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ABSTRACT

This paper proposes a new approach to evaluate contagion in financial markets. Our measure of contagion captures the co-incidence of extreme return shocks across countries within a region and across regions that cannot be explained by linear propagation models of shocks. We characterize the extent of contagion, its economic significance, and its determinants using a multinomial logistic regression model. Applying our approach to daily returns of emerging markets during the 1990s, we find that contagion, when measured by the co-incidence within and across regions of extreme return shocks, is predictable and depends on regional interest rates, exchange rate changes, and conditional stock return volatility. Evidence that contagion is stronger for extreme negative returns than for extreme positive returns is mixed.

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1. Introduction

Since 1997, economists, policymakers, and journalists have talked about the "Asian flu." It has generally been perceived that the adverse currency and stock market shock that first affected Thailand in July 1997 propagated across the world with little regard for economic fundamentals in the affected countries. Before the Asian flu, there was the 1994 Mexican "Tequila crisis," and since then, the 1998 "Russian virus." Emerging markets economic crises, in general, have been characterized as contagious. According to Webster's dictionary, contagion is defined as "a disease that can be communicated rapidly through direct or indirect contact." Emerging market economic crises have led to massive bailouts to quell contagion and have reduced support for free capital mobility. IMF deputy managing director Stanley Fischer rationalized the 1994 Mexican bailout in this way: "Of course, there was another justification: contagion effects. They were there and they were substantial."[1] Contagion has led Bhagwati (1998) and others to argue that "Capital flows are characterized, as the economic historian Charles Kindleberger of the Massachusetts Institute of Technology has famously noted, by panics and manias." If markets work this way, it is not surprising that Stiglitz (1998) called for greater regulation of capital flows, arguing that "…developing countries are more vulnerable to vacillations in international flows than ever before."

Even though this contagion connotes powerful images of economic and financial plagues, it is difficult to study scientifically. Evidence of this difficulty is that there is little agreement on even defining what financial contagion means.[2] Since equity market

[1] See his statement in Calvo (1996, p. 323).

[2] For a review of the difficulties in defining contagion, see Dornbusch, Park, and Claessens (2000). A recent conference, *International Financial Contagion: How it Spreads and How it Can be Stopped*, jointly sponsored by the World Bank and IMF featured almost two dozen papers including theoretical models of

valuations reflect future economic activity, much recent research attempts to learn about contagion by investigating whether equity markets move more closely together in turbulent periods. Recent investigations of this issue find at best mixed results, but there are considerable statistical difficulties involved in testing hypotheses of changes in correlations across quiet and turbulent periods.[3] Nevertheless, there does not seem to be strong evidence that stock returns in one country are more highly correlated with returns in other countries during crisis periods once one takes into account the fact that the conditional correlation of stock returns is higher during such periods even if the unconditional correlation is constant.[4] A related literature demonstrates that, even though correlations change over time, it is difficult to explain changes in correlations.[5]

An important difficulty with investigations of contagion that focus on correlations is that they assume a linear propagation mechanism, where contagion is proportional to returns. None of the concerns expressed about contagion seem based on a linear propagation mechanism. These concerns are generally founded on the presumption that there is something different about extremely bad events that leads to irrational outcomes, excess volatility, and even panics. In the context of stock returns, this means that if panic grips investors as stock returns fall and leads them to ignore economic fundamentals, one would expect large negative returns to be contagious in a way that small negative returns are not. Correlations that give equal weight to small and large returns are not appropriate

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contagion (Pritsker, 2000; Schiniasi and Smith, 2000), conceptual, survey contributions (Forbes and Rigobon, 2000), country case studies (De Gregorio and Valdes, 2000; Eichengreen, Hale, and Mody, 2000; Park and Song, 2000) and broad-based empirical studies (Kaminsky, Lyons, and Schmukler, 2000; Gelos and Sahay, 2000). Other important recent contributions include Masson (1999), Glick and Rose (1999), Kyle and Xiong (1999), Kaminsky and Reinhart (2000) and Allen and Gale (2000).

[3] See Baig and Goldfajn (1998) and Forbes and Rigobon (1998).

[4] See Boyer, Gibson, and Loretan (1997) and Rigobon (1998).

[5] See, for instance, Erb, Harvey, and Viskanta (1995), King, Wadhwani, and Sentana (1995), Longin and Solnik (1995, 2000), and Karolyi and Stulz (1996).

for an evaluation of the differential impact of large returns. It could be that large shocks, because they exceed some threshold or generate panic, propagate like wildfire across countries, but this propagation is hidden in correlation measures by the large number of days when little of importance happens.

In this paper, we abandon the correlation framework that previous research has focused on to study contagion and direct our attention instead to large absolute value daily returns. To avoid a situation where our results are dominated by a few observations, we do not compute correlations of large returns but instead measure joint occurrences of large returns. We show that linear models cannot explain patterns that we observe for large absolute value returns. We find that there is more contagion of large absolute value returns than linear models would predict. We then show that an approach that is well established in epidemiology research on contagious diseases, the multinomial logistic regression model, can be helpful in understanding financial contagion.[6] In the epidemiology literature, the model is used to answer questions such as: Given that N persons have been infected by a disease, how likely is it that K other persons will be affected by that disease? We use multinomial logistic regressions to predict occurrences of large returns, which we refer to as "exceedances." With this model, we can determine how likely it is that two Latin American countries will have large returns on a particular day given that two countries in Asia have large returns on that day and given control variables (or, covariates) measured using information up to the previous day. We find

[6] Hosmer and Lemeshow (1989) in the introduction to their book, *Applied Logistic Regression*, write that "…the logistic regression model has become the standard method for regression analysis of polychotomous data in many fields, but especially the health sciences. Nearly every issue of such major journals as *American Journal of Epidemiology*, *American Journal of Public Health*, *International Journal of Epidemiology*, and *Journal of Chronic Diseases* has articles whose analyses are based on the logistic regression model." Other important books on epidemiological research methods, such as Breslow and Day

that exchange rate changes, interest rate levels, and regional conditional volatility of equity market returns are important covariates that help predict and explain contagion. With our data, contagion differs across regions. Contagion appears to be much stronger within Latin America than it is within Asia. Further, large positive and large negative returns are equally contagious in Asia but not in Latin America where large negative returns are more contagious.

Our approach enables us to consider contagion across regions as well as within regions. An earlier literature looked extensively at the transmission of information across advanced markets during the calendar day.[7] Our investigation is related to this literature in that we consider the impact of large returns in one region on the probability of observing large returns in other regions. We find evidence of cross-region contagion. However, the U.S. seems completely insulated from any Asian contagion. We show that the extent of contagion from one region to another cannot be explained by a linear model of the propagation of shocks.

Our approach is also related to a growing literature in the field of risk management that shows that the behavior of tail observations for financial returns is different from the behavior of other observations.[8] This literature, drawing on a considerable statistical literature on so-called extreme-value theory, models the distribution of the tail observations ignoring the distribution of the other observations. In this paper, we draw

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(1980), Kleinbaum, Kupper, and Morgenstern (1982), Moolgavkar and Prentice (1986), and Clayton and Hills (1993), have many applications of multinomial logistic regression.

[7] Important investigations of daily and intraday international "spillovers" of returns and volatility include studies by Eun and Shim (1989), Hamao, Masulis, and Ng (1990), King and Wadhwani (1990), Engle, Ito, and Lin (1990), Lin, Engle, and Ito (1994), Susmel and Engle (1994), and Bae and Karolyi (1994). More recent contributions include Ramchand and Susmel (1997), Connolly and Wang (1999), and Ng (2000).

[8] See Longin (1996), Danielsson and de Vries (1997), Longin and Solnik (2000) and, especially, recent applications to Asian markets by Kaminsky and Schmukler (1999) and Pownall and Koedijk (1999).

inspiration from this literature in focusing on extreme returns and study the probability of joint occurrences, which we denote as "co-exceedances," of such returns across countries.

To apply our approach, we use a sample of daily returns that is constructed using uniform criteria. The sample we use is given by the daily returns of the investible indices of the International Finance Corporation (IFC indices) for 17 Asian and Latin American markets of the Emerging Markets Database.[9] These returns are particularly well suited to our analysis because they correspond to the returns of portfolios that can be held by foreign investors. Unfortunately, these returns are only available for a period of slightly more than three years (880 time-series observations).

The paper proceeds as follows. In Section 2, we present our data, provide statistics on joint occurrences of extreme returns, and calibrate the joint occurrences of extreme returns using Monte Carlo simulation evidence. In Section 3, we motivate the use of a multinomial logit model to explain joint occurrences of extreme events and estimate such a model. The model is then used to show how contagion takes place within regions. In Section 4, we investigate contagion across regions. We conclude in Section 5.

2. Can financial contagion be explained by linear models?

In this section, we first discuss our data and its properties. We then turn to the distribution of extreme returns that we use throughout the study and investigate whether contagion among extreme returns can be understood using a linear model.

[9] Detailed information can be obtained from *The IFC Indexes: Methodology, Definitions and Practices* (February, 1998, International Finance Corporation, Washington, DC).

2.1. Data

A number of explanations of contagion are based on actions by foreign investors. We therefore use indices that are representative of the capitalization of stocks that foreign investors can hold. The International Finance Corporation produces such indices for emerging markets. We use the IFC indices from Asia and Latin America. To study the extent to which contagion affects the U.S. and Europe, we also use the S&P 500 index for the U.S. and the Datastream International Europe index for Europe. Our focus is on daily returns. Daily returns are available for the IFC indices since December 31, 1995. Our sample of daily returns therefore starts on December 31, 1995, and ends on May 14, 1999. The sample period includes the 1997 Asian crisis as well as the 1998 Russian crisis.

Table 1 provides sample statistics, including correlations. Not surprisingly, the properties and composition of the indices vary dramatically across countries. Malaysia has the highest average capitalization over our sample period among the IFC indices we use, while Sri Lanka has the smallest. Sri Lanka's index has five stocks on average, while the index for Malaysia has 144 stocks on average. All IFC indices have a greater standard deviation than indices for the U.S. or Europe.

Correlations within regions are higher than correlations across regions. However, none are particularly high except for the correlations among Brazil, Argentina, Chile, and Mexico which are all above 0.5. On a given day, trading starts in Asia and ends in the Americas. Consequently, information that becomes available in Latin America at noon cannot affect stock prices in Asia the same day. We consider, therefore, correlations between returns in Asia and Latin America on the same day as well as those between returns in Asia today and Latin America on the preceding day. The correlation between returns in Asia and Latin America separated by one day are roughly the same size as the same day correlations.

Correlations have been much studied. For the reasons discussed in the introduction, we focus instead on joint occurrences of extreme returns. At this point, we arbitrarily define an extreme return, or exceedance, as one that lies in the 5 percent tails of the overall return distribution. Alternative definitions are used later.[10] We treat positive extreme returns separately from the negative extreme returns. Our next step is to count the number of joint occurrences of extreme returns, or co-exceedances, within a region. Table 2 presents the results with three panels associated with (i) the whole sample period, (ii) the pre-crisis period, and (iii) the crisis period. We define a co-exceedance count of *i* units for negative returns as the joint occurrence of *i* exceedances of negative returns. Looking at Asia first, the distribution of co-exceedances is mostly symmetric. There are two days with seven or more countries in the bottom tail and two days with seven or more countries in the top tail. The same symmetry holds for other numbers of co-exceedances. The one case where there is a substantial difference between the bottom tail co-exceedances and the top tail co-exceedances is for the category of three co-exceedances. In that case, there are 23 days with three countries in the bottom tail and only 13 days with three countries in the top tail. Indonesia was in the bottom tail for 13 of the 23 days and Korea was in the bottom tail for 10 days out of the 23 days. In general, a crisis country (Thailand, Korea, Malaysia, and Indonesia) seems more likely to be in the

[10] Longin (1996), Longin and Solnik (2000), Pownall and Koedijk (1999), and Kaminsky and Schmukler (1999) employ conditional parametric or non-parametric measures of extreme returns. Later, we employ a conditional approach as a robustness check on our (co-) exceedances using an EGARCH model of conditional volatility. We also employ different sizes for the tails.

bottom tail when other countries are in the bottom tail. Looking at the correlations of Table 1, these patterns in extreme returns are not a complete surprise since the crisis countries have higher correlations among themselves than with the non-crisis countries. We report in Table 2 the average returns for each of the 10 Asian countries when more than seven Asian countries experience an exceedance on a given day. The crisis countries have larger negative returns on such days than non-crisis countries. Interestingly, the absolute value average return is higher for positive returns than for negative returns on such days.

Though Latin America has only seven countries, there are four days where all seven countries are in the bottom tail at the same time and 10 days when six countries or more have extreme negative returns. This contrasts with the case for positive extreme returns in which there is only one day when six countries or more fall in the positive tail. In Latin America and unlike Asia, therefore, there is evidence of asymmetry in that co-exceedances of negative returns are more likely than co-exceedances of positive returns. Further, co-exceedances are more likely. For instance, each Asian country has at least 10 extreme negative returns alone, but there are only four days where Mexico is alone in having an extreme return. Put another way, 40 out of 44 of Mexico's negative extreme return days occur when some other Latin American country has a negative extreme return. As a further demonstration of the asymmetry, Mexico has 16 days out of 44 extreme positive return days where it experiences a positive extreme return alone in Latin America.

If we consider separately the periods before and after the devaluation of the Thai Baht (results not reported), all Asian co-exceedances involving three countries or more take place after the devaluation of the Thai Baht and all Latin American co-exceedances involving four countries or more experiencing negative extreme returns take place afterwards. The difference before and after the Thai Baht devaluation reflects the same result as that observed by Forbes and Rigobon (1998, 2000) and others of an increase in correlations during the Asian crisis period. Indeed, a result of this type is difficult to interpret because conditioning on the occurrence of large returns, we should see higher correlations. The reason for this is that, in the presence of a common factor, large returns are more likely to be associated with large realizations of the common factor. To understand whether the occurrence of co-exceedances can be explained by conditioning on large absolute value returns, we have to investigate what the distribution of co-exceedances would be if correlations were constant during the sample period. To this end, we perform a Monte Carlo simulation experiment.

