however, the results of the conditional autocorrelation equation (4) estimations remain robust regardless of the functional form of the Bivariate-GARCH models selected. Thus, we report the results for the parsimonious models and any conclusion we draw is not dependent on the model selection.

Conditional Autocorrelation Results

The specification of the covariance equation in the MGARCH model presented in equations (1) – (3) and (5), includes a time varying autocorrelation coefficient, which is specified as a function of volatility, large returns and the day-of-the-week which the past literature has found to be important. In this paper, volatility is proxied by the MRP3 (MRP4) variables which are the time series of filtered Markov regime probabilities of return regime 3 (4) which correspond to a period of high volatility and negative (positive) returns. The estimated coefficients for c_1 and c_{12} capture the nature of the relationship between autocorrelation and volatility for MRP3 and MRP4, respectively, and are presented in Table 4b. The estimated results reveal that the coefficient for c_1 is not significantly different from zero for all countries except Chile, China, Indonesia, Korea and Taiwan where a negative coefficient is estimated. The estimate for c_{12} is significant for seven indices and except for Chile, the sign is positive. A Wald test of coefficient equality (ie. H_0: $c_1 = c_{12}$) is undertaken and the results reject the null hypothesis of equality in 8 cases. This evidence suggests that volatility is not as significant a determinant of autocorrelation in country index returns as has previously been found in the individual stock setting. Further, the limited evidence of a relationship in our sample is more mixed compared to the past literature where higher levels of volatility are typically associated with lower levels of autocorrelation.

A second determinant of autocorrelation which the past literature has found to be important is large changes in price which are proxied by above average positive or negative returns. Ten of the coefficients capturing the impact of above average positive returns (c_2 on AAP_{t-1}) are significant and seven are negative. Only six of the above average negative return coefficients (c_3 on AAN_{t-1}) are significant and three of those are negative. In terms of the day-of-the-week effects, only 18 individual coefficients are significant and the only discernible trend across the markets in our sample is for the autocorrelation to be lower on a Tuesday (eight countries produced a significant and negative coefficient for c_{TUE}).

In general, it is interesting to note that the past literature has identified volatility, large returns and day-of-the-week effects as significant determinants of individual stock autocorrelation. When the impact of these variables is considered in a market context, the evidence is generally weaker although not entirely inconsistent. These results motivate our search for additional factors which may be significant in determining autocorrelation at a market level and in this paper we propose the presence of international investors. It is to this hypothesis which we now turn our attention.

The presence of international investors in a market is proxied by the level of integration which is estimated using the Bekaert and Harvey (1995)'s conditional integration model. The impact of the presence of international investors on stock market autocorrelation is captured by the c_4 coefficient in the model and parameter estimates are reported in Table 4b. Except for Korea, Malaysia, the Philippines, Singapore and Taiwan, a significant relationship is generated and all of these significant coefficients are negative except for that of Chile. These results suggest a fall in the level of conditional autocorrelation in returns in response to the increased presence of international investors which accompanies heightened integration. This result is consistent with the view that the international investors are positive feedback traders (see Dahlquist and Robertsson, 2003, Kim and Wei, 2002 and Choe, Kho and Stulz, 1999). As their presence in the market increases, their positive feedback trading activities lessen the observed level of autocorrelation, and may even lead to negative autocorrelation in the extreme. The US and the Japanese stock markets are included in this study as a control sample and the estimation results for this data are presented in Panel B of Table 4b. Most relevant to the current discussion, the c_4 coefficient is not significant for either market which is consistent with expectations. The value and volume of transactions in developed markets are substantial and the trading strategies employed by investors spans the full spectrum. As such, the presence of foreigners is not expected to significantly impact on the dominant trading strategy in the market.

III.E. The Asian Currency Crisis and Emerging Market Autocorrelation

In the early '90s, international investors began to seek out alternative investment opportunities as bearish sentiment came to dominate traditional financial markets. This resulted in a marked increase in the amount of funds directed into the emerging markets sector which provided a valuable source of diversification and high expected returns. In 1997, however, the Asian currency crisis caused many international investors to revise their expectations of the emerging markets sector and a flight to quality resulted. These events suggest that it is appropriate to test the robustness of the results presented in the previous section to this regime change. As such, the bivariate GARCH model summarised in equations (1) - (3) and (5) is fitted to data from the pre- and post-crisis where the onset of the crash is set relative to the floating of the Bhat on July 2, 1997.

The estimation results are summarised in Table 5 for the pre-crisis period. With respect to the central hypothesis, 11 of the estimated c_4 coefficients are significant and nine exhibit a negative sign. Thus, while the results are broadly consistent with the results estimated over the entire sample, some differences are noteworthy. First, Hong Kong and Turkey are both insignificant in this pre-crash period. Second, the Philippines, Singapore and Taiwan are all significant in the current sample and the latter two exhibit a negative sign. These results are consistent with Choe, Kho and Stulz (1999) who report strong evidence of positive feedback trading by foreign investors prior to the crisis period.

A summary of the estimation results for the post-crisis period are presented in Table 6 and the results suggest the speculative attack episode of 1997 did cause a change in the market dynamics. Eight of the estimated c_4 coefficients are significant and of those, only China, Malaysia and Turkey generated a negative sign. Chile, Greece, Korea, Singapore and Thailand all exhibited a positive and significant sign suggesting the increased presence of foreign traders led to higher levels of autocorrelation. Two possible interpretations of our results exist. On the one hand, international investors may have withdrawn from the market and the dominant trading strategy among the local investors may have been contrarian in nature. As the exodus of foreign capital continued immediately after the breakout of the Asian financial crisis, in the absence of the positive feedback trading of foreign investors, the influence of the contrarians on the market would have increased, and this resulted in higher levels of autocorrelation. This also explains the gradual decline in the integration probabilities in all Asian countries (see Figure 2) except for the Philippines. Alternatively, international investors may have modified their preferred trading strategy to suit the new regime. The trading strategies which prove profitable during the bull run observed in the lead up to the crisis are unlikely to prove successful in the post crisis market and so this is a rational response of investors to such a significant change to the market. This interpretation of our results is consistent with Choe, Kho and Stulz (1999) who found that the evidence of positive feedback trading by foreigners all but disappeared after the crisis.

IV. Conclusions

The capital flows of international investors have been subject of a great deal of interest in the academic literature. In this paper, we investigate the impact of the trading strategies employed by international investors on local stock market dynamics. Specifically, the stock market will exhibit a given level of autocorrelation which reflects the amount and type of feedback trading. The presence of international investors may influence the observed level of autocorrelation if they pursue feedback trading strategies and the nature of the relationship will reflect the type of feedback trading strategy employed. Drawing from a sample of stock indices for a range of emerging or newly emerged markets, we test this hypothesis where the presence of foreigners is proxied by a time varying measure of capital market integration.

The results of our analysis find important evidence of a significant relationship between the presence of international investors and the level of stock market autocorrelation. Specifically, lower levels of conditional autocorrelation in returns are associated with the increased presence of international investors. This result is consistent with the view that the international investors are positive feedback traders and is supported by previous research. The nature of the relationship however, may change over time. For example, analysis of our model for post-1997 Asian currency crisis data suggests that the extent to which positive feedback trading is a feature of the market has diminished and foreign investors either withdrew from the market or modified their trading strategies to suit the new regime. In addition, we find that volatility is not as significant a determinant of autocorrelation of emerging market stock index returns as has previously been found in the individual stock setting. The limited evidence of a relationship in our sample is more mixed compared to the past literature where higher levels of volatility are typically associated with lower levels of autocorrelation.

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Table 1: Summary of International Stock Market Returns

This table presents a statistical summary and unconditional autocorrelation (ρ_1) estimates for a range of daily stock market returns sampled over the longest period January 1988 to May 2005. The mean, maximum and minimum conditional autocorrelation (ρ_{it}) estimate generated by a bivariate GARCH model as specified in equations (3) and (4), are also provided.

	Annualised Mean	Annualised Std. Dev.	Skew.	Kurt.	Daily Max	Daily Min	Autocorrelation ρ_i [(a)]	Average $\rho_{i,t}$	Max $\rho_{i,t}$	Min $\rho_{i,t}$
Panel A: Sample Markets										
Argentina	13.51	65.71	-4.45	99.18	45.03	-93.71	0.00	0.12	0.50	-0.12
Brazil	0.78	32.70	-0.13	5.07	14.69	-12.12	0.17	0.19	0.60	-0.10
Chile	11.30	18.62	0.11	3.40	8.71	-5.67	0.17	0.21	0.47	0.00
China	5.05	31.24	0.04	4.69	10.71	-14.29	0.18	0.17	0.46	-0.16
Greece	10.55	29.71	0.02	5.82	15.41	-14.30	0.11	0.11	0.42	0.00
Hong Kong	9.38	25.73	-1.08	22.32	15.56	-25.41	0.02	0.10	0.26	-0.08
Indonesia	-10.85	48.25	-0.68	76.30	52.25	-52.95	-0.04	0.24	0.66	-0.77
Korea	2.42	37.36	0.32	12.07	26.87	-21.65	0.05	0.02	0.09	-0.06
Malaysia	6.04	28.53	-1.42	64.30	22.99	-36.77	0.09	0.13	0.30	-0.12
Mexico	16.21	30.49	-0.40	11.63	13.74	-20.68	0.13	0.17	0.44	-0.12
Philippines	5.32	27.19	0.77	10.28	19.55	-9.71	0.14	0.15	0.42	-0.04
Singapore	5.67	19.94	-0.10	7.28	10.62	-9.94	0.09	0.08	0.20	-0.02
Taiwan	4.56	34.25	0.00	2.52	13.73	-12.30	0.04	0.04	0.12	-0.07
Thailand	5.44	33.06	0.36	6.74	16.35	-15.89	0.12	0.11	0.35	-0.02
Turkey	3.31	51.88	-0.11	5.25	22.16	-26.94	0.07	0.12	0.38	-0.11
Panel B: Control Sample Markets										
Japan	-1.25	22.30	0.21	3.72	11.53	-8.22	0.08	0.08	0.21	-0.01
USA	9.20	16.05	-0.23	4.54	5.37	-7.03	0.02	0.08	0.24	-0.21

(a) All are significance at least at 5%.

Table 2: Markov Regime Switching Volatility Model Estimates

Regime 1 = low mean and low volatility, Regime 2 = high mean and low volatility,
Regime 3 = low mean and high volatility, and Regime 4 = high mean and high volatility.

	P_μ	Q_μ	P_σ	Q_σ	σ_1	σ_2	μ_1	μ_2	Log-L
Panel A: Sample Markets									
Argentina	0.9735***	0.3007***	0.9876***	0.9661***	0.0002***	0.0035***	-0.0002	0.0369***	-10093
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.4203}	{0.0000}	
Brazil	0.6192***	0.9275***	0.9695***	0.9227***	0.0001***	0.0010***	-0.0148***	0.0032***	-6703
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	
Chile	0.8768***	0.7496***	0.9547***	0.9203***	0.0000***	0.0003***	-0.0024***	0.0062***	-12137
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	
China	0.5882***	0.9452***	0.9463***	0.9102***	0.0001***	0.0008***	-0.0016***	0.0163***	-7490
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0003}	{0.0000}	
Greece	0.4684***	0.9283***	0.9690***	0.9342***	0.6398***	7.5648***	-0.1406***	1.5016***	7575
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	
Hong Kong	0.9982***	0.0462	0.9828***	0.9554***	0.9364***	5.7929***	-12.0725***	0.0909***	7256
	{0.0000}	{0.7508}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	
Indonesia	0.9567***	0.4315***	0.8218***	0.9753***	0.0002***	0.0060***	-0.0275***	0.0014***	-9395
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	
Korea	0.9265***	0.0809*	0.9864***	0.9734***	1.1393***	8.1182***	-0.1579***	2.2501***	8366
	{0.0000}	{0.0792}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	
Malaysia	0.9538***	0.4300***	0.9726***	0.8826***	0.4621***	8.8443***	-0.0238	1.5425***	6428
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.2459}	{0.0000}	
Mexico	0.9085***	0.5077***	0.9555***	0.8344***	0.6705***	7.8433***	-0.0949***	1.3726***	7261
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0015}	{0.0000}	
Philippines	0.9083***	0.6198***	0.9619***	0.8945***	0.5171***	5.2236***	-0.1714***	1.0242***	6816
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	
Singapore	0.4115***	0.9211***	0.9713***	0.9287***	0.3609***	3.2651***	-0.0846***	1.0941***	6012
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	
Taiwan	0.9239***	0.0000	0.9663***	0.9399***	1.2112***	8.4068***	-0.1118***	2.4657***	8656
	{0.0000}	{0.9505}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0003}	{0.0000}	
Thailand	0.9438***	0.3338***	0.9756***	0.9381***	0.9688***	8.5143***	-0.1047**	2.2245***	8027
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0284}	{0.0000}	
Turkey	0.9182***	0.5818***	0.9408***	0.9249***	1.8500***	14.6121***	-0.1974***	2.2591***	10109
	{0.0000}	{0.0001}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0018}	{0.0000}	
Panel B: Control Sample Markets									
Japan	0.7837***	0.7593***	0.9748***	0.9596***	0.4747***	2.7589***	-0.2787***	0.3172***	6361
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0004}	{0.0008}	
USA	0.9673***	0.1579**	0.9889***	0.9815***	0.3522***	1.9792***	-1.3776***	0.1080***	5551
	{0.0000}	{0.0495}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	

*, **, and ***: Significance at 10, 5 and 1%.

Table 3: Markov Integration Model Parameter Estimates

Regime 1: $r_t^i = \alpha_1 + \beta_1 \cdot r_{t-1}^i + \lambda_t \cdot COV(r_t^i, r_t^w) + \varepsilon_{1,t}^i$, Regime 2: $r_t^i = \alpha_2 + \beta_2 \cdot r_{t-1}^i + \lambda_t^i \cdot VAR(r_t^i) + \varepsilon_{2,t}^i$

Where r_t^i is a daily index return for country *i*, COV(.) is the conditional covariance between the country index *i* and the world index returns, λ_t is time varying world price of covariance risk, VAR(.) is the conditional variance of country index *i* returns, and λ_t^i is country *i*'s time varying price of risk.