2.2. Contagion versus co-exceedances: Monte Carlo simulation evidence.

We now consider the following experiment. Suppose that the covariance matrix of returns is stationary over the sample period and that the returns follow a multivariate Normal or Student-t distribution. Using that covariance matrix, we simulate 880 returns for the Asian countries with 5,000 replications. For each replication, we identify the 5 percent quantile extreme returns for the bottom and top tail of the return distributions and perform the same non-parametric count across countries by region as in Table 1. Doing so provides us with a distribution of exceedances and co-exceedances. We use that distribution to calibrate the observed sample of co-exceedances. The results are shown in

Table 3 and for each scenario we report the simulated mean, standard deviation, 5 percent and 95 percent quantiles, and the simulated p-value of the 5000 replications.

The distribution of the co-exceedances will depend on the assumptions made about the returns generating process To this end, we perform the Monte Carlo simulation with four scenarios that differ by the number of degrees of freedom underlying the Multivariate Student-t distribution, which equals N + K –1, where N is the number of countries (10 for Asia, 7 for Latin America) and where K is set to values ranging from one (significant positive excess co-kurtosis) to 25 (little excess co-kurtosis, approximating multivariate Normal). In the table, we report the results separately for Asia and Latin America. It is immediately apparent that we observe more co-exceedances than one would expect with a linear model for Latin America, but not necessarily for Asia. For example, we have two days where seven or more countries in Asia have extreme negative returns. Yet, in our simulations, we generate an average of 0.31 days where this occurs for the low co-kurtosis (multivariate Normal) scenario, around 1 day on average in the moderate co-kurtosis scenarios, but over 10 days with the high co-kurtosis scenario.[11] The simulation p-values indicate that the low co-kurtosis (multivariate Normal) scenario delivers only 40 replications out of 5000 (0.80 percent) in which two or more days of co-exceedances of negative returns of seven countries occur. However, the higher co-kurtosis scenarios generate the actual number of co-exceedances in 20 percent to 100 percent of the replications. For co-exceedances of positive returns, the results are similar. In these cases, the sample has two co-exceedances involving seven countries or more and

[11] It is important to note that the kurtosis implied by the high co-kurtosis (K=1) scenario for the marginal distributions of individual country index returns are much higher than the positive excess kurtosis in the actual returns. In fact, the simulated distributions generate excess kurtosis statistics ranging from 15 to 25, while the statistics for the actual returns are closer to the 3 to 6 range.

this count is larger than that generated by the low co-kurtosis scenario (simulated p-value of 0.00), but it is not unusual for the moderate to high co-kurtosis scenarios.

The results for Latin America are harder to reconcile with the simulations than the results for Asia. In these experiments, the low co-kurtosis (multivariate Normal) scenario fails to generate any (simulated p-values of 0.00) observations of five or more co-exceedances of negative returns of which there are 16 in the actual sample. What is more surprising is that even the moderate and high co-kurtosis scenario cannot deliver simulated co-exceedance counts as large as in the actual sample, especially for the four events with all seven Latin American countries in the bottom tail. By contrast, the number of positive tail co-exceedances in Latin America is not dramatically different from the simulated counts. For example, the five co-exceedance events in which five or more Latin American countries experience returns in the top 5 percent tail occur in more than 93 percent of the replications for the high co-kurtosis scenario. They occur in 27 percent to 51 percent of the replications for the moderate (K equals five or 10) co-kurtosis scenarios. This asymmetry in co-exceedance events represents another challenge for a linear model of contagion.

One of the concerns expressed by Dornbusch et al. (2000), Baig and Goldfajn (1998), and Forbes and Rigobon (1998, 2000) is that contagion -- as measured by changes in cross-market correlations across quiet and turbulent periods – can be biased by heteroscedasticity. Forbes and Rigobon (1998) show how the bias can be corrected by a measure of the relative increase in the volatility of market returns, say, for example, during a crisis period. To see if the co-exceedance results stem from a heteroscedasticity bias during the Asian crisis period, we performed additional Monte Carlo simulations in which we computed the covariance matrix of returns for the two regions during high and low volatility periods. For these alternative experiments, we simulated for the full sample period based on a multivariate distribution for which the parameters were estimated during only subperiods associated with the highest and lowest quartiles of regional index return volatility as computed with an EGARCH model. Interestingly, even the scenario associated with the highest return volatility quartile was unable to deliver co-exceedance counts of six or seven or more countries as in the actual data for Asia and Latin America. For example, the resultant simulation p-values for bottom tail co-exceedances of six and seven or more co-exceedances ranged from 0.86% to 2.54% for Asia and 0.00% to 0.12% for Latin America. Results are available from the authors.

The bottom line from our simulation experiments is that it is more difficult to explain the distribution of co-exceedances for Latin America than Asia. Our simulation evidence suggests that the frequency of bottom tail and top tail co-exceedances in Asia can be generated (in 20 percent or more of the 5000 replications) with a reasonable assumption about positive excess co-kurtosis. For Latin America, this is not the case for the bottom tail co-exceedance events. At the same time, however, it is important to emphasize that the number of puzzling observations is small. The events that occur too often compared to the multivariate Student t or normal distribution model are those in which most countries in a region have extreme returns at the same time. There are few such days, but from the perspective of contagion studies, those days are the most interesting.

3. Contagion within regions

In this section, we show how our approach is useful to understand contagion within regions. In the first part of the section, we present our approach of using multinomial logistic regressions. In the second part of the section, we provide estimates of the regressions for Asia and Latin America.

3.1. The logistic regression approach

Extreme value theory (EVT) has proposed three possible types of limiting distributions for minima or maxima of a variable including the Gumbel, Fréchet, and Weibull distributions (Longin, 1996) and each of these has been applied to time series of financial returns. These studies typically estimate the parameters of these distributions using parametric (maximum likelihood, regression) and non-parametric approaches. We know of one application of multivariate EVT to stock returns, but, in this case, a dependence function between the Fréchet, Gumbel, or Weibull distributions across variables must be assumed and it is typically a logistic function (Longin and Solnik, 2000). Our approach is different.

Exceedances in terms of extreme positive or negative returns in a particular country can be modeled as a dichotomous variable. However, our interest in co-exceedances to capture contagion across many countries within a region requires classification into many categories using a polychotomous variable. Multinomial logistic regression models, not very different from the multivariate EVT applications, are popular approaches to estimate the probabilities associated with events captured in a polychotomous variable (Maddala, 1986, Chapter 2; Hosmer and Lemeshow, 1989, Chapter 8). If P_i is the probability associated with a category i of m possible categories, then we can define a multinomial distribution given by,

$$P_i = G(b_i'x)/[1 + S_{j=1}^{m-1} G(b_j'x)] \qquad (1),$$

where x is the vector of covariates and b_i the coefficients associated with the covariates. Often, the function $G(b_i'x)$ is simplified using a logistic function $exp(b_i'x)$ which reduces (1) to a multinomial logistic model. The model is estimated using maximum likelihood with (log-) likelihood function for a sample of n observations given by,

$$logL = S_{i=1}^{n} S_{j=1}^{m} I_{ij}\, logP_{ij} \qquad (2),$$

where I_{ij} is an indicator variable that equals 1 if the i-th observation falls in the j-th category, and zero, otherwise. Because P_{ij} is a nonlinear function of the bs, an iterative estimation procedure is employed and, for this purpose, we choose the Broyden, Fletcher, Goldfard, and Shanno algorithm. The matrix of second partial derivatives delivers the information matrix and asymptotic covariance matrix of the maximum likelihood estimator for tests of significance of the individual estimated coefficients. Goodness of fit is measured using the pseudo-R^2 approach of McFadden (1974) where both unrestricted (full model) likelihood, L_w, and restricted (constants only) likelihood, L_W, functions are compared,

$$\text{pseudo } R^2 = 1 – [logL_w / logL_W] \qquad (3).$$

In our application to co-exceedances across countries within Asia and Latin America, we balance the need to have a parsimonious model, and yet one that richly captures the range of possible outcomes. We therefore choose to restrict our categories to total five in number: 0, 1, 2, 3, and 4 or more co-exceedances. For a simple model of constants, only m-1, or four parameters need to be estimated, for example. But, for every covariate added to the model such as the conditional volatility of returns for the regional index, four additional parameters need to be estimated. We choose to estimate the co-exceedances separately for positive and negative extreme returns (though we test the importance of this distinction later). Finally, we compute the probability of a co-exceedance of a specific level, P_i, by evaluating the covariates at their unconditional values,

$$P_i^* = exp(b_i'x^*)/[1 + S_{j=1}^{m-1} exp(b_j'x^*)] \quad (4),$$

where x^* is the unconditional mean value of x. From this measure and following Greene (1997, Chapter 19), we compute the marginal change in the probability for a given unit change in the independent covariate and test whether this change is statistically significantly different from zero. Because it is often difficult to judge whether changes in probabilities of a given co-exceedance level are large or small economically, we further compute the sensitivity or response of our probability estimates to the full range of values associated with different covariates instead of just at its unconditional mean. These probabilities across the five categories add up to one and we use plots to illustrate visually the changes in these probabilities, a new approach in finance that we call the "co-exceedance response curve."[12]

Note that our key hypotheses relate to the existence of contagion across regions as well as measuring contagion within regions. Specifically, we will assess the importance of the co-exceedance events within Asia and Latin America for the likelihood of an

[12] There are many examples of applications in epidemiology of multinomial logistic regression that test the sensitivity of probabilities of difference events to groups of covariates. Gillespie, Halpern, and Warner (1994) study lung cancer deaths per year among ex-smokers and employ covariates such as age, gender, college attendance, smoker, and years since quitting for ex-smokers. Our co-exceedance response curves are inspired by their study. Marketing applications to sales growth models of new product innovation or "diffusion" employ multinomial logistic models (Lilien and Kotler, 1992).

exceedance in the U.S. and Europe. To this end, we will need to estimate a logistic regression model for the U.S. but it must necessarily be for a dichotomous variable, or binomial logistic regression. This is a simple version of our multinomial logistic regression model and all estimation procedures, inference tests, pseudo-R^2, and even "exceedance response curve" plots are computed accordingly. For simplicity, we compute the analogous models for Europe as a single entity.

3.2. Contagion within regions.

Table 4 provides estimates of our multinomial logistic regressions for Asia and Latin America. We estimate the regressions separately for the bottom tails and the top tails. Panel A shows estimates for Asia and Panel B shows estimates for Latin America. Column (1) reports estimates of regressions for the bottom tails for Asia that provide us with estimates of probabilities of co-exceedances. We find (not reported) that there is a probability of 69.77 percent that no Asian country has a bottom tail return. If bottom tail exceedances were independent, this probability would be 59.87 percent. The coefficient β_{01} is associated with the event "Y = 1" or the case where one country has an extreme return and its probability is 19.66 percent. Since there are no covariates, these probabilities are the sample frequencies. In column (2), we add the conditional volatility of the regional index as an explanatory variable. We find that the conditional volatility increases the probability of extreme returns significantly. To see the impact of conditional volatility, it is useful to evaluate the marginal probability of exceedances with respect to the conditional volatility. An increase in conditional volatility increases the probability of all exceedances, but the effect decreases as we look at a higher number of joint occurrences. For instance, a 1 percent increase in the conditional volatility increases the probability of one exceedance by 0.146 percent and the probability of four or more occurrences by 0.027 percent. All the partial derivatives are significant at 5 percent level or better. The pseudo-R^2 is 7.62 percent.

In column (3), we add the average exchange rate change in the region as well as the average interest rate level in the region.[13] This allows us to answer the question of whether the probability of co-exceedances is affected by exchange rate shocks to the region and by the level of the interest rates. We see that this is indeed the case if we look at the regression coefficients. If currencies fall on average, extreme returns are more likely. Further, if interest rates are higher, exceedances are more likely. In the case of interest rates, however, the significance of an increase in interest rates on the probability of exceedances differs depending on whether we look at the regression coefficients or at the partial derivatives of the exceedance probabilities. The partial derivatives are computed at the means of the regressors and are not significant for three or four or more exceedances. Adding exchange rate changes and the level of interest rates more than doubles the pseudo-R^2 to 17.95 percent. Further, it is clear from looking at the probabilities of co-exceedances evaluated at the mean of the regressors that for the probabilities of co-exceedances to be at their unconditional mean, the regressors have to be much larger than their mean values. The significance of exchange rates as predictors of contagion raises the question of whether the stock return contagion we measure is actually foreign exchange contagion since we measure returns in dollars. To examine this

[13] Data on daily exchange rates relative to the U.S. dollar and interest rates for each country are obtained from Datastream International. The interest rate series chosen is typically the short-term rate of interest available in Datastream with availability back to 1995. We computed simple equally-weighted average exchange rate changes and average interest rate by region for these covariates.

issue, we estimated but do not report our models in local currency returns. Our results are similar using local currency returns.

When we look at the top-tail events (models 4 to 6 in Table 4), we find no evidence that contagion is less likely for positive extreme returns than it is for negative extreme returns. A pairwise comparison of the coefficients in column (1) and (4) cannot reject that the coefficients are equal (Wald χ^2 statistic of 0.21, p-value of 0.65, not reported). Hence, for Asia, there is no evidence that contagion is somehow more important for negative returns than it is for positive returns. Conditional volatility is helpful in predicting positive co-exceedances. The exchange rate coefficients are negative and significant. In other words, the likelihood of seeing positive extreme returns in more than one country increases when on average the exchange rate in the region appreciates. The interest rate variables provide no information for positive co-exceedances. The pseudo-R^2s are much lower for positive returns than they are for negative returns, so that our covariates are more successful at explaining contagion for negative returns than for positive returns.

In the second panel of Table 4, we see that the results for Latin America differ substantially from those for Asia. The probability of no extreme return on a day is much higher for Latin America than it is for Asia. We estimate the probability of no extreme return to be 82.72 percent for Latin America, while it is 69.77 percent for Asia. The probability of having four or more Latin American countries experience an extreme return on the same day is higher than the corresponding probability for Asia. The explanatory variables are significant for Latin America in the same way that they are for Asia except that interest rates do not appear to be useful in explaining contagion of extreme negative returns in Latin America. The partial derivatives of the probabilities with respect to regressors are significant except for interest rates, but they are smaller for conditional volatility and larger for exchange rates than those for Asia. Turning to the positive extreme returns, we see that the probability of no positive extreme return is lower than the probability of no negative extreme return. There seems to be an asymmetry between positive and negative extreme returns in Latin America. A pairwise comparison of the probability of positive extreme return and negative extreme return co-exceedances confirms the asymmetry for co-exceedances of four or more extreme returns in that co-exceedances of four or more extreme returns are more likely for negative extreme returns than for positive extreme returns (Wald χ^2 statistic of 3.17, p-value of 0.07, not reported).