	P	Q	α_1	α_2	β_1	β_2	σ_1	σ_2	LogL	p*	P*-Pre97	P*-Post97
Panel A: Sample Markets												
Argentina	0.9746***	0.9898***	-0.0629	-0.409***	-0.0173	0.1011***	7.2238***	1.5687***	-10060	0.287	0.3975	0.1313
	{0.0000}	{0.0000}	{0.7460}	{0.0000}	{0.4892}	{0.0000}	{0.0000}	{0.0000}				
Brazil	0.9479***	0.9763***	-0.3772***	-0.1861***	0.1456***	0.1789***	3.0866***	1.2689***	-5104	0.3088	0.2516	0.3343
	{0.0000}	{0.0000}	{0.0033}	{0.0000}	{0.0003}	{0.0000}	{0.0000}	{0.0000}				
Chile	0.9418***	0.9628***	0.0026	-0.0758***	0.1538***	0.2287***	1.6123***	0.7197***	-5684	0.3811	0.4432	0.3072
	{0.0000}	{0.0000}	{0.9512}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}				
China	0.9353***	0.9427***	-0.0125	-0.2623***	0.1957***	0.1069***	2.6229***	0.9658***	-5461	0.4588	0.3444	0.5263
	{0.0000}	{0.0000}	{0.8788}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}				
Greece	0.9518***	0.9749***	-0.0154	-0.221***	0.1219***	0.0945***	2.7806***	1.0829***	-8034	0.3362	0.3231	0.3546
	{0.0000}	{0.0000}	{0.8316}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}				
Hong Kong	0.9357***	0.9821***	-0.3074***	-0.0808***	0.0063	0.0412**	2.8242***	1.044***	-7400	0.2097	0.1462	0.2993
	{0.0000}	{0.0000}	{0.0058}	{0.0001}	{0.8956}	{0.0277}	{0.0000}	{0.0000}				
Indonesia	0.9385***	0.9827***	-0.5186**	-0.3293***	-0.0686***	0.0601***	5.9372***	1.3565***	-7781	0.2149	0.0936	0.3458
	{0.0000}	{0.0000}	{0.0163}	{0.0000}	{0.0000}	{0.0003}	{0.0000}	{0.0000}				
Korea	0.9711***	0.9882***	-0.0921	-0.3015***	0.0769***	-0.0216	3.7412***	1.4319***	-8936	0.2792	0.1222	0.5005
	{0.0000}	{0.0000}	{0.3288}	{0.0000}	{0.0048}	{0.2342}	{0.0000}	{0.0000}				
Malaysia	0.9258***	0.9856***	-0.3051**	-0.0894***	0.0733***	0.1256***	3.9021***	0.8945***	-6869	0.1628	0.0928	0.2615
	{0.0000}	{0.0000}	{0.0208}	{0.0000}	{0.0043}	{0.0000}	{0.0000}	{0.0000}				
Mexico	0.8631***	0.972***	-0.2394*	-0.1714***	0.0987***	0.1677***	3.7563***	1.1885***	-7951	0.1668	0.1774	0.152
	{0.0000}	{0.0000}	{0.0839}	{0.0000}	{0.0034}	{0.0000}	{0.0000}	{0.0000}				
Philippines	0.9601***	0.891***	0.0053	-0.5104***	0.1051***	0.1322***	1.0087***	2.8448***	-7639	0.7379	0.7288	0.7508
	{0.0000}	{0.0000}	{0.7805}	{0.0000}	{0.0003}	{0.0000}	{0.0000}	{0.0000}				
Singapore	0.9454***	0.9833***	-0.1923***	-0.0537***	0.1033***	0.0518***	2.0671***	0.8361***	-6400	0.2298	0.1126	0.395
	{0.0000}	{0.0000}	{0.0038}	{0.0004}	{0.0000}	{0.0064}	{0.0000}	{0.0000}				
Taiwan	0.9467***	0.9711***	-0.1346	-0.2747***	0.0505**	0.0071	3.1131***	1.3759***	-8887	0.3546	0.3765	0.3238
	{0.0000}	{0.0000}	{0.1067}	{0.0000}	{0.0426}	{0.7516}	{0.0000}	{0.0000}				
Thailand	0.939***	0.9729***	-0.1555*	-0.207***	0.1218***	0.0928***	3.2627***	1.1843***	-8399	0.3063	0.2109	0.4409
	{0.0000}	{0.0000}	{0.0932}	{0.0000}	{0.0005}	{0.0000}	{0.0000}	{0.0000}				
Turkey	0.9347***	0.9578***	-0.2124*	-0.6528***	0.0664***	0.0625***	4.6075***	1.945***	-10634	0.3917	0.3171	0.4969
	{0.0000}	{0.0000}	{0.0670}	{0.0000}	{0.0002}	{0.0040}	{0.0000}	{0.0000}				
Panel B: Control Sample Markets												
Japan	0.9663***	0.9765***	-0.1322***	-0.1262***	0.0797***	0.0713***	1.8777***	0.9237***	-7130	0.4022	0.2922	0.5573
	{0.0000}	{0.0000}	{0.0039}	{0.0000}	{0.0005}	{0.0010}	{0.0000}	{0.0000}				
USA	0.974***	0.9865***	-0.194***	0.0148	-0.0035	0.0506***	1.4602***	0.6421***	-5534	0.3461	0.1514	0.6206
	{0.0000}	{0.0000}	{0.0000}	{0.2333}	{0.9054}	{0.0061}	{0.0000}	{0.0000}				

Table 4a: B-GARCH(1,1) Estimations: January 1988 – May 2004

$$R_{1,t} = \alpha_{1,c} + \alpha_{1,Lag} \cdot R_{1t-1} + \alpha_{1,WRTN} \cdot WRTN_{t-1} + \sum_{i=MON}^{THU} \alpha_{1,i,} \cdot DayDum_{i,t} + e_{1,t}\,,\; R_{2,t} = \alpha_{2,c} + \alpha_{2,Lag} \cdot R_{2t-1} + \alpha_{2,WRTN} \cdot WRTN_{t-2} + \sum_{i=MON}^{THU} \alpha_{1,i,} \cdot DayDum_{i,t-1} + e_{2,t} \tag{1}$$

$$h_{R1t} = \beta_{1c} + \beta_{1h} \cdot h_{1,t-1} + \beta_{e11} \cdot e^2_{1,t-1} + \beta_{e12} \cdot e^2_{1,t-1} \cdot I_{1t} + \beta_{1WVLT} \cdot WVLT_{t-1} + \sum_{i=Mon}^{Thu} \beta_{1i} \cdot DayDum_{it}, \tag{2}$$

$$h_{R2t} = \beta_{2c} + \beta_{2h} \cdot h_{2,t-1} + \beta_{e21} \cdot e^2_{2,t-1} + \beta_{e22} \cdot e^2_{2,t-1} \cdot I_{2t} + \beta_{2WVLT} \cdot WVLT_{t-2} + \sum_{i=Mon}^{Thu} \beta_{2i} \cdot DayDum_{it-1}$$