We also include the U.S. and Europe in third and fourth panels of Table 4. For the U.S., the coefficient on the conditional volatility of the market is positive and significant for both negative and positive tail events, but the partial derivative of the probability of an exceedance with respect to the conditional volatility is significant only for positive tail events. Exchange rate and interest rate levels do not offer any predictive power.[14] The pseudo-R^2s are low especially for the bottom tail. For Europe, there is clear evidence that an increase in the conditional volatility of returns increases the probability of tail events. The evidence is more mixed for exchange rate and interest rate variables. The pseudo-R^2s are substantially higher than those of the emerging market regions for the positive tail

[14] For the U.S. we employed the equally-weighted average exchange rate for both the Asian and Latin American regions in the binomial tests as well as the daily Fed funds rate. For Europe, we used the DM-U.S. dollar bilateral exchange rate and the short rate in Germany as a proxy.

events, but adding interest rate and exchange rate variables has almost no impact on pseudo-R^2s.

Figure 1 illustrates the co-exceedance response curve of Asia associated with the model in column (3) of Table 4. Note that these plots apply only to the bottom tail events. Such curves are important in understanding the impact of the covariates on the probability of exceedances. In the tables, we provide estimates of the partial derivatives of the exceedance probabilities with respect to the regressors evaluating the partial derivatives at the means of the regressors. However, these partial derivatives give an incomplete picture of the impact of changes in the regressors because the probabilities are not linear functions of the regressors. Plotting the probability of exceedances as a function of a regressor over the whole relevant range of the regressor permits us to better assess how changes in the regressor affect the probability of exceedances. Consider the top plot that shows the sensitivity of implied conditional probabilities of different numbers of co-exceedances to the conditional volatility of Asian index returns. The different areas of the plot correspond to different co-exceedance events. Clearly, the probability of various co-exceedances in Asia increases with the conditional volatility, but it does so nonlinearly, so that a linear approximation provides an incomplete picture of the impact of changes in the conditional volatility. At very high levels of volatility (about 3.5 percent per day), for example, the probability of two or more co-exceedances reaches almost 45 percent. An obvious issue is that one has to be cautious in evaluating such a result because we end up focusing on a subset of an already small number of tail events The two bottom plots are associated with the model for the exchange rate change and interest rate level covariates. Interestingly, the sensitivity of co-exceedances to interest rate levels is similar to conditional volatility, but the sensitivity to exchange rate changes – no doubt in large part due to the crisis period – is dramatic and highly non-linear. The response curve slope is relatively flat until rather large average exchange rate depreciations of 1 percent or more after which the probability of regional contagion rises to a maximum of 50 percent to 80 percent.

Two robustness checks follow. First, we provide a full set of Wald χ^2 tests of the restriction that the regression coefficients are the same for positive exceedances and negative exceedances to which we have already referred above. We find that for Asia we cannot reject the hypothesis that positive and negative return joint exceedances are equally likely. For Latin America, there is an asymmetry in co-exceedances of four or more where negative co-exceedances are more likely. Second, it is important to remember that the analysis of Table 4 uses contemporaneous covariates. We also extended the analysis to incorporate some dynamics in co-exceedances by considering whether knowing the number of extreme returns of yesterday is helpful in predicting the number of extreme returns today. The results (not reported) show that the lagged values of co-exceedances are statistically significant for Latin America, Asia, less so for Europe, but clearly not for the exceedances in the U.S. This specification ignores, however, the lagged effects of the interest rate, exchange rate, and regional conditional volatility covariates or the multi-day horizon for measuring co-exceedance events. We address these supplementary issues in the next section.

How well specified these particular models are is an open question. Our primary focus is on the extent of contagion across regions, so it is important that our tests condition on reasonable covariates or factors that affect contagion within regions. We offer a number of sensitivity tests to address this concern in this and later sections.

4. Contagion across regions.

In this section, we investigate contagion across regions. The type of question we address is whether the fact that there are co-exceedances, or joint occurrences of extreme returns, of a given number in Asia can help predict the number of co-exceedances or extreme returns in Latin America or in other regions. In the first part of the section, we answer this type of question using a base model. In the second part of the section, we explore alternate specifications.

4.1. The base case model.

To investigate the question we are interested in, we re-estimate the models of Table 4 for Asia, Latin America, U.S., and Europe, respectively, but add two covariates related to co-exceedances (Y_{jt}^*) and regional market volatility (h_{jt}^*) from each of the other regions during the preceding trading session that day. Timing conventions are important since U.S. and Latin American markets open after the markets for Asia have closed. Therefore, we add to the Asian contagion regressions the number of extreme returns in Latin America on the previous trading day and the conditional volatility of the Latin American regional index as of the previous day. The re-estimated model for Asia is given in column (1) of Table 5 for the bottom tails and in column (4) for the top tails. The regression coefficients on the number of exceedances in Latin America are significant (β_{5k} for k equals 1 to 4 are all significant at the one percent level). In evaluating the derivative of the exceedance probabilities ("Δ prob" in table), we note that an increase in the number of exceedances in Latin America increases the probability of all four exceedance outcomes in Asia except for the outcome of four exceedances or more for negative tail events. It seems surprising at first that the coefficient β_{54} is significant but its associated probability, P_4, is not, but this no doubt reflects the non-linear logistic mapping (e.g. equation 1). It is also important to note that the slope of the probability function is evaluated at the unconditional mean of the covariate, which does not capture the possible non-linearity in the response function.[15]

A concern with these results is that the number of exceedances in Latin America might proxy for an exceedance in the U.S. This turns out not to be the case. We re-estimated our regressions adding a variable that takes a value of one if the U.S. has an exceedance and zero otherwise. Adding this dummy variable does not change our results. This indicates that there is something unique about contagion among emerging markets. The coefficients are significant for all exceedance outcomes for positive tails, but the partial derivatives of the probabilities are not. We add two Wald chi-squared statistics associated with tests of the null hypothesis that the block of coefficients associated with the conditional volatility and the number of exceedances in the other market are jointly zero. The conditional volatility of Latin America does not seem to be very helpful in predicting exceedances in Asia. Introducing this variable weakens the estimates of the

[15] Greene (1997, p. 667) also points out that computation of the marginal effects of the regressors on the probabilities in multinomial logit models and the standard errors are likely to be "exceedingly complex." The challenge is the higher dimensionality which complicates the use of the linear approximation approach for the inverse of the Hessian at the maximum likelihood estimates. He states that "for any particular x_k, $\partial P_j/\partial x_k$ need not even have the same sign as β_{jk}" (footnote 44, p. 667).

impact of changes in the conditional volatility of Asia on the probability of exceedances in Asia.

When we turn to contagion from the U.S. (Models 2 and 5), we see that the coefficient on the U.S. exceedance has a significant coefficient, but the effect on the probability is small. Again, however, the conditional volatility of the U.S. is not helpful to predict exceedances in Asia. Further, whether the U.S. had an extreme return seems more helpful in predicting the number of negative extreme returns in Asia than the number of positive extreme returns, although the Wald statistics indicate both are significant at the one percent level. Finally, the results from adding European covariates (models 3 and 6) are similar to those obtained from adding U.S. covariates. Comparing the regressions of Table 5 for Asia with those of Table 4, we see that the pseudo-R^2 is substantially higher in all cases. We also see that we cannot reject the hypothesis that the new coefficients on the conditional variances and on the number of exceedances are significantly different from zero, except that the Latin American conditional volatility does not significantly affect the number of positive exceedances in Asia.

The contagion tests for Latin America are presented in the second panel. Remember that Asia closes before the markets in Latin America open on the same day; as a result, we use same day returns in measuring contagion from Asia to Latin America. For the negative extreme returns, we find that Latin America has more negative extreme returns if Asia has more negative extreme returns. The results for conditional volatility are more mixed, except that the coefficient on conditional volatility is significant for four or more exceedances. The same results apply for extreme returns from the U.S. and Europe. Surprisingly, positive exceedances for four countries or more become less likely for Latin

America when the conditional volatility of Asia is high. The pseudo-R^2s of the Latin American regressions increase much more by adding covariates from another region than the pseudo-R^2s of Asia. For all the regressions, we cannot reject the hypothesis that the coefficients on the added variables are significant.

Finally, we turn to the U.S. and Europe in the third and fourth panels of Table 5. Asian extreme returns or conditional volatility have no effect on the probability of a negative extreme return for the U.S. or the probability of a positive extreme return for the U.S. In contrast, extreme returns from Latin America and from Europe have a significant effect. Since markets in Latin America are open when markets in the U.S. are open, a concern is that contagion from Latin America is really contagion indirectly from the U.S. itself. Finally, Europe's probability of negative extreme returns is significantly affected by extreme returns in all other regions. Again, however, we have to be concerned about the interpretation of this result, since European markets are open part of the time when U.S. and Latin American markets are open.

The co-exceedance response curve plots in Figure 2 for Asia show how the conditional volatility and the number of extreme returns in Latin America, U.S., and Europe affects the probability of extreme returns in Asia. The plots for Latin America, U.S., and Europe are given in Figures 3, 4, and 5, respectively. We can see that the probability of exceedances in Asia increases as the conditional volatility of the Latin American returns increases and as the number of exceedances in Latin America increases. However, the impact of an increase in the number of Latin American exceedances on the probability of four or more exceedances in Asia never exceeds 5 percent. The impact of Asian exceedances on the probability of one or two exceedances in Latin America (Figure 3) seems modest and the impact of Asian exceedances on three and four exceedances in Latin America is similar to the impact of Latin American exceedances on the probability that Asia will have three or four or more exeedances. Viewed from this perspective, contagion seems sharper from Latin America to Asia than it is from Asia to Latin America. Further, contagion affecting emerging markets is stronger than contagion affecting developed countries. Figure 4 shows that the U.S. is largely unaffected by co-exceedances or conditional volatility from Asia. It is somewhat more dramatically affected by co-exceedances in Latin America, but as discussed earlier, the relation between exceedances in Latin America and an exceedance in the U.S. is hard to interpret. Europe is even more insulated from these effects than the U.S.

4.2. Calibrating contagion across regions: Monte Carlo evidence.

The returns among countries of the regions we consider are correlated as evidenced by Table 1. One would, therefore, expect that extreme returns in one region are more likely to be accompanied by extreme returns in another region and that the co-exceedance patterns derive from a linear model. To evaluate whether our new multinomial logistic regression approach can uncover non-linearities in co-exceedances, we extend the simulation experiment in Section 2.2. In this experiment, we perform Monte Carlo simulations of 880 returns (corresponding to the December 31, 1995 to May 14, 1999 period) for each country in Asia and Latin America using 1000 replications using the historical variance-covariance matrix and assumptions about the joint returns generating process. As before, we propose the multivariate Student t distribution and allow for different scenarios that correspond to a range of values for the degrees of freedom underlying the distribution. Specifically, N+K–1 is the degrees of freedom where N is the number of markets (17, for all of Latin America and Asia) and we allow K to take values of 1 (significant positive excess co-kurtosis), 5, 10, and 25 (low co-kurtosis, approximating the multivariate Normal). For each replication, we count co-exceedance events in both regions and estimate the multinomial logistic regression model of Table 5. To proceed with the experiments, we only examine whether the number of co-exceedances in one region can be forecast with the number of co-exceedances in another region. We perform the experiments for contagion from Latin America to Asia and from Asia to Latin America. Table 6 summarizes the key findings.

We find that we cannot explain the coefficients on co-exceedances from the other region for Asia or Latin America. Looking at the high co-kurtosis (K=1) scenario, we cannot explain the magnitude of these coefficients. For example, the β_{1j} coefficients associated with Y_{jt}^* co-exceedances from the other region for Asia yield a simulation p-value of at most 6 percent for the high co-kurtosis scenario in the bottom tails. For Latin America, the highest simulation p-value for any co-exceedance coefficient is 2 percent for the top tail in the highest co-kurtosis scenario. Perhaps even more striking, the pseudo-R^2 is at least three times higher in the data than it is in any of the simulations.

Earlier we discussed alternative Monte Carlo simulation experiments to address the potential bias in the frequency of co-exceedances induced by heteroscedasticity (Dornbusch et al., 2000; Baig and Goldfajn, 1998; and, Forbes and Rigobon, 1998, 2000). We repeat the contagion experiment, as for the multivariate Student t distribution above, but we computed the covariance matrix of returns for the two regions separately during high and low volatility periods. That is, we simulated for the full sample period based on a multivariate distribution for which the parameters were estimated during only subperiods associated with the highest and lowest quartiles of regional index return volatility as computed with an EGARCH model. Whether for Asian or Latin American returns, the simulated β_{1j} coefficients associated with Y_{jt}^{*} co-exceedances from the other region were almost never as large as in the actual data even for the high volatility scenario. Simulation p-values of at most five percent result for the high volatility scenario in the bottom tails in Asia and at most only one percent occur for Latin America. Again, these results are available from the authors.

4.3. Alternate specifications.

We turn next to several alternate specifications. Though we do not reproduce these results, we re-estimated our multinomial logistic regressions with Monday dummies. These dummies are insignificant. We also re-estimated the models of Table 6 using local currency returns. The results were unchanged. In Table 7, we report our contagion tests using lagged conditioning variables. Though it is an in-sample experiment, it allows us to investigate the predictability of contagion. We see immediately that the pseudo-R^2 falls. However, the significance of yesterday's co-exceedances from the other regions is not less than the significance of same day co-exceedances. The table provides evidence that contagion across regions is predictable and that the number of co-exceedances of another region provides useful information in predicting contagion.