	α_{1c}	α_{1Lag}	α_{1WRTN}	α_{1MON}	α_{1TUE}	α_{1WED}	α_{1THU}	β_{1c}	β_{1h}	β_{1e11}	β_{1e12}	β_{1WVLTt}	β_{1MON}	β_{1TUE}	β_{1WED}	β_{1THU}	Log-L	Q(20)	$Q^2(20)$
Panel A: Sample Markets																			
Argentina	0.0453 **	-0.1674 ***	0.0154	-0.0441	0.0545	0.1675 ***	0.1956 ***	-0.1892 ***	0.8980 ***	0.1244 ***	-0.0222 **	-0.0129 **	0.8783 ***	-0.1853 ***	0.3321 ***	0.2878 ***	-11930	35.9576 **	7.28436
	{0.0143}	{0.0000}	{0.6707}	{0.3165}	{0.3815}	{0.0018}	{0.0001}	{0.0000}	{0.0000}	{0.0000}	{0.0477}	{0.0487}	{0.0000}	{0.0000}	{0.0000}	{0.0000}		{0.0156}	{0.9956}
Brazil	0.2066 ***	-0.2044 ***	0.1318 ***	-0.2055 **	-0.1736 *	-0.0963	-0.1284	-0.4283 ***	0.8638 ***	0.1209 ***	-0.0226	0.1213	0.9824 ***	0.2717	0.4885 *	0.6751 ***	-5381	30.3176 *	32.2742 **
	{0.0000}	{0.0000}	{0.0007}	{0.0500}	{0.0681}	{0.2997}	{0.1429}	{0.0000}	{0.0000}	{0.0000}	{0.2016}	{0.1249}	{0.0000}	{0.2434}	{0.0742}	{0.0006}		{0.0649}	{0.0405}
Chile	0.1718 ***	-0.1054 ***	0.0944 ***	-0.2002 ***	-0.2329 ***	-0.1778 ***	-0.0411	0.1103 ***	0.8575 ***	0.1282 ***	-0.0446 *	0.0181	0.1568 ***	-0.1588 ***	-0.1181 **	-0.1753 ***	-4267	99.0452 ***	25.0561
	{0.0000}	{0.0004}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.2843}	{0.0078}	{0.0000}	{0.0000}	{0.0722}	{0.5878}	{0.0000}	{0.0000}	{0.0195}	{0.0000}		{0.0000}	{0.1993}
China	0.1234 ***	-0.1004	0.3067 ***	-0.1119	-0.1538 *	-0.1531 **	-0.1680 **	-0.1845	0.9216 ***	0.0751	-0.0064	-0.0177	0.6352 ***	0.0454	0.6126 **	-0.1167	-5667	32.0963 **	28.7913 *
	{0.0004}	{0.1011}	{0.0000}	{0.1051}	{0.0616}	{0.0291}	{0.0253}	{0.2021}	{0.0000}	{0.1425}	{0.8067}	{0.3943}	{0.0005}	{0.8169}	{0.0136}	{0.4840}		{0.0423}	{0.0920}
Greece	0.1399 ***	-0.0590 **	0.2592 ***	-0.1914 ***	-0.2138 ***	-0.1383 ***	-0.0762 *	0.2828 ***	0.8963 ***	0.0874 ***	0.0002	0.0182 ***	0.6083 ***	-0.8363 ***	-0.6297 ***	-0.2736 ***	-8326	20.428	19.7709
	{0.0000}	{0.0400}	{0.0000}	{0.0000}	{0.0000}	{0.0003}	{0.0698}	{0.0000}	{0.0000}	{0.0000}	{0.9698}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}		{0.4315}	{0.4723}
Hong Kong	0.1101 ***	-0.1838 ***	0.5260 ***	-0.1155 ***	-0.0073	0.0064	-0.1090 ***	-0.1006 ***	0.8723 ***	0.1144 ***	-0.0241 ***	0.0016	0.8479 ***	-0.4035 ***	0.2980 ***	0.0643 ***	-6640	26.9071	41.7179 ***
	{0.0000}	{0.0000}	{0.0000}	{0.0085}	{0.8529}	{0.8770}	{0.0028}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.6488}	{0.0000}	{0.0000}	{0.0000}	{0.0000}		{0.1379}	{0.0030}
Indonesia	0.1330	-0.0529	0.2867 ***	-0.0942	-0.1495	-0.0716	0.0136	-4.0061 ***	0.8011 ***	0.1199 ***	0.0959 ***	0.2946 *	4.2354 ***	3.9340 ***	4.0089 ***	8.9229 ***	-8899	52.4673 ***	0.72791
	{0.1343}	{0.2161}	{0.0000}	{0.3393}	{0.1129}	{0.4608}	{0.9008}	{0.0005}	{0.0000}	{0.0078}	{0.0068}	{0.0551}	{0.0001}	{0.0011}	{0.0007}	{0.0003}		{0.0001}	{1.0000}
Korea	0.0122	-0.3664 ***	0.3456 ***	0.0108	0.0265	-0.0170	-0.0093	-0.1406 ***	0.9040 ***	0.0575 ***	0.0272 ***	0.1305 ***	1.0817 ***	-0.9269 ***	0.2692 ***	0.4631 ***	-9607	29.5808 *	15.8129
	{0.5037}	{0.0000}	{0.0000}	{0.8320}	{0.7290}	{0.7803}	{0.8410}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}		{0.0769}	{0.7282}
Malaysia	0.1016 **	0.1262 ***	0.2375 ***	-0.2162 ***	-0.0604	0.0012	-0.0147	0.0854 ***	0.9277 ***	0.0514 ***	0.0316 ***	-0.0031	0.1956 **	-0.5182 ***	0.0980 ***	-0.1056 ***	-6047	36.238 **	7.80048
	{0.0413}	{0.0000}	{0.0000}	{0.0003}	{0.3744}	{0.9838}	{0.7926}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.2692}	{0.0381}	{0.0000}	{0.0000}	{0.0000}		{0.0144}	{0.9931}
Mexico	0.1885 ***	-0.1707 ***	0.0341	-0.1984 ***	-0.1370 ***	-0.0234	0.0232	0.1323 ***	0.9042 ***	0.0551 ***	0.0367 ***	-0.0272 ***	0.0176	-0.3124 ***	0.3465 ***	-0.2176 ***	-8185	26.8039	15.3785
	{0.0000}	{0.0000}	{0.1855}	{0.0000}	{0.0049}	{0.6345}	{0.6170}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.2493}	{0.0000}	{0.0000}	{0.0000}		{0.1409}	{0.7544}
Philippines	0.1169 ***	-0.0301	0.3152 ***	-0.1309 ***	-0.1708 ***	-0.1159 ***	-0.0209	-0.0321 ***	0.8189 ***	0.1458 ***	0.0042	0.0740 ***	0.8863 ***	-0.5400 ***	0.0379 ***	0.1635 **	-7437	48.4629 ***	3.19074
	{0.0000}	{0.1298}	{0.0000}	{0.0009}	{0.0000}	{0.0080}	{0.5825}	{0.0000}	{0.0000}	{0.0000}	{0.3857}	{0.0000}	{0.0000}	{0.0000}	{0.0032}	{0.0291}		{0.0004}	{1.0000}
Singapore	0.1194 ***	-0.0682 ***	0.3143 ***	-0.1787 ***	-0.0853 **	-0.0376	-0.0230	0.0648 ***	0.7993 ***	0.1389 ***	-0.0287 ***	0.0668 ***	0.4039 ***	-0.3250 ***	-0.1057 ***	0.0411 ***	-4836	21.5871	14.8716
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0147}	{0.2242}	{0.4309}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0056}		{0.3633}	{0.7837}
Taiwan	0.0325 *	-0.1576 ***	0.3905 ***	-0.0107	-0.1200	0.0157	0.0544	0.0608 ***	0.9161 ***	0.0728 ***	-0.0182 ***	0.0271 ***	1.5890 ***	-1.9068 ***	0.1646 ***	0.1596 ***	-9598	50.79 ***	24.392
	{0.0882}	{0.0004}	{0.0000}	{0.8776}	{0.2527}	{0.7904}	{0.3773}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0001}	{0.0000}	{0.0000}	{0.0000}	{0.0000}		{0.0002}	{0.2257}
Thailand	0.2145 ***	-0.2273 ***	0.3407 ***	-0.2988 ***	-0.2045 ***	-0.0626	-0.1249 **	0.0936 ***	0.9204 ***	0.0603 ***	0.0210 ***	-0.0097 ***	0.2083 ***	-0.1716 **	0.1398 ***	-0.4005 ***	-8783	52.0058 ***	26.931
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0006}	{0.2379}	{0.0149}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0006}	{0.0002}	{0.0238}	{0.0000}	{0.0000}		{0.0001}	{0.1372}
Turkey	0.1537 **	-0.0740 ***	0.1841 ***	-0.4463 ***	-0.3194 ***	-0.1943 **	-0.0525	0.4899 ***	0.9016 ***	0.0861 ***	-0.0041	0.0247	3.5487 ***	-4.0394 ***	-0.4837 **	-0.7019 ***	-13164	37.1325 **	33.0628 **
	{0.0111}	{0.0000}	{0.0003}	{0.0000}	{0.0001}	{0.0348}	{0.5999}	{0.0000}	{0.0000}	{0.0000}	{0.4627}	{0.4580}	{0.0000}	{0.0000}	{0.0101}	{0.0000}		{0.0113}	{0.0332}
Panel B: Control Sample Markets																			
Japan	-0.0419 **	-0.1013 ***	0.5557 ***	-0.0697	0.0704 *	0.0187	0.0792 **	-0.0429 ***	0.8550 ***	0.0910 ***	0.0074	0.0887 ***	0.4647 ***	-0.1640 ***	0.1622 ***	-0.0383 ***	-6082	27.6897	18.7694
	{0.0289}	{0.0000}	{0.0000}	{0.1199}	{0.0582}	{0.6345}	{0.0435}	{0.0000}	{0.0000}	{0.0000}	{0.3769}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0067}		{0.1169}	{0.5369}
USA	0.0062	-0.3729	0.0188	0.0372	0.0274	0.0410	0.0141	0.2338 ***	0.3397 ***	0.0348	0.0067	0.9641 ***	-0.1288 *	-0.1033 ***	-0.2019 ***	-0.1004 ***	-3322	33.0391 **	11.2671
	{0.6894}	{0.2901}	{0.3252}	{0.2170}	{0.4195}	{0.1201}	{0.6481}	{0.0000}	{0.0000}	{0.4754}	{0.7734}	{0.0000}	{0.0713}	{0.0000}	{0.0000}	{0.0013}		{0.0334}	{0.9390}

*, ** and ***: Significance at 10, 5 and 1%, respectively

Q(20) and $Q^2(20)$ are the Ljung-Box test of white noize for the linear and non-linear (squared) standaridized residuals

Table 4b: The Determinants of Autocorrelation: January 1988 – May 2004

$$\rho_t = d_0 + d_1 \cdot \rho_{t-1} + d_2 \cdot (e_{1,t-1} \cdot e_{2,t-1}) / \sqrt{h_{R1,t-1} \times h_{R2,t-1}} + c_1 \cdot MRP3_{t-1} + c_{12} \cdot MRP4_{t-1} + c_2 \cdot AAP_{t-1} + c_3 \cdot AAN_{t-1} + c_4 \cdot MarkovInt_{t-1} + \sum_{i=Mon}^{Thu} c_i \cdot DayDum_{i,t} \quad (5)$$

	d_0	d_1	d_3	c_1	c_{12}	c_2	c_3	c_4	H0: c_1=c_{12}
Panel A: Sample Markets									
Argentina	0.2717 ***	0.3430 ***	-0.0054	12.4681	0.0418 ***	-0.0818 ***	-0.1131 ***	-0.1638 ***	0.1978
	{0.0000}	{0.0000}	{0.4080}	{0.6555}	{0.0004}	{0.0000}	{0.0000}	{0.0000}	{0.6565}
Brazil	0.3478 ***	0.2526 ***	-0.0232 ***	-0.0061	-0.0383	0.0383 *	-0.0160	-0.0869 ***	0.2809
	{0.0000}	{0.0026}	{0.0013}	{0.9173}	{0.6171}	{0.0752}	{0.3935}	{0.0001}	{0.5961}
Chile	0.4328 ***	0.0217	0.0035	-0.3653 ***	-0.0556 ***	-0.1149 ***	-0.0086	0.0380 ***	179.949 ***
	{0.0000}	{0.3995}	{0.1145}	{0.0000}	{0.0000}	{0.0000}	{0.4888}	{0.0000}	{0.0000}
China	0.5772 ***	-0.3939 ***	0.0073	-0.1449 ***	-0.0447	-0.0366	-0.0748 *	-0.1095 ***	9.7316 ***
	{0.0000}	{0.0000}	{0.3266}	{0.0000}	{0.2265}	{0.3353}	{0.0716}	{0.0003}	{0.0018}
Greece	0.2680 ***	-0.9065 ***	-0.0019	-0.0942	0.0875 *	0.0192	0.0697 ***	-0.0920 **	7.8614 ***
	{0.0001}	{0.0000}	{0.7708}	{0.1267}	{0.0624}	{0.4559}	{0.0030}	{0.0280}	{0.0051}
Hong Kong	0.1495 ***	-0.0470	0.0013	-0.0458	0.0628 ***	0.0567 **	0.0540 ***	-0.1026 ***	2.6291
	{0.0000}	{0.5164}	{0.7613}	{0.4556}	{0.0038}	{0.0150}	{0.0042}	{0.0000}	{0.1049}
Indonesia	0.4009 ***	-0.4324 ***	0.0126	-0.3685 ***	0.3288 ***	-0.1953 ***	-0.1166 *	-0.0890 ***	24.7838 ***
	{0.0000}	{0.0008}	{0.1447}	{0.0000}	{0.0005}	{0.0002}	{0.0621}	{0.0001}	{0.0000}
Korea	0.4303 ***	-0.1154 ***	-0.0068	-0.2750 ***	0.2226 ***	-0.0616 ***	-0.0355 *	0.0072	26.3239 ***
	{0.0000}	{0.0000}	{0.2704}	{0.0000}	{0.0004}	{0.0061}	{0.0683}	{0.6550}	{0.0000}
Malaysia	-0.0774	-0.9797 ***	0.0045	0.0324	0.0887	-0.0067	0.0076	0.0098	0.9325
	{0.3368}	{0.0000}	{0.4967}	{0.7167}	{0.3006}	{0.7877}	{0.7514}	{0.8005}	{0.3342}
Mexico	0.4017 ***	0.1167 ***	0.0080	-0.0341	0.1764 ***	-0.0582 ***	-0.0884 ***	-0.2102 ***	55.0382 ***
	{0.0000}	{0.0000}	{0.1490}	{0.2951}	{0.0000}	{0.0049}	{0.0000}	{0.0000}	{0.0000}
Philippines	-0.0388 **	0.9808 ***	0.0021	0.0438	-0.0110	-0.0264	-0.0460	-0.0066	0.0372
	{0.0248}	{0.0000}	{0.8846}	{0.6434}	{0.9582}	{0.6405}	{0.2900}	{0.8924}	{0.8471}
Singapore	0.0785 ***	0.2048	0.0025	-0.0649	0.1361 ***	-0.0906 ***	0.0219	0.0133	7.1910 ***
	{0.0048}	{0.2756}	{0.7346}	{0.1076}	{0.0028}	{0.0022}	{0.2034}	{0.4249}	{0.0073}
Taiwan	0.1490 ***	0.0376	0.0056	-0.2045 ***	0.0301	0.0789 ***	0.1227 ***	-0.0212	16.1408 ***
	{0.0000}	{0.6588}	{0.4198}	{0.0000}	{0.5471}	{0.0029}	{0.0000}	{0.2546}	{0.0001}
Thailand	0.3297 ***	0.1972 ***	0.0000	0.0331	0.0106	-0.0551 ***	-0.0186	-0.0987 ***	0.2692
	{0.0000}	{0.0095}	{0.9938}	{0.1593}	{0.7621}	{0.0078}	{0.4014}	{0.0000}	{0.6038}
Turkey	0.0811 ***	0.6947 ***	-0.0117 **	0.0444	0.0109	0.0480 **	-0.0680 ***	-0.0557 ***	0.2804
	{0.0000}	{0.0000}	{0.0198}	{0.2844}	{0.6886}	{0.0219}	{0.0020}	{0.0008}	{0.5965}
Panel B: Control Sample Markets									
Japan	-0.0340 ***	-0.6558 ***	0.0073	-0.0331	0.1616 ***	0.0710 ***	0.0394 **	0.0139	6.7796 ***
	{0.0007}	{0.0000}	{0.2904}	{0.5027}	{0.0051}	{0.0000}	{0.0123}	{0.3701}	{0.0092}
USA	0.1470 *	0.6545 ***	-0.0188 *	0.0312	0.0496	0.0593	-0.0700 **	-0.0866	0.0263
	{0.0728}	{0.0000}	{0.0852}	{0.8470}	{0.4051}	{0.2130}	{0.0481}	{0.3698}	{0.8713}

Table 5: The Determinants of Autocorrelation – Pre Crash Results: January 1988 – June 1997

$$\rho_t = d_0 + d_1 \cdot \rho_{t-1} + d_2 \cdot (e_{1,t-1} \cdot e_{2,t-1}) / \sqrt{h_{R1,t-1} \times h_{R2,t-1}} + c_1 \cdot MRP3_{t-1} + c_{12} \cdot MRP4_{t-1} + c_2 \cdot AAP_{t-1} + c_3 \cdot AAN_{t-1} + c_4 \cdot MarkovInt_{t-1} + \sum_{i=Mon}^{Thu} c_i \cdot DayDum_{i,t} \quad (5)$$