A concern we have expressed is that contagion is just the outcome of high volatility. We investigated this concern in a preliminary way with our Monte Carlo simulations using high co-kurtosis scenarios. Another approach to investigate this concern is to define exceedances differently from how we have defined them so far. With the exceedances defined in terms of the sample period returns, we necessarily have an outcome where we have more exceedances in periods of higher conditional volatility. Alternatively, we can define exceedances using conditional volatility itself, so that the probability of observing an exceedance is always the same (assuming multivariate normality for returns and a constant conditional mean). In Table 8, we define positive extreme returns to be those that exceed 1.65 times the conditional volatility and negative extreme returns those that are below –1.65 times the conditional volatility. The main impact of defining extreme returns this way is that a region's conditional volatility is no longer useful in predicting that region's co-exceedances. However, co-exceedances in one region still provide useful information in predicting co-exceedances in another region. For instance, the number of co-exceedances in Latin America still helps explain the number of co-exceedances in Asia. Surprisingly, with this definition of exceedances, interest rates are no longer useful to predict exceedances, but exchange rate changes still are.

We use two more definitions of exceedances. We re-estimate (not reported) the base model regression but use exceedances computed over three days instead of over one day as regressors. That is, a co-exceedance event is defined as one in which more than one market experiences an extreme return within a moving three-day window. The objective of this robustness check is to assess in a rough way the nature of the dynamics in co-exceedances within a region. Overall, the results are similar to those of the base case in Table 5 for Asia, but weaker for Latin America. Finally, we define exceedances by the 2.5 percent quantile rather than the 5 percent quantile. Proceeding this way, we have fewer exceedances. The results (again, not reported) reveal a similar pattern in coefficients, partial derivatives of probabilities relative to covariates and co-exceedance responses to Table 5, but inference tests lose power.

Throughout the paper, we reported estimates for multinomial logistic models. We considered several alternative specifications, including the ordered multinomial logit model and the negative binomial regression model. The ordered logit model is proposed for multinomial choice variables, such as bond ratings, opinion surveys, levels of insurance coverage, which are inherently ordered. In unreported results, we replicated our contagion tests across regions using the ordered model and found that our inferences about the co-exceedance variable Y^{*}_{j} (coefficients and marginal effects) and the pseudo-R^2 were consistent and very similar. We preferred the unordered multinomial model as it imposes less structure on the relative probabilities of different co-exceedance events. Nevertheless, these additional results are available from the authors. The negative binomial model, a generalization of a Poisson regression model that allows the variance to differ from the mean, is often used to study count data, such as the number of shipping accidents by type per year (Greene, 1997, Chapter 19). In this model, we do not need to assign categories as in the ordered and unordered logit models and, as a result, the system is smaller with only one coefficient is estimated for each covariate.[16] We replicated our tests for contagion across region with this model (unreported) and found that our inferences about contagion effects were even stronger. Pseudo-R^2 for bottom-tail co-exceedances for Asia, for example, increased from 19 percent to 22 percent for Y_j^* from Latin America; those from Asia to Latin America increased from 15 percent to 27

[16] We tested the restriction in the multinomial logit models in Section 4.1that the coefficients across the categories of one, two, three and four or more co-exceedances are equal and rejected these restrictions easily for the case of Asia and Latin America. These restricted models are closest in spirit to the negative binomial model.

percent. Contagion shocks from Asia and Latin America to the U.S. were measurably lower, however.

5. Conclusion

In this paper, we have proposed a new approach to the study of contagion. The key presumption of our approach is that contagion is a nonlinear phenomenon: If there is contagion, small return shocks have to propagate differently from large return shocks. We, therefore, investigate the propagation of large return shocks within regions and across regions. Such an approach faces two problems. First, focusing on large return shocks, by definition, decreases sample size and limits the power of our tests. One must be careful not to let our inferences be dominated by a few datapoints. As a result, we choose to focus on counts of co-incidences of extreme returns rather than on correlations of joint extreme returns. Our modeling approach employs the multinomial logistic regression approach to reflect this new and different focus. Second, one would expect large returns to be more highly correlated than small returns. As a result, one has to make sure that the apparent contagion of large returns is not simply the outcome of conditioning a study on large returns. We use Monte Carlo simulations to calibrate our results to what one would find if returns satisfied a multivariate Student t distribution with different scenarios associated with co-kurtosis in returns. We find that we have too many cases where large negative returns occur in most countries of a region, particularly for Latin America. Further, we find that the number of large negative returns in one region is more useful to predict the number of large negative returns in another region than if the returns in the two regions were distributed multivariate Student t or multivariate normal with different levels of market volatility. We also find that the number of joint occurrences of extreme returns within a region can be predicted using regional conditional volatility, the level of interest rates, and exchange rate changes.

Contagion is a source of great concern for policymakers and has generated a large and growing academic literature. We find in our study of emerging markets that the propagation of large negative returns across regions is anomalous if stock return indices follow a linear return generating model that allows for significant co-kurtosis. Whether this anomalous propagation should be a matter of serious concern will depend on the views of readers. Nevertheless, our paper has a number of clear results:

1) Contagion is more important in Latin America than in Asia.
2) Contagion from Latin America to other regions of the world is more important than contagion from Asia.
3) The U.S. is largely insulated from contagion from Asia.
4) Contagion is predictable conditional on prior information.

A natural extension of our study would be to investigate whether alternate distributional assumptions besides multivariate Student t could explain our results. Further, our study uses daily returns and focuses on same day, lagged one-day, and even three-day contagion. But a useful extension of the study would be to look at longer-horizon contagion. Such an analysis would make it possible to investigate whether there are thresholds of cumulative returns above which propagation of returns becomes more intense. It would also be useful to apply the approach to a broader cross-section of individual stock or sector index returns within countries. The approach developed in this paper would be well suited for such analyses.

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Table 1. Summary statistics of daily returns on International Financial Corporation (IFC) emerging markets indices, December 31, 1995 to May 14, 1999. Each index from the Emerging Market Database (EMDB) is adjusted to reflect accessibility of the market and individual stocks for foreign investors. Summary statistics include the mean, median, standard deviation (S.D.), number of stocks, average US dollar market value of index in millions, and correlations of daily index returns. EMDB countries include China (CHN), Korea (KOR), Philippine (PHI), Taiwan (TWN), India (INA), Indonesia (IND), Malaysia (MAL), Pakistan (PAK), Sri Lanks (SRI), Thailand (THA), Argentina (ARG), Brazil (BRA), Chile (CHI), Colombia (COL), Mexico (MEX), Peru (PER), and Venzuela (VEN). We also include daily returns of S&P 500 index for US and Datastream International Europe index. The correlations in the upper triangular matrix are between daily returns of Asian indices in calendar time t and those of Latin America, U.S., and Europe indices in calendar time t-1.

	CHN	KOR	PHI	TWN	INA	IND	MAL	PAK	SRI	THA	ARG	BRA	CHI	COL	MEX	PER	VEN	US	Europe
Mean in percent	-0.052	-0.058	-0.051	0.027	0.010	-0.111	-0.087	-0.063	-0.044	-0.161	0.040	0.035	-0.013	-0.003	0.064	-0.008	0.069	0.095	0.076
S.D. in percent	2.436	3.406	2.206	1.693	1.636	4.611	2.930	2.337	1.402	3.111	2.111	2.602	1.178	1.370	1.898	1.328	2.489	1.079	0.873
Median	0.000	-0.043	-0.015	0.000	0.000	0.000	-0.031	0.000	0.000	-0.113	0.059	0.096	-0.014	0.000	0.059	0.002	0.011	0.081	0.123
No. of Stocks	36	161	42	93	77	50	144	24	5	70	31	74	45	15	62	21	10		
Mkt. Value	5,554	25,784	15,355	49,408	14,520	19,986	103,333	4,092	390	15,039	28,083	80,119	39,048	6,755	74,378	7,635	5,041		
Correlation	CHN	KOR	PHI	TWN	INDIA	IND	MAL	PAK	SRI	THA	ARG	BRA	CHI	COL	MEX	PER	VEN	US	Europe
CHN	1.00										0.18	0.15	0.17	0.05	0.20	0.15	0.09	0.18	0.20
KOR	0.12	1.00									0.14	0.15	0.14	0.02	0.16	0.11	0.10	0.10	0.17
PHI	0.29	0.22	1.00								0.29	0.25	0.24	0.09	0.29	0.20	0.18	0.22	0.30
TWN	0.22	0.12	0.23	1.00							0.15	0.09	0.13	0.04	0.17	0.10	0.05	0.13	0.19
INA	0.09	0.11	0.13	0.05	1.00						0.04	0.10	0.10	0.02	0.07	0.06	0.04	0.07	0.05
IND	0.29	0.18	0.43	0.22	0.11	1.00					0.16	0.14	0.16	0.11	0.16	0.16	0.10	0.14	0.15
MAL	0.32	0.20	0.29	0.19	0.12	0.40	1.00				0.08	0.10	0.11	0.02	0.11	0.07	0.08	0.22	0.10
PAK	0.08	0.01	0.03	0.12	0.06	0.07	0.12	1.00			0.01	0.04	0.01	0.02	0.03	-0.01	0.02	0.02	0.01
SRI	-0.02	0.03	0.10	0.03	0.05	0.08	0.03	0.06	1.00		0.09	0.11	0.12	0.06	0.12	0.16	0.10	0.05	0.16
THA	0.26	0.28	0.44	0.24	0.16	0.39	0.39	0.11	0.11	1.00	0.17	0.13	0.17	0.04	0.17	0.12	0.13	0.12	0.18
ARG	0.13	0.12	0.16	0.07	0.04	0.13	0.15	0.09	-0.01	0.15	1.00								
BRA	0.07	0.15	0.16	0.06	0.06	0.09	0.07	0.06	0.03	0.13	0.72	1.00							
CHI	0.14	0.10	0.21	0.10	0.08	0.16	0.11	0.11	0.05	0.17	0.55	0.52	1.00						
COL	0.03	0.06	0.07	0.09	0.04	0.13	0.06	0.04	0.07	0.07	0.16	0.15	0.22	1.00					
MEX	0.12	0.13	0.19	0.03	0.07	0.11	0.17	0.08	-0.02	0.12	0.67	0.65	0.53	0.13	1.00				
PER	0.12	0.10	0.18	0.04	0.12	0.13	0.14	0.05	0.01	0.15	0.46	0.46	0.44	0.17	0.48	1.00			
VEN	0.15	0.08	0.13	0.09	0.08	0.12	0.11	0.06	-0.04	0.17	0.32	0.29	0.28	0.11	0.34	0.26	1.00		
US	0.03	0.11	0.12	0.03	0.02	0.04	0.00	0.03	0.06	0.06	0.52	0.48	0.37	0.09	0.49	0.29	0.17	1.00	
Europe	0.16	0.14	0.20	0.08	0.09	0.15	0.21	0.02	0.02	0.20	0.37	0.35	0.37	0.12	0.46	0.39	0.25	0.35	1.00

Table 2. Summary statistics of (co-) exceedances for daily emerging market index returns, December 31, 1995 to May 14, 1999. Extreme returns are defined as exceedances beyond a threshold, θ. For example, "top tail" ("bottom tail") exceedances for China's daily index returns correspond to the subset of ordered returns that comprise the highest (lowest) five percent of all returns. Co-exceedances represent joint occurrences of exceedances across country indices by day. A co-exceedance of i means that i countries have an exceedance jointly. Co-exceedances are reported for i = 1,…,6 separately and for i equal to seven or more as >7. For example, of 880 trading days, there are 50 occurrences of bottom tail co-exceedances for Asia with two countries only, and 13 of those occurrences include China with co-exceedances of a particular number. "Cum. %" cumulates the fraction of the total number of return observations (880 days) by category. Numbers in parenthesis are the number of Mondays.

		Number of (co-) exceedances in the bottom tails								Number of (co-) exceedances in the top tails								
	Mean return when > 7	> 7	6	5	4	3	2	1	0	0	1	2	3	4	5	6	> 7	Mean return when > 7
CHN	-3.63%	1	1	2	5	8	13	14	614	600	15	14	4	2	5	2	2	7.23%
KOR	-8.09%	1	2	4	1	10	11	15	614	600	15	14	1	8	3	2	1	8.78%
PHI	-9.70%	1	1	4	6	7	9	16	614	600	14	8	5	9	4	2	2	11.20%
TWN	-4.22%	1	2	3	3	4	10	21	614	600	29	3	4	4	1	1	2	5.89%
INA	-5.30%	2	2	2	3	2	6	27	614	600	27	8	2	2	3	1	1	3.46%
IND	-9.70%	2	1	3	5	13	8	12	614	600	12	10	7	8	4	1	2	23.40%
MAL	-5.29%	2	3	5	4	7	13	10	614	600	13	10	8	7	4	1	1	10.60%
PAK	-5.63%	1	2	2	1	4	11	23	614	600	28	12	0	2	1	0	1	3.70%
SRI	-5.90%	1	1	2	2	5	9	24	614	600	33	7	1	3	0	0	0	-
THA	-8.21%	2	3	3	6	9	10	11	614	600	9	12	7	7	5	2	2	13.82%
Total	-6.57%	2(1)	3(1)	6(2)	9(3)	23(4)	50(10)	173(42)	614(113)	600(109)	195(46)	49(10)	13(3)	13(5)	6(1)	2(1)	2(1)	9.79%
Cum. %		0.2%	0.6%	1.3%	2.3%	4.9%	10.6%	30.2%	100.0%	100.0%	31.8%	9.7%	4.1%	2.6%	1.1%	0.5%	0.2%	
ARG	-11.91%	4	6	5	5	9	7	8	728	680	13	11	8	7	4	0	1	8.43%
BRA	-13.34%	4	5	5	5	10	4	11	728	680	14	15	7	4	3	0	1	8.93%
CHI	-5.55%	4	6	5	6	4	6	13	728	680	15	14	5	5	4	0	1	6.23%
COL	-3.63%	4	3	3	2	3	5	24	728	680	31	7	1	2	2	0	1	2.16%
MEX	-10.18%	4	6	6	5	8	11	4	728	680	16	11	7	6	3	0	1	7.00%
PER	-6.44%	4	4	3	5	4	8	16	728	680	18	9	6	7	3	0	1	5.67%
VEN	-5.69%	4	6	3	4	7	7	13	728	680	31	5	5	1	1	0	1	6.80%
Total	-8.11%	4(1)	6(0)	6(0)	8(2)	15(5)	24(5)	89(19)	728(144)	680(136)	138(25)	36(9)	13(5)	8(1)	4(0)	0(0)	1(0)	6.46%
Cum. %		0.5%	1.1%	1.8%	2.7%	4.4%	7.2%	17.3%	100.0%	100.0%	22.7%	7.0%	3.0%	1.5%	0.6%	0.1%	0.1%	

Table 3. Monte Carlo simulation results of (co-) exceedances for daily emerging market returns. Under the null hypothesis that national emerging market index returns in Asia and Latin America are drawn from a multivariate Student-t distribution, we employ a Monte Carlo simulation to evaluate the number of (co-) exceedances within each region. We compute the sample mean and the variance-covariance matrix of returns and generate 5000 random realizations. For each realization we compute the number of (co-) exceedances for a random threshold θ where θ equals five percent as in Table 2. Summary statistics of the distribution of co-exceedance counts across the 5000 replications include the mean, standard deviation, 5% quantile, 95% quantile, and simulated p-value (the number of replications with co-exceedances in a given category exceeding the actual number of co-exceedances). Four different scenarios are run which reflect the degrees of freedom underlying the multivariate Student-t distribution, where degrees of freedom equal N + K – 1, where N is the sum of number of countries (10 for Asia, 7 for Latin America) and K equals 1 (high excess kurtosis and co-kurtosis), 5, 10 and 25 (low excess kurtosis and co-kurtosis, approximating multivariate Normal distribution).