	d_0	d_1	d_3	c_1	c_{12}	c_2	c_3	c_4	H0: $c_1=c_{12}$
Panel A: Sample Markets									
Argentina	0.0344	0.9770 ***	-0.0031 ***	16.7698 ***	0.0045	0.0022	-0.0030	-0.0079 ***	36.9120 ***
	{0.2004}	{0.0000}	{0.0002}	{0.0000}	{0.1939}	{0.6006}	{0.7535}	{0.0001}	{0.0000}
Brazil	0.3212 ***	0.2750 ***	-0.0200	0.1518 ***	0.1099 ***	-0.0322	-0.1529 ***	-0.1069 ***	1.5564
	{0.0000}	{0.0000}	{0.2638}	{0.0003}	{0.0000}	{0.3840}	{0.0002}	{0.0001}	{0.2122}
Chile	0.9644 ***	-0.4951 ***	-0.0064	-0.6833 ***	-0.2263 ***	-0.1106 ***	0.0927 **	0.0680 ***	70.820 ***
	{0.0000}	{0.0000}	{0.4530}	{0.0000}	{0.0000}	{0.0028}	{0.0119}	{0.0081}	{0.0000}
China	0.2387 ***	-0.3745	0.0257 *	0.2175 ***	-0.1857 ***	0.2674 ***	-0.0713 ***	-0.2487 ***	42.9718 ***
	{0.0000}	{0.2159}	{0.0635}	{0.0000}	{0.0000}	{0.0000}	{0.0065}	{0.0000}	{0.0000}
Greece	0.0203 ***	-0.8866 ***	-0.0109	-0.0076	0.2054 ***	0.0457	0.0958 ***	-0.1301 ***	97.9822 ***
	{0.0000}	{0.0000}	{0.1267}	{0.6203}	{0.0000}	{0.1548}	{0.0001}	{0.0000}	{0.0000}
Hong Kong	0.9969 ***	-0.0909 **	-0.0012	-0.2303 ***	0.0111	0.0018	-0.0254 *	-0.0898	24.5191 ***
	{0.0000}	{0.0179}	{0.2722}	{0.0004}	{0.7467}	{0.8931}	{0.0751}	{0.1446}	{0.0000}
Indonesia	0.1212 ***	0.0200	-0.0067 **	-0.2801 ***	-0.0432	0.0477	0.1015 ***	-0.0636 ***	17.8548 ***
	{0.0003}	{0.8551}	{0.0266}	{0.0006}	{0.5299}	{0.4761}	{0.0000}	{0.0062}	{0.0000}
Korea	0.0625 **	0.7209 ***	-0.0077	-0.0718	0.0587	0.0134	-0.1280 ***	-0.0148	0.9738
	{0.0194}	{0.0000}	{0.6017}	{0.3730}	{0.3499}	{0.7505}	{0.0017}	{0.6287}	{0.3237}
Malaysia	-0.0865 **	0.6383 ***	0.0093	-0.1959 ***	0.4199 ***	0.0116	-0.0029	-0.0352	31.9933 ***
	{0.0116}	{0.0000}	{0.1668}	{0.0002}	{0.0000}	{0.7760}	{0.9342}	{0.3161}	{0.0000}
Mexico	0.8403 ***	-0.1879 ***	0.0119 ***	-0.1937 ***	0.2792 **	-0.0473	-0.1029 ***	-0.2785 ***	14.0734 ***
	{0.0000}	{0.0001}	{0.0100}	{0.0029}	{0.0123}	{0.4147}	{0.0040}	{0.0000}	{0.0002}
Philippines	0.3265 ***	-0.6401 ***	-0.0059	0.3321 ***	0.2184 ***	-0.0042	-0.0781 *	0.2558 ***	1.5916
	{0.0000}	{0.0000}	{0.5814}	{0.0001}	{0.0000}	{0.9150}	{0.0645}	{0.0000}	{0.2071}
Singapore	0.0644	0.7289 ***	-0.0044	0.1638 ***	0.2111 ***	-0.0762 **	-0.0969 ***	-0.1207 ***	0.3748
	{0.4425}	{0.0000}	{0.5637}	{0.0001}	{0.0000}	{0.0164}	{0.0004}	{0.0002}	{0.5404}
Taiwan	0.1500 ***	0.2728 *	0.0032	-0.1632 ***	0.0509 ***	0.1292 ***	0.1370 ***	-0.0257 **	122.4524 ***
	{0.0000}	{0.0505}	{0.2448}	{0.0000}	{0.0027}	{0.0000}	{0.0000}	{0.0149}	{0.0000}
Thailand	0.7227 ***	-0.0346	-0.0087	0.0213	0.0787 **	-0.0085	-0.0115	-0.2033 ***	3.4113 *
	{0.0000}	{0.1962}	{0.1215}	{0.4533}	{0.0292}	{0.7724}	{0.7028}	{0.0000}	{0.0648}
Turkey	0.3239 ***	0.2382 ***	-0.0035	0.0044	-0.0277	-0.0454	-0.1972 ***	0.0254 *	0.2331
	{0.0000}	{0.0000}	{0.8622}	{0.9017}	{0.5099}	{0.2056}	{0.0000}	{0.0864}	{0.6292}
Panel B: Control Sample Markets									
Japan	-0.2389 ***	-0.7269 ***	0.0129 ***	0.1315 ***	0.1377 ***	0.0732 ***	0.0170	0.1063 ***	0.0600
	{0.0000}	{0.0000}	{0.0000}	{0.0002}	{0.0000}	{0.0000}	{0.3761}	{0.0000}	{0.8066}
USA	0.0811 **	-0.6129	0.0058	-0.3276 ***	-0.0399	0.1531 ***	0.0010	0.0269	8.1795 ***
	{0.0206}	{0.1376}	{0.6945}	{0.0092}	{0.4603}	{0.0001}	{0.9616}	{0.3669}	{0.0042}

Table 6 : The Determinants of Autocorrelation - Post Crash Results: July 1997 - May 2004

$$\rho_t = d_0 + d_1 \cdot \rho_{t-1} + d_2 \cdot (e_{1,t-1} \cdot e_{2,t-1}) / \sqrt{h_{R1,t-1} \times h_{R2,t-1}} + c_1 \cdot MRP3_{t-1} + c_{12} \cdot MRP4_{t-1} + c_2 \cdot AAP_{t-1} + c_3 \cdot AAN_{t-1} + c_4 \cdot MarkovInt_{t-1} + \sum_{i=Mon}^{Thu} c_i \cdot DayDum_{i,t} \quad (5)$$

	d_0	d_1	d_3	c_1	c_{12}	c_2	c_3	c_4	H0: c_1=c_{12}
Panel A: Sample Markets									
Argentina	0.6738 ***	0.1922	0.0058	0.0144 ***	0.0218	-0.1247	-0.1498	-0.3123	0.0000
	{0.0000}	{0.5289}	{0.3903}	{0.0000}	{0.9835}	{0.4983}	{0.2883}	{0.8591}	{0.9944}
Brazil	0.0457	0.8639 ***	-0.0294 ***	0.0588 *	0.0703 **	0.1282 ***	0.0660 **	0.0183	0.0897
	{0.1900}	{0.0000}	{0.0002}	{0.0597}	{0.0275}	{0.0000}	{0.0119}	{0.4441}	{0.7646}
Chile	0.0028	0.7746 ***	0.0017	-0.2005 ***	-0.1828 ***	-0.0377	-0.0331	0.1619 ***	0.198
	{0.8869}	{0.0000}	{0.8213}	{0.0000}	{0.0000}	{0.2346}	{0.1901}	{0.0001}	{0.6567}
China	0.0573	0.8566 ***	0.0049	0.0821 ***	0.2398 ***	-0.1426 ***	-0.1114 ***	-0.0541 ***	8.2487 ***
	{0.1071}	{0.0000}	{0.7344}	{0.0005}	{0.0000}	{0.0000}	{0.0001}	{0.0010}	{0.0041}
Greece	0.1662 ***	-0.1341 **	0.0127 ***	-0.4191 ***	0.1080	-0.1087 ***	0.0872 ***	0.0892 ***	72.6749 ***
	{0.0000}	{0.0242}	{0.0097}	{0.0000}	{0.1569}	{0.0000}	{0.0001}	{0.0007}	{0.0000}
Hong Kong	0.0307 **	-0.2965 **	0.0075 **	-0.0103	0.0025	0.2012 ***	0.1232 ***	-0.0226	0.3136
	{0.0145}	{0.0314}	{0.0320}	{0.6152}	{0.8227}	{0.0000}	{0.0000}	{0.4198}	{0.5755}
Indonesia	0.3386 ***	-0.7441 ***	0.0031	-0.2054	0.0800	-0.0775	0.0036	-0.0717	0.7771
	{0.0000}	{0.0000}	{0.8145}	{0.1282}	{0.7117}	{0.3476}	{0.9126}	{0.1600}	{0.3780}
Korea	0.3750 ***	-0.5851 ***	-0.0069	-0.5017 ***	-0.0389	-0.0106	0.0697 ***	0.1060 ***	91.9744 ***
	{0.0000}	{0.0000}	{0.3314}	{0.0000}	{0.2169}	{0.6623}	{0.0083}	{0.0000}	{0.0000}
Malaysia	0.9299 ***	-0.0322	-0.0172 ***	-0.1376 ***	0.0010	-0.0320	-0.0060	-0.4904 ***	3.3377 *
	{0.0000}	{0.7219}	{0.0008}	{0.0034}	{0.9843}	{0.3077}	{0.8421}	{0.0000}	{0.0677}
Mexico	0.6358 ***	0.2636 ***	-0.0077	-0.0667	0.0259	0.0194	-0.0481 *	-0.0592	1.7960
	{0.0000}	{0.0000}	{0.5914}	{0.2312}	{0.6325}	{0.4970}	{0.0694}	{0.1664}	{0.1802}
Philippines	0.5339 *	-0.7142	0.0238	-0.3247 ***	-0.4722	0.1727	0.1056	-0.1887	0.0413
	{0.0502}	{0.6682}	{0.8993}	{0.0000}	{0.5277}	{0.8820}	{0.9154}	{0.9136}	{0.8390}
Singapore	0.0666 ***	0.1021	0.0033	-0.5092 ***	-0.0456 *	-0.0886 ***	0.1928 ***	0.2276 ***	295.724 ***
	{0.0000}	{0.3408}	{0.2729}	{0.0000}	{0.0877}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
Taiwan	0.0655	-0.2067 *	0.0094 ***	-0.4029 ***	0.2708 ***	0.0775	0.3345 **	-0.0493	14.8593 ***
	{0.6296}	{0.0985}	{0.0022}	{0.0000}	{0.0039}	{0.4045}	{0.0210}	{0.4540}	{0.0001}
Thailand	0.2575 ***	-0.4632 ***	0.0222 ***	-0.1196 ***	-0.1937 ***	0.0482 ***	0.1613 ***	0.1090 ***	6.5628 **
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0027}	{0.0000}	{0.0000}	{0.0104}
Turkey	0.2999 ***	0.5074 ***	-0.0269 ***	0.1741 ***	0.0490	0.0941 **	-0.0457	-0.2737 ***	2.1243
	{0.0000}	{0.0000}	{0.0058}	{0.0001}	{0.4634}	{0.0170}	{0.2286}	{0.0000}	{0.1450}
Panel B: Control Sample Markets									
Japan	-0.0471	0.7399	-0.0140 *	-0.0813	0.0874	0.1495 ***	0.0453	-0.0803 **	1.8362
	{0.3733}	{0.1385}	{0.0749}	{0.4465}	{0.3433}	{0.0052}	{0.4435}	{0.0461}	{0.1754}
USA	0.0233 *	0.5070 ***	-0.0307 **	0.2548 ***	0.1810 ***	-0.0356	-0.0924 ***	-0.1888 ***	2.4636
	{0.0728}	{0.0000}	{0.0186}	{0.0000}	{0.0000}	{0.3637}	{0.0001}	{0.0000}	{0.1165}

Figure 1
Markov Regime Switching Probabilities for Argentina

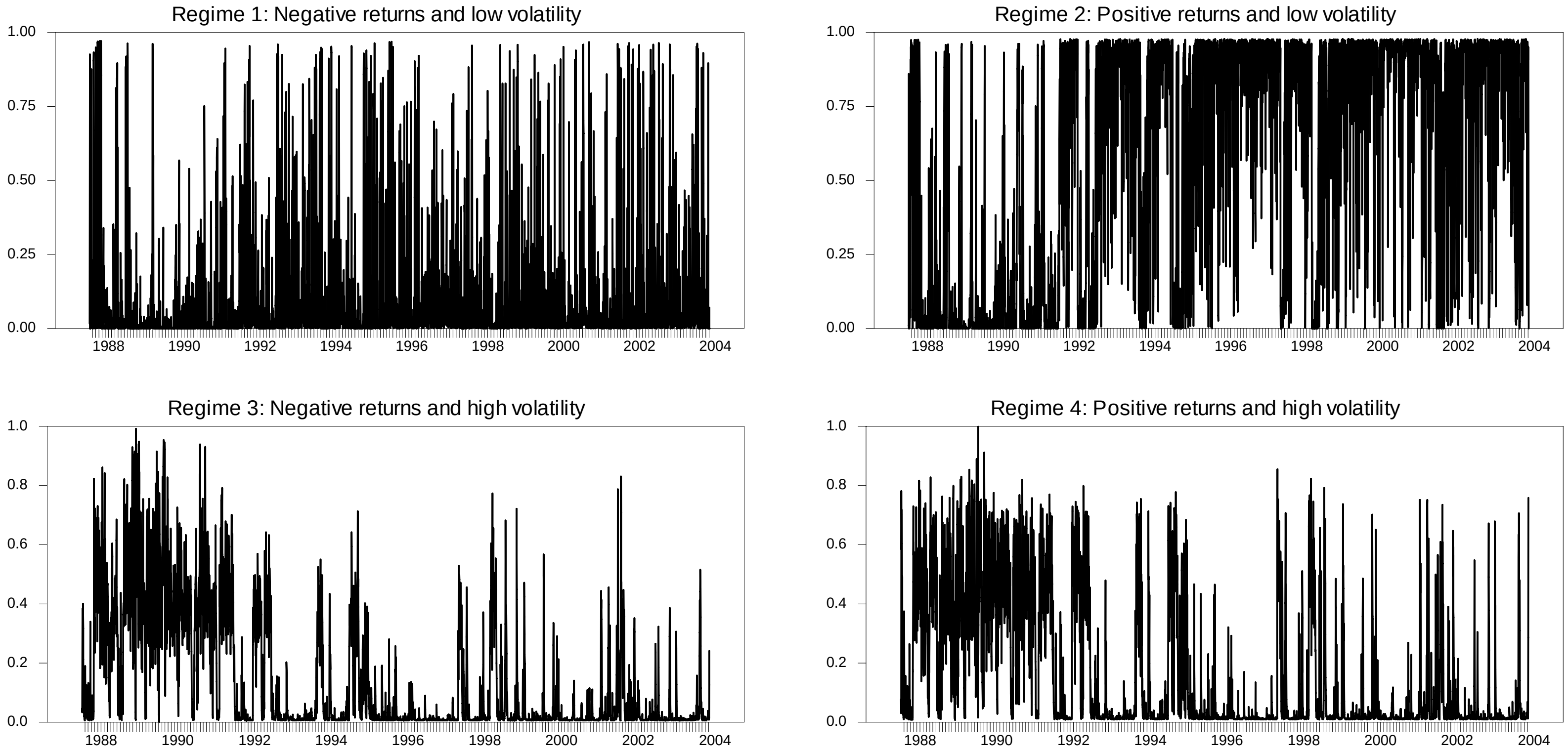


Figure 2: Time-Varying Integration Measures

The following figures present estimates of time-varying integration which is the time series of the smoothed probabilities of individual counties being in the integration state ($S_t = 1$) where the transition probabilities are P = prob[$S_t = 1 \mid S_{t-1} = 1$], and the integrated market returns are given by $r_t^i = \alpha_1 + \beta_1 \cdot r_{t-1}^i + \lambda_t \cdot COV(r_t^i, r_t^w) + \varepsilon_{1,t}^i$.