Panel A: Asia

	Number of (co-) exceedances in the bottom tails								Number of (co-) exceedances in the top tails							
	> 7	6	5	4	3	2	1	0	0	1	2	3	4	5	6	> 7
Actual	2	3	6	9	23	50	173	614	600	195	49	13	13	6	2	2
Monte Carlo Simulations																
A. High Co-kurtosis (K=1) Scenario																
Simulated Mean	10.05	8.59	12.11	16.49	22.41	32.01	54.27	723.06	722.50	54.76	32.13	22.35	16.73	12.12	8.58	9.83
Standard Deviation	2.79	2.68	3.12	3.74	4.75	5.69	7.92	8.26	8.18	8.06	5.48	4.38	3.72	3.14	2.61	2.59
(5th, 95th) quantile	(6,15)	(5,13)	(7,17)	(11,23)	(15,30)	(23,42)	(41,67)	(710,737)	(709,735)	(42,68)	(23,41)	(15,29)	(10,23)	(7,18)	(6,13)	(6,14)
p-value	1.00	0.99	0.98	0.98	0.38	0.00	0.00	1.00	1.00	0.00	0.00	0.98	0.81	0.98	1.00	1.00
B. Moderately High Co-kurtosis (K=5) Scenario																
Simulated Mean	1.53	2.65	5.61	12.00	24.87	56.05	150.04	626.25	626.21	150.21	55.98	24.78	11.91	5.72	2.64	1.54
Standard Deviation	1.22	1.54	2.32	3.20	4.61	6.74	10.69	8.39	8.85	11.54	6.68	4.31	3.13	2.29	1.58	1.17
(5th, 95th) quantile	(0,4)	(0,6)	(2,10)	(7,18)	(18,33)	(45,68)	(133,168)	(612,640)	(611,640)	(132,169)	(45,67)	(18,32)	(7,18)	(2,10)	(0,5)	(0,4)
p-value	0.20	0.26	0.34	0.78	0.61	0.80	0.01	0.93	1.00	0.00	0.84	1.00	0.28	0.34	0.48	0.20
C. Moderately Low Co-kurtosis (K=10) Scenario																
Simulated Mean	0.59	1.51	3.95	9.73	23.32	60.51	177.03	602.36	602.66	176.84	60.28	23.35	9.77	3.94	1.53	0.63
Standard Deviation	0.77	1.17	1.87	2.79	4.02	6.59	11.86	8.42	8.59	11.69	6.86	4.43	2.80	1.94	1.24	0.77
(5th, 95th) quantile	(0,2)	(0,4)	(1,7)	(5,14)	(17,30)	(50,71)	(157,197)	(589,616)	(588,616)	(158,196)	(49,71)	(16,31)	(5,15)	(1,7)	(0,4)	(0,2)
p-value	0.02	0.05	0.09	0.52	0.47	0.94	0.64	0.07	0.59	0.06	0.94	0.99	0.09	0.10	0.19	0.02
D. Low Co-kurtosis (K=25) Scenario																
Simulated Mean	0.31	0.87	2.89	7.87	21.86	62.77	195.48	586.95	586.41	196.60	62.13	21.89	8.00	2.76	0.93	0.29
Standard Deviation	0.56	0.94	1.59	2.56	4.08	6.61	11.28	7.77	7.69	11.25	6.76	4.13	2.65	1.61	0.93	0.52
(5th, 95th) quantile	(0,1)	(0,3)	(1,6)	(4,12)	(15,29)	(52,74)	(177,214)	(575,600)	(574,599)	(179,216)	(51,73)	(15,28)	(4,12)	(0,6)	(0,3)	(0,1)
p-value	0.01	0.01	0.02	0.26	0.33	0.97	0.98	0.00	0.03	0.52	0.97	0.98	0.03	0.02	0.06	0.00

Table 3. Continued.

Panel B: Latin America

	Number of (co-) exceedances in the bottom tails								Number of (co-) exceedances in the top tails							
	> 7	6	5	4	3	2	1	0	0	1	2	3	4	5	6	> 7
Actual	4	6	6	8	15	24	89	728	680	138	36	13	8	4	0	1
Monte Carlo Simulations																
A. High Co-kurtosis (K=1) Scenario																
Simulated Mean	1.16	4.11	8.32	13.86	20.49	30.79	55.13	745.14	744.77	55.24	31.17	20.71	13.54	8.43	4.05	1.10
Standard Deviation	1.07	1.89	2.54	3.22	4.10	5.39	7.85	6.97	7.21	8.20	5.45	4.15	3.37	2.67	1.87	1.00
(5th, 95th) quantile	(0,3)	(1,8)	(4,13)	(9,19)	(14,27)	(22,40)	(43,68)	(733,756)	(733,756)	(42,69)	(23,40)	(14,28)	(8,19)	(4,13)	(1,7)	(0,3)
p-value	0.00	0.11	0.76	0.96	0.93	0.87	0.00	0.99	1.00	0.00	0.15	0.97	0.94	0.93	0.99	0.31
B. Moderately High Co-kurtosis (K=5) Scenario																
Simulated Mean	0.10	0.66	2.54	6.89	17.06	42.23	127.45	682.07	682.02	127.59	42.14	16.97	7.08	2.40	0.70	0.10
Standard Deviation	0.30	0.78	1.50	2.40	3.58	5.56	9.87	6.93	7.35	10.39	5.75	3.72	2.33	1.50	0.81	0.31
(5th, 95th) quantile	(0,1)	(0,2)	(0,5)	(3,11)	(12,23)	(33,52)	(111,145)	(670,693)	(670,694)	(110,145)	(33,52)	(11,23)	(3,11)	(0,5)	(0,2)	(0,1)
p-value	0.00	0.00	0.01	0.25	0.75	1.00	1.00	0.00	0.60	0.15	0.85	0.81	0.27	0.10	0.51	0.00
C. Moderately Low Co-kurtosis (K=10) Scenario																
Simulated Mean	0.03	0.32	1.49	5.16	15.01	43.18	146.35	667.45	667.79	145.91	43.15	15.03	5.27	1.51	0.31	0.03
Standard Deviation	0.18	0.55	1.18	2.14	3.42	5.49	10.07	6.73	7.01	10.43	5.47	3.42	2.08	1.24	0.56	0.17
(5th, 95th) quantile	(0,0)	(0,1)	(0,4)	(2,9)	(10,21)	(34,52)	(129,163)	(656,679)	(656,679)	(129,163)	(34,52)	(10,21)	(2,9)	(0,4)	(0,1)	(0,0)
p-value	0.00	0.00	0.00	0.07	0.55	1.00	1.00	0.00	0.03	0.76	0.90	0.65	0.07	0.02	0.27	0.00
D. Low Co-kurtosis (K=25) Scenario																
Simulated Mean	0.01	0.13	0.93	4.13	13.52	42.90	159.59	657.78	658.06	159.07	43.10	13.62	4.08	0.89	0.17	0.02
Standard Deviation	0.11	0.37	0.95	1.95	3.26	5.32	9.79	6.51	6.54	9.99	5.45	3.29	1.94	0.92	0.41	0.13
(5th, 95th) quantile	(0,0)	(0,1)	(0,3)	(1,7)	(9,19)	(34,52)	(144,176)	(647,668)	(648,669)	(143,175)	(35,53)	(9,19)	(1,7)	(0,3)	(0,1)	(0,0)
p-value	0.00	0.00	0.00	0.02	0.37	1.00	1.00	0.00	0.00	0.98	0.90	0.49	0.02	0.00	0.15	0.00

Table 4. Multinomial logit regression results for daily return co-exceedances of emerging market indices, December 31, 1995 to May 14, 1999. The number of co-exceedances of daily returns is modeled as an ordered polychotomous variable and estimated using a multinomial logit regression model. P_j is defined as the probability that a given day is associated with j co-exceedances where j equals 0, 1, 2, 3, 4 or more (five categories). The multinomial logit regression model is given by

$$P_j = \exp(x'\beta_j) / [1 + \textstyle\sum_k \exp(x'\beta_k)]$$

where β is the vector of coefficients, x, the vector of independent variables, and k equals 1 to 4. The probability that there are no (co-) exceedances equals $P_0 = 1 / [1 + \sum_k \exp(x'\beta_k)]$, which represents our base case. The independent variables, x, include the intercept, conditional volatility of regional index at time t (h_t), the average exchange rate (per \$US) changes in the region (e_t), and the average interest rate level in the region (i_t). The conditional volatility is estimated as EGARCH(1,1) using the IFC investible regional index. The likelihood for the multinomial logit model (McFadden, 1975) is numerically evaluated using the Broyden, Fletcher, Goldfarb, and Shanno algorithm. Partial derivatives of probabilities with respect to the vector of independent variables are computed at the means of x (Greene, 1997, Chapter 19) and are reported next to the coefficient estimates. Goodness of fit is measured by McFadden's pseudo-R^2 equal to 1- (L_ω/L_Ω) where L_ω is the unrestricted likelihood, and L_Ω is the restricted likelihood (Maddala, 1983, Chapter 2). The logit regression is estimated separately for positive (top tail) and negative (bottom tail) co-exceedances. $^{a, b, c}$ denotes significance levels at the 1%, 5%, and 10%, respectively.

	Bottom tails						Top tails					
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.
Asia												
β_{01} (constant)	-1.267^{a}	-0.140^{a}	-2.450^{a}	-0.309^{a}	-3.948^{a}	-0.568^{a}	-1.124^{a}	-0.132^{a}	-1.623^{a}	-0.204^{a}	-2.066^{a}	-0.304^{a}
β_{02}	-2.508^{a}	-0.111^{a}	-4.596^{a}	-0.176^{a}	-6.407^{a}	-0.234^{a}	-2.505^{a}	-0.110^{a}	-4.253^{a}	-0.166^{a}	-4.863^{a}	-0.165^{a}
β_{03}	-3.285^{a}	-0.071^{a}	-5.561^{a}	-0.097^{a}	-7.570^{a}	-0.083^{a}	-3.832^{a}	-0.049^{a}	-6.361^{a}	-0.055^{b}	-5.970^{a}	-0.033
β_{04}	-3.424^{a}	-0.065^{a}	-6.702^{a}	-0.073^{b}	-9.736^{a}	-0.040	-3.261^{a}	-0.071^{a}	-5.805^{a}	-0.087^{a}	-6.955^{a}	-0.056^{c}
β_{11} (h_{it})			1.109^{a}	0.146^{a}	0.663^{a}	0.095^{a}			0.482^{a}	0.057^{b}	0.519^{a}	0.073^{c}
β_{12}			1.780^{a}	0.067^{a}	1.210^{a}	0.045^{a}			1.469^{a}	0.058^{a}	1.490^{a}	0.052^{a}
β_{13}			1.906^{a}	0.032^{b}	0.977^{a}	0.010			1.968^{a}	0.017^{c}	2.070^{a}	0.012^{c}
β_{14}			2.510^{a}	0.027^{b}	1.572^{a}	0.006			1.977^{a}	0.030^{b}	1.791^{a}	0.014^{c}
β_{21} (e_{it})					1.339^{a}	0.194^{a}					-0.821^{a}	-0.119^{a}
β_{22}					1.946^{a}	0.069^{a}					-2.017^{a}	-0.069^{a}
β_{23}					2.934^{a}	0.033^{a}					-2.834^{a}	-0.016^{c}
β_{24}					3.317^{a}	0.014^{c}					-2.887^{a}	-0.023^{b}
β_{31} (i_{it})					0.152^{a}	0.023^{a}					0.037	0.006
β_{32}					0.176^{a}	0.006^{b}					0.040	0.001
β_{33}					0.185^{a}	0.002					-0.061	0.000
β_{34}					0.223^{a}	0.001					0.065	0.001
Log-Likelihood	-805.303		-743.914		-660.785		-803.779		-765.002		-709.020	
Pseudo-R^2			7.62%		17.95%				4.82%		11.79%	

Table 4. Continued.

	Bottom tails						Top tails					
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.
Latin												
β_{01} (constant)	-2.102^{a}	-0.166^{a}	-2.828^{a}	-0.223^{a}	-3.359^{a}	-0.268^{a}	-1.595^{a}	-0.174^{a}	-1.938^{a}	-0.220^{a}	-2.918^{a}	-0.341^{a}
β_{02}	-3.412^{a}	-0.080^{a}	-4.344^{a}	-0.096^{a}	-2.598^{a}	-0.045^{c}	-2.939^{a}	-0.100^{a}	-3.681^{a}	-0.123^{a}	-4.702^{a}	-0.126^{a}
β_{03}	-3.882^{a}	-0.058^{a}	-4.876^{a}	-0.067^{a}	-4.200^{a}	-0.049^{b}	-3.957^{a}	-0.051^{a}	-5.614^{a}	-0.050^{b}	-4.841^{a}	-0.039^{c}
β_{04}	-3.412^{a}	-0.080^{a}	-4.894^{a}	-0.088^{a}	-5.549^{a}	-0.067^{b}	-3.957^{a}	-0.051^{a}	-5.872^{a}	-0.046^{b}	-6.618^{a}	-0.045^{c}
β_{11} (h_{it})			0.486^{a}	0.039^{a}	0.511^{a}	0.040^{a}			0.246^{a}	0.027^{b}	0.270^{a}	0.030^{b}
β_{12}			0.595^{a}	0.013^{a}	0.746^{a}	0.014^{b}			0.488^{a}	0.016^{a}	0.503^{a}	0.013^{b}
β_{13}			0.626^{a}	0.008^{b}	0.705^{a}	0.008^{b}			0.883^{a}	0.008^{b}	1.046^{a}	0.009^{b}
β_{14}			0.833^{a}	0.015^{a}	0.808^{a}	0.010^{b}			0.965^{a}	0.008^{b}	1.049^{a}	0.007^{b}
β_{21} (e_{it})					3.271^{a}	0.259^{a}					-2.620^{a}	-0.312^{a}
β_{22}					3.726^{a}	0.069^{a}					-4.187^{a}	-0.114^{a}
β_{23}					4.112^{a}	0.048^{b}					-2.500^{a}	-0.018
β_{24}					5.266^{a}	0.063^{a}					-3.299^{a}	-0.021^{c}
β_{31} (i_{it})					0.017	0.002					0.057^{b}	0.007^{b}
β_{32}					-0.132^{b}	-0.003					0.053	0.001
β_{33}					-0.065	-0.001					-0.057	-0.001
β_{34}					0.002	0.000					0.035	0.000
Log-Likelihood	-575.936		-546.435		-502.041		-655.652		-627.044		-593.904	
Pseudo-R^2				5.12%		12.83%				4.37%		9.42%
US												
β_{01} (constant)	-2.944^{a}	-0.140^{a}	-3.522^{a}	-0.164^{a}	-4.647^{b}	-0.211^{a}	-2.944^{a}	-0.140^{a}	-4.243^{a}	-0.181^{a}	-2.680	-0.114
β_{11} (h_{it})			0.456^{c}	0.021^{a}	0.375	0.017			0.970^{a}	0.041^{a}	0.996^{a}	0.042^{a}
β_{21} (e_{it})					0.609^{c}	0.028^{b}					-0.086	-0.004
β_{31} (i_{it})					0.226	0.010					-0.301	-0.013
Log-Likelihood	-174.693		-173.318		-171.582		-174.693		-165.777		-165.518	
Pseudo-R^2				0.79%		1.79%				5.11%		5.53%
Europe												
β_{01} (constant)	-2.944^{a}	-0.140^{a}	-4.764^{a}	-0.178^{a}	-2.868^{a}	-0.099^{b}	-2.944^{a}	-0.140^{a}	-5.631^{a}	-0.165^{a}	-3.168^{a}	-0.082^{b}
β_{11} (h_{it})			1.907^{a}	0.071^{a}	1.680^{a}	0.058^{a}			2.649^{a}	0.078^{a}	2.514^{a}	0.065^{a}
β_{21} (e_{it})					-0.565^{b}	-0.020^{b}					0.023	0.001
β_{31} (i_{it})					-0.418	-0.014					-0.582^{c}	-0.015^{a}
Log-Likelihood	-174.693		-158.750		-155.934		-174.693		-142.518		-140.722	
Pseudo-R^2				9.92%		10.74%				18.41%		19.45%

Table 5. Contagion test results of multinomial logit regression for daily return co-exceedances of emerging market indices, December 31, 1995 to May 14, 1999. The number of co-exceedances of daily returns is modeled as an ordered polychotomous variable and estimated using a multinomial logit regression model. P_j is defined as the probability that a given day is associated with j co-exceedances where j equals 0, 1, 2, 3, 4 or more (five categories). The multinomial logit regression model is given by

$$P_j = \exp(x'\beta_j) / [1 + \sum_k \exp(x'\beta_k)]$$

where β is the vector of coefficients, x, the vector of independent variables, and k equals 1 to 4. The probability that there are no (co-) exceedances equals $P_0 = 1 / [1 + \sum_{k=1,4}\exp(x'\beta_k)]$, which represents our base case. The independent variables, x, include those in Table 3 plus the number of daily return co-exceedances from another region (Y^*) and a measure of conditional volatility from another region (h^*_j). The conditional volatility is estimated as EGARCH(1,1) using the IFC investible regional index. Partial derivatives of probabilities with respect to the vector of independent variables are computed at the means of x and are reported next to the coefficient estimates. Goodness of fit is measured by McFadden's pseudo-R^2 equal to 1- (L_ω/L_Ω) where L_ω is the unrestricted likelihood, and L_Ω is the restricted likelihood (Maddala, 1983, Chapter 2). The logit regression is estimated separately for positive (top tail) and negative (bottom tail) co-exceedances. χ^2 (h_{jt}^*) and χ^2 (Y_{jt}^*) are Wald chi-squared tests for the restrictions that $\beta_{k1}= \beta_{k2}= \beta_{k3}=\beta_{k4}=0$ where k is 4 and 5, respectively. $^{a, b, c}$ denotes significance levels at the 1%, 5%, and 10%, respectively.

	Bottom tails						Top tails					
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.
Asia	From Latin		From US		From Europe		From Latin		From US		From Europe	
β_{01} (constant)	-4.175^{a}	-0.609^{a}	-4.522^{a}	-0.662^{a}	-4.386^{a}	-0.643^{a}	-2.207^{a}	-0.334^{a}	-1.838^{a}	-0.260^{a}	-2.244^{a}	-0.341^{a}
β_{02}	-6.775^{a}	-0.242^{a}	-7.338^{a}	-0.261^{a}	-6.660^{a}	-0.240^{a}	-5.283^{a}	-0.175^{a}	-5.400^{a}	-0.176^{a}	-4.933^{a}	-0.165^{a}
β_{03}	-8.729^{a}	-0.071^{c}	-8.797^{a}	-0.077^{c}	-9.128^{a}	-0.060^{c}	-7.103^{a}	-0.031	-7.000^{a}	-0.039	-6.753^{a}	-0.034
β_{04}	-10.17^{a}	-0.034	-10.89^{a}	-0.029	-10.52^{a}	-0.030	-9.125^{a}	-0.045	-8.848^{a}	-0.057^{c}	-9.263^{a}	-0.043
β_{11} (h_{it})	0.255	0.036	0.420^{b}	0.059	0.258	0.033	0.454^{b}	0.066	0.607^{a}	0.095^{b}	0.285	0.036
β_{12}	0.682^{c}	0.026	0.848^{a}	0.031^{c}	0.918^{a}	0.037^{b}	1.408^{a}	0.048^{b}	1.238^{a}	0.039^{b}	1.261^{a}	0.045^{a}
β_{13}	-0.076	-0.002	0.818^{b}	0.007	0.442	0.003	1.960^{a}	0.009	1.522^{a}	0.008	1.671^{a}	0.009
β_{14}	1.063^{c}	0.004	1.558^{a}	0.004	1.261^{a}	0.004	1.117^{b}	0.005	0.922^{c}	0.005	1.263^{a}	0.006
β_{21} (e_{it})	1.354^{a}	0.198^{a}	1.342^{a}	0.197^{a}	1.402^{a}	0.206^{a}	-0.787^{a}	-0.119^{a}	-0.817^{a}	-0.121^{a}	-0.764^{a}	-0.114^{a}
β_{22}	2.007^{a}	0.070^{a}	1.995^{a}	0.070^{a}	1.997^{a}	0.071^{a}	-1.906^{a}	-0.063^{a}	-2.015^{a}	-0.065^{a}	-1.921^{a}	-0.065^{a}
β_{23}	3.209^{a}	0.027^{b}	2.986^{a}	0.027^{b}	3.226^{a}	0.021^{b}	-2.723^{a}	-0.012^{c}	-2.860^{a}	-0.016^{c}	-2.761^{a}	-0.014^{c}
β_{24}	3.445^{a}	0.011	3.381^{a}	0.009	3.505^{a}	0.010	-2.846^{a}	-0.014^{c}	-3.000^{a}	-0.019^{b}	-2.893^{a}	-0.013^{c}
β_{31} (i_{it})	0.175^{a}	0.027^{a}	0.172^{a}	0.026^{a}	0.155^{a}	0.024^{a}	0.046^{b}	0.008	0.029	0.004	0.036	0.006
β_{32}	0.210^{a}	0.007^{b}	0.211^{a}	0.007^{b}	0.178^{a}	0.006^{b}	0.066	0.002	0.076	0.002	0.041	0.001
β_{33}	0.259^{a}	0.002	0.237^{a}	0.002	0.206^{a}	0.001	0.001	0.000	-0.001	0.000	-0.054	0.000
β_{34}	0.249^{a}	0.001	0.826^{a}	0.001	0.241^{a}	0.001	0.198^{b}	0.001	0.166^{b}	0.001	0.113	0.001
β_{41}(h_{jt}^*)	0.174^{c}	0.026	0.433^{a}	0.066^{c}	0.959^{a}	0.151^{a}	-0.013	-0.002	-0.167	-0.034	0.488^{c}	0.083
β_{42}	0.225	0.008	0.625^{a}	0.022^{c}	0.552	0.014	-0.048	-0.002	0.162	0.007	0.261	0.005
β_{43}	0.559^{a}	0.005	0.301	0.002	1.405^{a}	0.009	-0.096	0.000	0.640^{c}	0.004	1.153^{c}	0.006
β_{44}	0.123	0.000	-0.203	-0.001	0.423	0.001	0.224	0.001	0.972^{a}	0.007^{c}	1.988^{a}	0.009
β_{51} (Y_{jt}^*)	0.319^{a}	0.048^{a}	0.646^{c}	0.091	0.176	0.011	0.311^{a}	0.049^{b}	-0.538	-0.114	0.626	0.098
β_{52}	0.397^{a}	0.013^{b}	1.047^{c}	0.036	1.198^{b}	0.048^{c}	0.576^{a}	0.018^{b}	1.505^{a}	0.059^{a}	1.447^{a}	0.049^{b}
β_{53}	0.643^{a}	0.005^{c}	2.390^{a}	0.023^{c}	2.809^{a}	0.021^{c}	0.933^{a}	0.004	0.331	0.002	0.927	0.004
β_{54}	0.731^{a}	0.002	2.974^{a}	0.008	2.806^{a}	0.009	0.988^{a}	0.005^{c}	1.399^{b}	0.010	1.093^{c}	0.004
Log-Likelihood	-644.588		-647.525		-637.479		-690.851		-695.796		-694.985	
Pseudo-R^2	19.96%		19.59%		20.84%		14.04%		13.43%		13.54%	
χ^2 (h_{jt}^*)	8.434^{c}		10.308^{b}		16.733^{a}		2.241		12.875^{a}		17.078^{a}	
χ^2 (Y_{jt}^*)	21.211^{a}		25.826^{a}		31.515^{a}		31.772^{a}		15.609^{a}		9.454^{b}	

Table 5. Continued.