Panel A: Latin American Countries

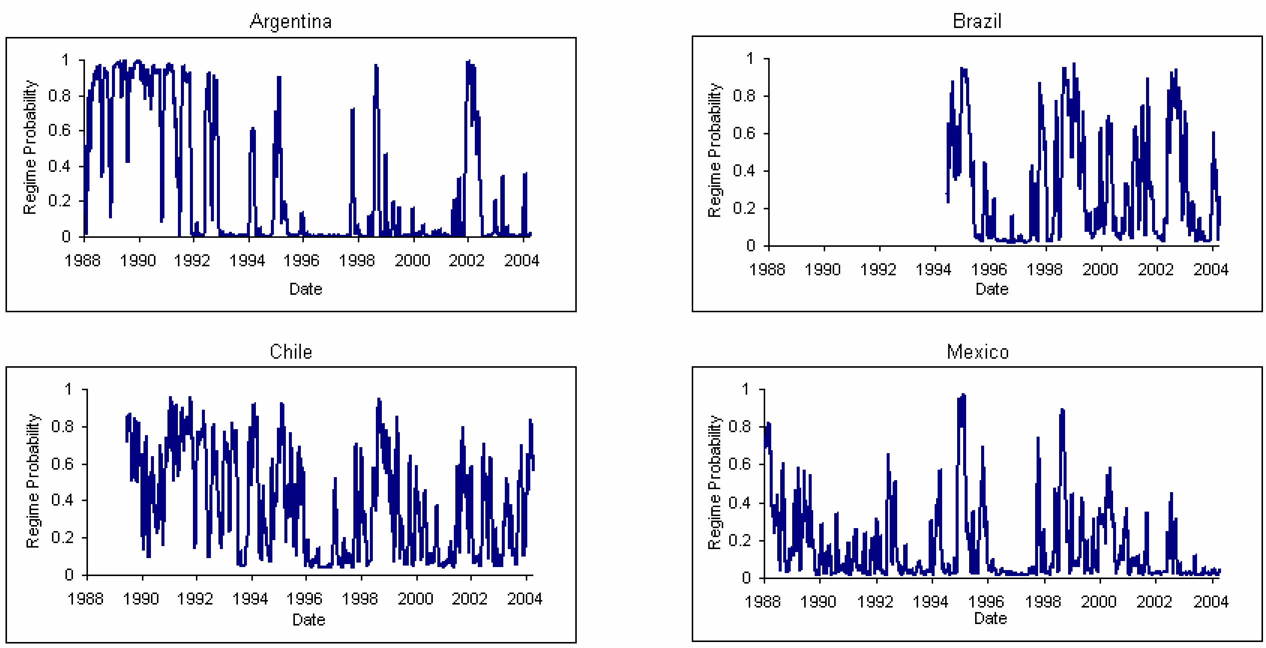


Figure 2 (continued)

Panel B: Asian Countries

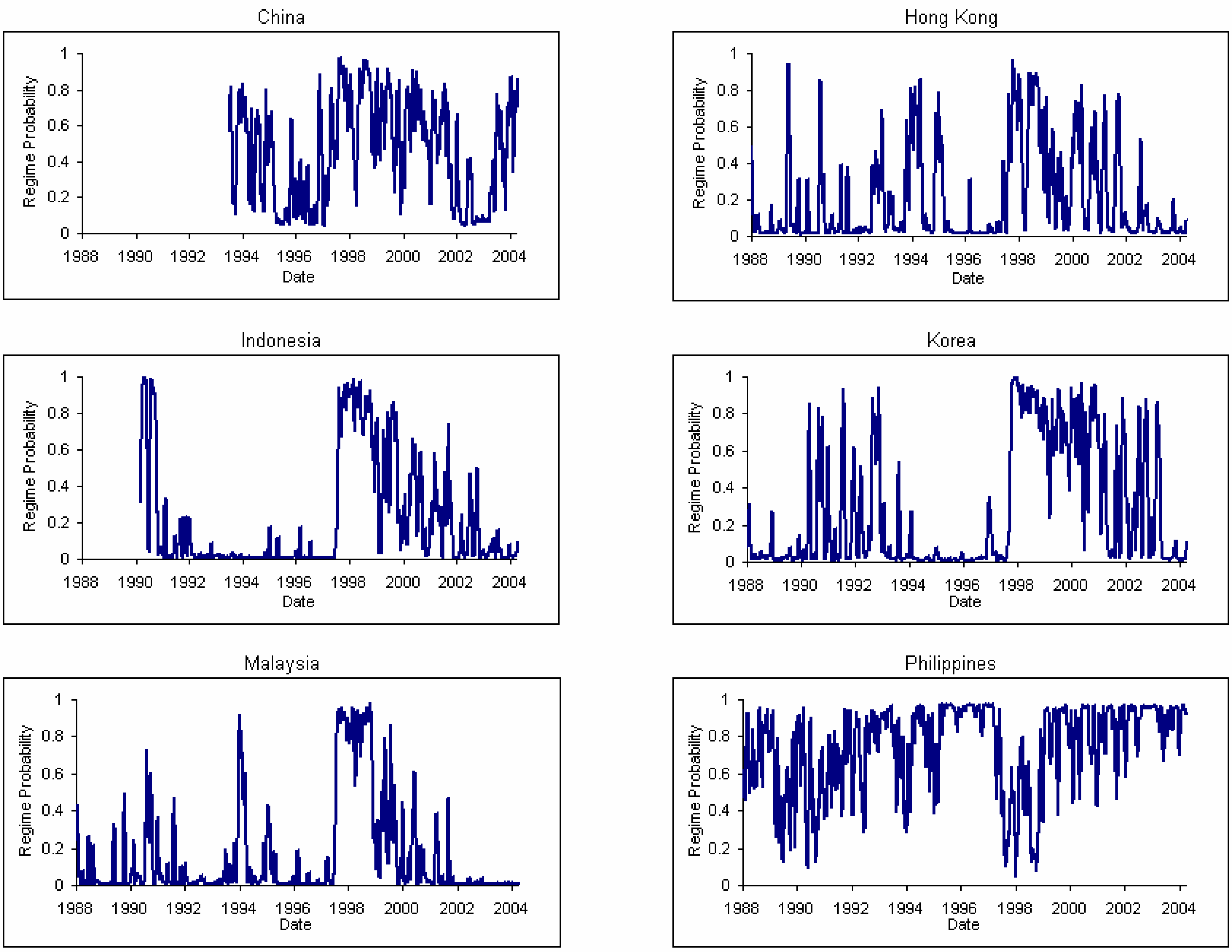
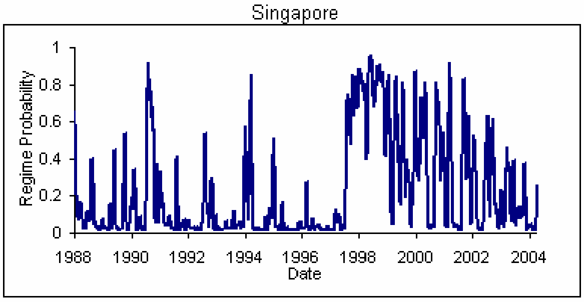
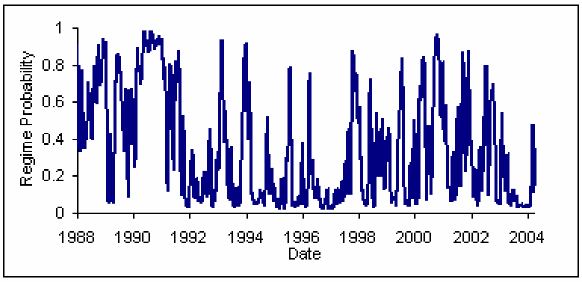


Figure 2 (continued)

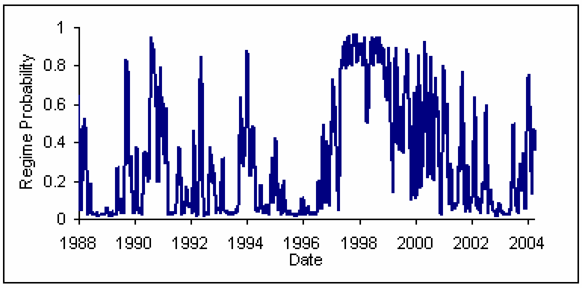
Singapore



Taiwan

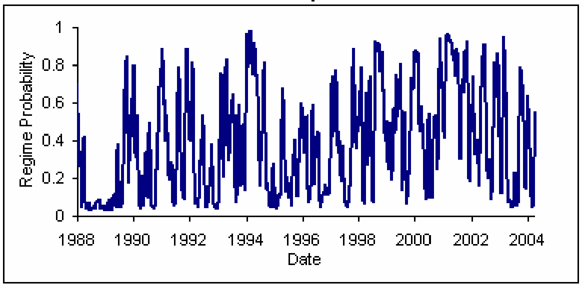


Thailand



Panel C: Other

Turkey



Greece

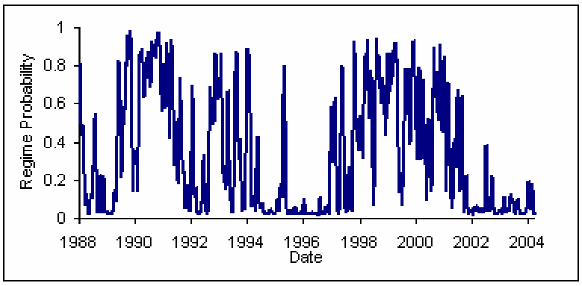


Figure 3: Conditional Correlation for Argentina