	Bottom tails						Top tails					
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.
Latin	From Asia		From US		From Europe		From Asia		From US		From Europe	
β_{01} (constant)	-3.681[a]	-0.294[a]	-3.388[a]	-0.276[a]	-4.057[a]	-0.327[a]	-2.753[a]	-0.323[a]	-2.459[a]	-0.288[a]	-3.175[a]	-0.380[a]
β_{02}	-3.382[a]	-0.055[c]	-3.224[a]	-0.051[c]	-3.445[a]	-0.058[b]	-4.798[a]	-0.126[a]	-4.453[a]	-0.106[a]	-5.557[a]	-0.136[a]
β_{03}	-5.093[a]	-0.053[c]	-4.207[a]	-0.039[c]	-5.216[a]	-0.053[b]	-5.312[a]	-0.037[c]	-6.046[a]	-0.040[c]	-5.657[a]	-0.025
β_{04}	-7.219[a]	-0.058[c]	-7.113[a]	-0.047[c]	-6.863[a]	-0.045[c]	-6.757[a]	-0.033	-6.245[a]	-0.034[c]	-7.220[a]	-0.038
β_{11} (h_{it})	0.332[a]	0.026[b]	0.483[a]	0.039[a]	0.057	0.004	0.387[a]	0.046[b]	0.427[a]	0.051[b]	0.050	0.006
β_{12}	0.615[a]	0.011[b]	0.551[a]	0.009[c]	0.178	0.003	0.513[a]	0.013[c]	0.662[a]	0.016[c]	-0.150	-0.004
β_{13}	0.487[b]	0.005	0.728[a]	0.007[c]	0.072	0.001	1.012[a]	0.007[c]	0.585[b]	0.004	0.385	0.002
β_{14}	0.435[b]	0.003	0.417[c]	0.002	0.051	0.000	1.324[a]	0.007[c]	1.278[a]	0.007[c]	0.547[a]	0.003
β_{21} (e_{it})	3.164[a]	0.253[a]	3.084[a]	0.252[a]	3.116[a]	0.249[a]	-2.531[a]	-0.304[a]	-2.727[a]	-0.329[a]	-2.576[a]	-0.313[a]
β_{22}	3.497[a]	0.058[b]	3.450[a]	0.056[b]	3.474[a]	0.061[b]	-4.156[a]	-0.110[a]	-4.429[a]	-0.106[a]	-4.392[a]	-0.108[a]
β_{23}	3.977[a]	0.041[b]	3.607[a]	0.033[c]	3.889[a]	0.039[c]	-2.442[b]	-0.015	-2.573[a]	-0.015	-2.327[c]	-0.009
β_{24}	5.485[a]	0.044[b]	5.321[a]	0.035[b]	5.126[a]	0.033[b]	-3.146[a]	-0.014	-3.885[a]	-0.020	-2.802[a]	-0.013
β_{31} (i_{it})	0.021	0.002	0.021	0.002	0.029	0.003	0.060[a]	0.008[b]	0.055[b]	0.007[c]	0.060[a]	0.008[b]
β_{32}	-0.086	-0.002	-0.128[b]	-0.002	-0.129[a]	-0.003	0.061	0.002	0.063[a]	0.001	0.049	0.001
β_{33}	-0.038	0.000	-0.062	-0.001	-0.058	-0.001	-0.048	0.000	-0.039	0.000	-0.133	-0.001
β_{34}	0.018	0.000	0.003	0.000	-0.025	0.000	0.103	0.000	0.044	0.000	0.014	0.000
β_{41}(h_{jt}^*)	0.432[c]	0.036	0.029	0.001	1.320[a]	0.105[b]	-0.469[b]	-0.058[c]	-0.547[c]	-0.068	0.630	0.070
β_{42}	-0.243	-0.006	0.454	0.008	1.754[a]	0.031	-0.291	-0.006	-0.736	-0.017	2.095[a]	0.054[b]
β_{43}	0.352	0.004	-0.374	-0.004	1.867[a]	0.019	-0.125	0.000	0.975[b]	0.008	2.879[a]	0.014
β_{44}	1.216[a]	0.010	1.060[a]	0.007	2.544[a]	0.017	-2.024[a]	-0.010	-0.982	-0.005	1.589[b]	0.008
β_{51} (Y_{jt}^*)	0.808	0.005	-0.427	-0.046	1.002[b]	0.077[c]	0.218[b]	0.025[c]	0.446	0.043	0.204	0.022
β_{52}	0.625[a]	0.011[b]	2.468[a]	0.045[b]	1.571[a]	0.028[c]	0.429[a]	0.011[b]	2.326[a]	0.059[a]	0.429	0.010
β_{53}	0.482[a]	0.005	2.892[a]	0.029[b]	2.137[a]	0.022[c]	0.623[a]	0.004	2.248[a]	0.015	1.543[a]	0.008
β_{54}	0.408[b]	0.003	3.418[a]	0.024[c]	3.055[a]	0.021[c]	0.798[a]	0.004	2.552[a]	0.014	1.940[a]	0.011
Log-Likelihood	-486.539		-470.333		-474.289		-581.178		-575.472		-574.989	
Pseudo-R^2	15.52%		18.34%		17.65%		11.36%		12.33%		12.31%	
χ^2 (h_{jt}^*)	10.023[b]		8.921[c]		23.167[a]		9.842[b]		12.992[a]		22.763[a]	
χ^2 (Y_{jt}^*)	17.933[a]		65.230[a]		36.074[a]		20.815[a]		33.485[a]		12.520[a]	
US	From Asia		From Latin		From Europe		From Asia		From Latin		From Europe	
β_1 (constant)	-4.533[c]	-0.204[b]	-4.281[c]	-0.128[c]	-4.529[b]	-0.173[c]	-1.591	-0.064	-4.039[c]	-0.152[c]	-3.759	-0.141
β_2 (h_{it})	0.381	0.017	-0.639[c]	-0.019	-0.301	-0.012	0.738[a]	0.030[a]	0.518	0.019	0.463[c]	0.017
β_3 (e_{it})	0.611[c]	0.027[c]	0.599[c]	0.018[c]	0.632[c]	0.024[c]	-0.069	-0.003	-0.086	-0.003	-0.134	-0.005
β_4 (i_{it})	0.213	0.010	0.193	0.006	0.165	0.006	-0.596	-0.024	-0.035	-0.001	-0.133	-0.005
β_4 (h_{jt}^*)	-0.131	-0.006	0.202	0.006	0.909[c]	0.035[c]	0.705	0.028[b]	0.125	0.005	0.758[c]	0.028
β_4 (Y^*_{jt})	0.167	0.008	0.976[a]	0.029[a]	2.063[a]	0.079[a]	-0.023	-0.001	0.622[a]	0.023[a]	1.633[a]	0.061[a]
Log-Likelihood	-171.119		-136.513		-157.298		-162.882		-155.099		-155.712	
Pseudo-R^2	2.05%		21.86%		9.96%		6.77%		11.22%		10.77%	
χ^2 (h_{jt}^*)	0.168		0.961		3.685[c]		2.532		0.599		2.925[c]	
χ^2 (Y_{jt}^*)	0.905		66.565[a]		23.161[a]		0.022		22.363[a]		15.163[a]	
Europe	From Asia		From Latin		From US		From Asia		From Latin		From US	
β_1 (constant)	-2.830[a]	-0.079[c]	-2.626[b]	-0.079[c]	-3.249[a]	-0.103[b]	-3.154[a]	-0.076[c]	-3.491[a]	-0.091[b]	-3.257[a]	-0.084[b]
β_2 (h_{it})	1.362[a]	0.038[a]	0.896[c]	0.027	1.521[a]	0.048[a]	2.223[a]	0.053[a]	2.563[a]	0.067[a]	2.545[a]	0.065[a]
β_3 (e_{it})	-0.505[b]	-0.014[c]	-0.410	-0.012	-0.339	-0.011	0.027	0.001	0.017	0.000	-0.007	0.000
β_4 (i_{it})	-0.560[c]	-0.016[c]	-0.433	-0.013	-0.362	-0.012	-0.627[b]	-0.015[b]	-0.498	-0.013[c]	-0.546[c]	-0.014[c]
β_4 (h_{jt}^*)	0.319	0.009	0.083	0.002	0.071	0.002	0.169	0.004	-0.119	-0.003	-0.113	-0.003
β_4 (Y^*_{jt})	0.531[a]	0.015[a]	0.628[a]	0.019[a]	1.871[a]	0.059[a]	0.322[a]	0.008[b]	0.276[c]	0.007[c]	0.742	0.019
Log-Likelihood	-146.433		-142.984		-147.557		-137.632		-138.974		-139.696	
Pseudo-R^2	6.18%		19.16%		15.53%		21.22%		20.45%		20.04%	
χ^2 (h_{jt}^*)	1.023		0.259		0.057		0.271		0.593		0.163	
χ^2 (Y_{jt}^*)	16.604[a]		28.101[a]		18.956[a]		5.416[b]		3.681[c]		2.276	

Table 6. Monte Carlo simulation results of contagion tests using multinomial logit regression for daily return co-exceedances of emergin market indices. Under the null hypothesis that international emerging market index returns in Asia and Latin America are drawn from a multivariate Student-t distribution, we employ a Monte Carlo simulation to evaluate the impact of the number of co-exceedances in one region on that of the other region. For each realization, we compute the number of (co-) exceedances for a threshold θ where θ equals 5% as in Tables 2 and 3. We compute the sample mean and covariance matrix of returns for all 10 Asian and 7 Latin American indices and generate 1000 random realizations. For each realization, we model and estimate the number of co-exceedances as an ordered polychotomous variable using a multinomial logit regression model. P_j is defined as the probability that a given day is associated with j co-exceedances where j equals 0, 1, 2, 3, 4 or more (five categories). The multinomial logit regression model is given by,

$$P_j = \exp(x'\beta_j) / [1 + \sum_k \exp(x'\beta_k)]$$

where β is the vector of coefficients, x, the vector of independent variables, and k equals 1 to 4. The probability that there are no (co-) exceedances equals $P_0 = 1 / [1 + \sum_{k=1,4}\exp(x'\beta_k)]$, which represents our base case. The independent variables, x, include only a constant and the co-exceedances in the other region, as generated by the simulation. The first column reports estimates for the actual indices. [a, b, c] denotes significance levels at the 1%, 5%, and 10%, respectively. Goodness of fit is measured by McFadden's pseudo-R^2 equal to 1- (L_ω/L_Ω) where n is the number of observations, L_ω is the unrestricted likelihood, and L_Ω is the restricted likelihood (Maddala, 1983, Chapter 2). The logit regression is estimated separately for positive (top tail) and negative (bottom tail) co-exceedances. Four different scenarios are run which reflect the degrees of freedom underlying the multivariate Student-t distribution, where degrees of freedom equal N + K – 1, where N is the sum of number of countries (17 in total with 10 for Asia, 7 for Latin America) and K equals 1 (high excess kurtosis and co-kurtosis), 5, 10 and 25 (low excess kurtosis and co-kurtosis, approximating multivariate Normal distribution). For each scenario, we report the mean, standard deviation ("S.D."), 5% and 95% fractiles of the 1000 replications. We also compute the simulation p-value ("p-val") which counts the number of simulation estimates that are greater than those with the actual data.

Panel A. Asia

	Actual	High Co-kurtosis (K=1) Scenario					Moderately High Co-kurtosis (K=5) Scenario					Moderately Low Co-kurtosis (K=10) Scenario					Low Co-kurtosis (K=25) Scenario				
A. Top tails																					
	Coefficient	Mean	S.D.	5%	95%	p-val	Mean	S.D.	5%	95%	p-val	Mean	S.D.	5%	95%	p-val	Mean	S.D.	5%	95%	p-val
β_{01}	-1.200[a]	-1.135	0.034	-1.194	-1.082	0.96	-1.127	0.037	-1.178	-1.062	1.00	-1.120	0.037	-1.183	-1.061	0.98	-1.132	0.031	-1.183	-1.085	0.98
β_{02}	-2.674[a]	-2.501	0.066	-2.614	-2.388	1.00	-2.494	0.059	-2.587	-2.407	1.00	-2.512	0.062	-2.622	-2.422	0.99	-2.505	0.062	-2.598	-2.401	1.00
β_{03}	-4.000[a]	-3.812	0.130	-4.007	-3.627	0.94	-3.829	0.127	-4.065	-3.622	0.91	-3.843	0.144	-4.059	-3.630	0.85	-3.856	0.126	-4.057	-3.643	0.87
β_{04}	-3.895[a]	-3.248	0.100	-3.419	-3.093	1.00	-3.251	0.098	-3.429	-3.099	1.00	-3.254	0.100	-3.400	-3.064	1.00	-3.276	0.107	-3.450	-3.125	1.00
$\beta_{11}(Y^*_{jt})$	0.231[b]	0.013	0.096	-0.138	0.174	0.00	-0.012	0.112	-0.208	0.133	0.00	-0.032	0.114	-0.224	0.152	0.00	0.005	0.090	-0.136	0.146	0.00
β_{12}	0.440[a]	-0.043	0.210	-0.453	0.257	0.00	-0.054	0.185	-0.361	0.209	0.00	-0.001	0.175	-0.272	0.270	0.00	-0.029	0.216	-0.379	0.220	0.00
β_{13}	0.429	-1.349	5.908	-1.175	0.349	0.04	-1.514	6.361	-2.465	0.436	0.06	-1.018	5.359	-1.136	0.448	0.06	-0.860	4.937	-1.084	0.446	0.06
β_{14}	0.951[a]	-0.402	2.763	-0.943	0.347	0.00	-0.116	0.366	-0.907	0.366	0.00	-0.442	3.339	-1.086	0.312	0.00	-0.331	3.073	-0.638	0.376	0.00
Log-L	-787.386	-800.179	1.447	-801.830	-797.465	0.00	-800.313	1.309	-801.910	-797.944	0.00	-800.112	1.610	-802.009	-797.454	0.00	-800.368	1.416	-801.930	-797.824	0.00
Pseudo-R^2	0.021	0.005	0.002	0.003	0.008	0.00	0.005	0.002	0.003	0.008	0.00	0.005	0.002	0.003	0.008	0.00	0.005	0.002	0.003	0.008	0.00
B. Bottom tails																					
	Coefficient	Mean	S.D.	5%	95%	p-val	Mean	S.D.	5%	95%	p-val	Mean	S.D.	5%	95%	p-val	Mean	S.D.	5%	95%	p-val
β_{01}	-1.407[a]	-1.094	0.283	-1.392	-0.864	0.95	-0.974	0.112	-1.163	-0.827	0.99	-0.954	0.083	-1.092	-0.840	1.00	-0.937	0.080	-1.057	-0.807	1.00
β_{02}	-2.785[a]	-2.214	0.264	-2.547	-1.974	0.97	-2.118	0.142	-2.358	-1.899	1.00	-2.085	0.128	-2.293	-1.877	1.00	-2.096	0.126	-2.285	-1.921	1.00
β_{03}	-3.442[a]	-3.261	0.230	-3.587	-2.919	0.82	-3.216	0.219	-3.580	-2.937	0.81	-3.196	0.187	-3.541	-2.909	0.89	-3.211	0.212	-3.630	-2.917	0.86
β_{04}	-3.880[a]	-3.836	0.276	-4.319	-3.397	0.61	-3.925	0.345	-4.462	-3.466	0.48	-3.979	0.311	-4.526	-3.599	0.47	-3.927	0.318	-4.460	-3.470	0.52
$\beta_{11}(Y^*_{jt})$	0.448[a]	-0.056	0.210	-0.284	0.269	0.03	-0.171	0.153	-0.435	0.074	0.00	-0.208	0.136	-0.425	0.017	0.00	-0.217	0.125	-0.430	-0.024	0.00
β_{12}	0.668[a]	-0.212	0.364	-0.755	0.320	0.03	-0.398	0.282	-0.879	0.025	0.00	-0.455	0.297	-1.028	-0.064	0.00	-0.448	0.265	-0.851	-0.068	0.00
β_{13}	0.481[b]	-1.247	5.266	-1.596	0.512	0.06	-1.613	6.488	-1.719	0.119	0.02	-7.540	18.180	-6.610	0.047	0.00	-3.009	10.209	-2.996	-0.034	0.00
β_{14}	0.853[a]	-6.740	11.954	-30.209	0.518	0.02	-2.242	13.538	-9.571	0.107	0.00	-9.541	13.251	-8.753	0.213	0.00	-4.004	14.594	-3.035	-0.009	0.00
Log-L	-781.276	-817.510	36.938	-831.142	-806.527	0.03	-822.867	6.017	-830.232	-813.092	0.00	-822.398	4.256	-828.756	-813.831	0.00	-822.614	4.924	-829.120	-813.398	0.00
Pseudo-R^2	0.031	0.009	0.017	0.002	0.014	0.03	0.008	0.004	0.003	0.017	0.00	0.010	0.004	0.004	0.017	0.00	0.009	0.004	0.004	0.016	0.00

Table 6. Continued.

Panel B. Latin America

	Actual	High Co-kurtosis (K=1) Scenario					Moderately High Co-kurtosis (K=5) Scenario					Moderately Low Co-kurtosis (K=10) Scenario					Low Co-kurtosis (K=25) Scenario				
A. Top tails	Coefficient	Mean	S.D.	5%	95%	p-val	Mean	S.D.	5%	95%	p-val	Mean	S.D.	5%	95%	p-val	Mean	S.D.	5%	95%	p-val
β_{01}	-1.687[a]	-1.715	0.166	-1.877	-1.523	0.45	-1.654	0.100	-1.826	-1.500	0.67	-1.662	0.091	-1.797	-1.515	0.62	-1.684	0.098	-1.826	-1.523	0.50
β_{02}	-3.228[a]	-2.891	0.181	-3.222	-2.589	0.95	-2.869	0.168	-3.160	-2.663	0.96	-2.895	0.160	-3.181	-2.643	0.97	-2.867	0.172	-3.154	-2.613	0.97
β_{03}	-4.655[a]	-3.717	0.265	-4.243	-3.312	1.00	-3.749	0.239	-4.186	-3.368	1.00	-3.739	0.258	-4.149	-3.357	1.00	-3.734	0.266	-4.195	-3.362	1.00
β_{04}	-4.612[a]	-3.960	0.287	-4.419	-3.455	1.00	-4.102	0.282	-4.535	-3.708	0.97	-4.054	0.305	-4.619	-3.687	0.93	-4.090	0.297	-4.531	-3.710	0.95
β_{11} (Y^*_{jt})	0.196[b]	-0.041	0.118	-0.264	0.107	0.02	-0.025	0.114	-0.208	0.160	0.01	-0.012	0.115	-0.199	0.172	0.01	0.015	0.094	-0.143	0.141	0.00
β_{12}	0.474[a]	-0.068	0.263	-0.543	0.247	0.00	-0.037	0.216	-0.474	0.260	0.00	-0.022	0.205	-0.385	0.261	0.00	-0.055	0.240	-0.352	0.269	0.00
β_{13}	0.825[a]	-0.168	0.521	-0.902	0.344	0.00	-0.136	0.516	-0.797	0.350	0.00	-0.106	0.432	-0.934	0.405	0.00	-0.149	0.447	-1.081	0.397	0.00
β_{14}	0.794[a]	-0.235	0.555	-1.166	0.315	0.00	-0.178	0.691	-1.330	0.457	0.00	-0.309	0.714	-1.507	0.305	0.00	-0.179	0.596	-1.350	0.432	0.00
Log-L	-639.184	-647.523	18.328	-662.352	-627.289	0.18	-654.561	7.768	-666.227	-640.886	0.04	-653.713	8.075	-664.776	-639.370	0.05	-653.306	8.399	-665.422	-638.629	0.06
Pseudo-R^2	0.025	0.004	0.003	0.001	0.010	0.00	0.004	0.002	0.001	0.007	0.00	0.004	0.002	0.001	0.008	0.00	0.004	0.002	0.001	0.008	0.00
B. Bottom tails	Coefficient	Mean	S.D.	5%	95%	p-val	Mean	S.D.	5%	95%	p-val	Mean	S.D.	5%	95%	p-val	Mean	S.D.	5%	95%	p-val
β_{01}	-2.232[a]	-1.726	0.189	-1.968	-1.539	0.98	-1.672	0.104	-1.835	-1.517	1.00	-1.666	0.091	-1.793	-1.506	1.00	-1.647	0.098	-1.799	-1.501	1.00
β_{02}	-3.995[a]	-2.912	0.165	-3.222	-2.689	1.00	-2.880	0.151	-3.098	-2.621	1.00	-2.885	0.164	-3.151	-2.649	1.00	-2.868	0.169	-3.138	-2.639	1.00
β_{03}	-4.376[a]	-3.762	0.284	-4.237	-3.351	0.97	-3.772	0.303	-4.346	-3.337	0.95	-3.749	0.298	-4.262	-3.318	0.96	-3.718	0.263	-4.133	-3.354	0.97
β_{04}	-3.966[a]	-3.964	0.307	-4.491	-3.488	0.50	-4.035	0.290	-4.592	-3.638	0.46	-4.027	0.279	-4.522	-3.638	0.43	-4.140	0.293	-4.594	-3.617	0.30
β_{11} (Y^*_{jt})	0.271[a]	-0.003	0.106	-0.154	0.146	0.00	-0.022	0.114	-0.239	0.146	0.01	-0.024	0.111	-0.210	0.145	0.00	-0.016	0.099	-0.153	0.148	0.00
β_{12}	0.754[a]	-0.075	0.223	-0.447	0.270	0.00	-0.023	0.214	-0.385	0.269	0.00	-0.050	0.206	-0.441	0.208	0.00	-0.044	0.178	-0.346	0.196	0.00
β_{13}	0.687[a]	-0.145	0.416	-0.915	0.380	0.00	-0.072	0.456	-0.627	0.363	0.00	-0.039	0.373	-0.648	0.370	0.00	-0.135	0.400	-0.955	0.400	0.00
β_{14}	0.734[a]	-0.053	0.384	-0.621	0.402	0.00	-0.303	0.640	-1.300	0.366	0.00	-0.237	0.505	-1.256	0.316	0.00	-0.213	0.684	-1.382	0.344	0.00
Log-L	-554.004	-646.100	20.092	-661.772	-629.783	0.01	-652.392	8.683	-664.250	-638.171	0.00	-653.680	7.163	-666.067	-642.163	0.00	-655.455	7.771	-665.857	-638.776	0.00
Pseudo-R^2	0.038	0.004	0.002	0.001	0.008	0.00	0.004	0.002	0.001	0.008	0.00	0.003	0.002	0.001	0.006	0.00	0.003	0.002	0.001	0.007	0.00

Table 7. Contagion test results of multinomial logit regression for daily return co-exceedances of emerging market indices using lagged conditioning variables, December 31, 1995 to May 14 1999. The number of co-exceedances of daily returns is modeled as an ordered polychotomous variable and estimated using a multinomial logit regression model. P_j is defined as the probability that a given day is associated with j co-exceedances where j equals 0, 1, 2, 3, 4 or more (five categories). The multinomial logit regression model is given by $P_j = \exp(x'\beta_j) / [1 + \sum_{k=1,4}\exp(x'\beta_k)]$ where β is the vector of coefficients and x is the vector of independent variables. The probability that there are no (co-) exceedances equals $P_0 = 1 / [1 + \sum_k \exp(x'\beta_k)]$ where k equals 1 to 4, which represents our base case. The independent variables, x, include the intercept, conditional volatility of regional index at time t (h_t), the lagged average exchange rate (per \$US) changes in the region (e_{t-1}), the lagged average interest rate level in the region (i_{t-1}), the number of daily return co-exceedances from another region (Y^*_j), and a measure of conditional volatility from another region (h^*_j). The conditional volatility is estimated as EGARCH(1,1) using the IFC investible regional index. For the contagion test from Latin, US, and Europe to Asia, lagged h^*_j and Y^*_j are used to adjust for the nonsynchronous trading. Partial derivatives of probabilities with respect to the vector of independent variables are computed at the means of x and are reported next to the coefficient estimates. Goodness of fit is measured by McFadden's pseudo-R^2 equal to 1- (L_ω/L_Ω) where L_ω is the unrestricted likelihood, and L_Ω is the restricted likelihood (Maddala, 1983, Chapter 2). The logit regression is estimated separately for positive (top tail) and negative (bottom tail) co-exceedances. χ^2 (h_{jt}^*) and χ^2 (Y_{jt}^*) are Wald chi-squared tests for the restrictions that $\beta_{k1}= \beta_{k2}= \beta_{k3}=\beta_{k4}=0$ where k is 4 and 5, respectively. $^{a,\ b,\ c}$ denotes significance levels at the 1%, 5%, and 10%, respectively.

	Bottom tails						Top tails					
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.
Asia	From Latin		From US		From Europe		From Latin		From US		From Europe	
β_{01} (constant)	-3.728^{a}	-0.503^{a}	-4.082^{a}	-0.559^{a}	-3.949^{a}	-0.540^{a}	-2.224^{a}	-0.309^{a}	-1.902^{a}	-0.241^{a}	-2.276^{a}	-0.316^{a}
β_{02}	-6.153^{a}	-0.227^{a}	-6.748^{a}	-0.247^{a}	-6.143^{a}	-0.226^{a}	-5.428^{a}	-0.201^{a}	-5.436^{a}	-0.202^{a}	-5.221^{a}	-0.196^{a}
β_{03}	-8.157^{a}	-0.106^{b}	-8.022^{a}	-0.101^{b}	-8.664^{a}	-0.092^{b}	-8.138^{a}	-0.051	-8.131^{a}	-0.064^{c}	-8.066^{a}	-0.058
β_{04}	-9.227^{a}	-0.065^{c}	-9.258^{a}	-0.053	-9.689^{a}	-0.060	-9.374^{a}	-0.079^{c}	-9.053^{a}	-0.097^{b}	-9.749^{a}	-0.077^{c}
β_{11} (h_{it})	0.340	0.041	0.435^{b}	0.055	0.308	0.035	0.217	0.021	0.404^{b}	0.055	0.093	0.001
β_{12}	0.954^{a}	0.038^{b}	0.974^{a}	0.037^{b}	1.074^{a}	0.043^{b}	1.178^{a}	0.047^{b}	1.044^{a}	0.039^{b}	1.018^{a}	0.042^{b}
β_{13}	0.472	0.005	1.147^{a}	0.015	0.788^{c}	0.008	1.781^{a}	0.012	1.372^{a}	0.011	1.424^{a}	0.011
β_{14}	1.903^{a}	0.014	2.051^{a}	0.013	1.785^{a}	0.012	1.195^{a}	0.010	0.998^{b}	0.010	1.153^{a}	0.009
β_{21} (e_{it-1})	0.285^{c}	0.036	0.327^{b}	0.043^{c}	0.327^{b}	0.044^{c}	-0.254^{c}	-0.040	-0.299^{b}	-0.046^{c}	-0.241^{c}	-0.037
β_{22}	0.529^{a}	0.020^{c}	0.600^{a}	0.022^{b}	0.524^{a}	0.019^{c}	-0.311	-0.010	-0.382^{c}	-0.012	-0.288	-0.009
β_{23}	1.031^{a}	0.014^{b}	1.011^{a}	0.013^{b}	1.055^{a}	0.012^{c}	-0.597^{c}	-0.004	-0.663^{b}	-0.005	-0.621^{c}	-0.004
β_{24}	0.925^{a}	0.007^{c}	1.016^{a}	0.006^{c}	1.000^{a}	0.006^{c}	-0.670^{a}	-0.005	-0.790^{a}	-0.008^{c}	-0.733^{a}	-0.006
β_{31} (i_{it-1})	0.138^{a}	0.020^{a}	0.142^{a}	0.020^{a}	0.125^{a}	0.018^{a}	0.057	0.009	0.039	0.005	0.044	0.007
β_{32}	0.159^{a}	0.005^{c}	0.175^{a}	0.006^{b}	0.144^{a}	0.005^{c}	0.095^{a}	0.003	0.094^{c}	0.003	0.077^{c}	0.003
β_{33}	0.241^{a}	0.003^{c}	0.222^{a}	0.003	0.220^{a}	0.002	0.114	0.001	0.121	0.001	0.086	0.001
β_{34}	0.227^{a}	0.002	0.255^{a}	0.001	0.257^{a}	0.002	0.250^{a}	0.002	0.222^{a}	0.002	0.196^{a}	0.002
β_{41}(h_{jt}^*)	0.136	0.020	0.370^{b}	0.057^{c}	0.843^{a}	0.130^{a}	0.043	0.007	-0.087	-0.021	0.587^{a}	0.094^{c}
β_{42}	0.134	0.005	0.495^{b}	0.018	0.364	0.008	-0.001	-0.001	0.243	0.010	0.426	0.011
β_{43}	0.340^{c}	0.005	-0.085	-0.003	0.902	0.009	-0.087	-0.001	0.615^{c}	0.005	1.189^{a}	0.008
β_{44}	-0.306	-0.003	-0.891^{b}	-0.007	-0.403	-0.004	0.195	0.002	0.846^{a}	0.010^{c}	1.945^{a}	0.015
β_{51} (Y_{jt}^*)	0.313^{a}	0.045^{b}	0.714^{c}	0.095	0.209	0.013	0.312^{a}	0.046^{b}	-0.564	-0.116	0.551	0.081
β_{52}	0.359^{a}	0.012^{c}	1.067^{c}	0.037	1.155^{b}	0.047^{c}	0.586^{a}	0.021^{b}	1.302^{a}	0.060^{a}	1.316^{a}	0.051^{b}
β_{53}	0.512^{a}	0.006^{c}	2.233^{a}	0.030^{c}	2.425^{a}	0.028^{b}	0.926^{a}	0.006	0.118	0.002	0.755	0.004
β_{54}	0.554^{a}	0.004	2.458^{a}	0.015	2.346^{a}	0.016	0.913^{a}	0.007^{c}	1.079^{c}	0.014	0.916	0.006
Log-Likelihood	-707.106		-707.056		-699.483		-733.904		-741.998		-738.498	
Pseudo-R^2	12.20%		12.21%		13.15%		8.70%		7.69%		8.13%	
χ^2 (h_{jt}^*)	6.388		8.777^{c}		12.990^{a}		1.714		10.452^{b}		18.832^{a}	
χ^2 (Y_{jt}^*)	16.023^{a}		20.472^{a}		29.857^{a}		34.327^{a}		12.426^{a}		8.160^{c}	

Table 7. Continued.

	Bottom tails						Top tails					
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.
Latin	From Asia		From US		From Europe		From Asia		From US		From Europe	
β_{01} (constant)	-3.583^{a}	-0.296^{a}	-3.178^{a}	-0.267^{a}	-3.776^{a}	-0.317^{a}	-2.865^{a}	-0.340^{a}	-2.674^{a}	-0.314^{a}	-3.234^{a}	-0.392^{a}
β_{02}	-2.977^{a}	-0.048^{c}	-2.771^{a}	-0.045	-2.980^{a}	-0.051^{c}	-4.523^{a}	-0.144^{a}	-4.442^{a}	-0.134^{a}	-5.089^{a}	-0.157^{a}
β_{03}	-4.969^{a}	-0.056^{b}	-3.943^{a}	-0.038	-4.934^{a}	-0.053^{b}	-5.790^{a}	-0.042^{c}	-6.617^{a}	-0.047^{c}	-6.097^{a}	-0.028
β_{04}	-6.170^{a}	-0.083^{b}	-6.747^{a}	-0.076^{b}	-6.013^{a}	-0.057^{b}	-8.745^{a}	-0.038	-8.273^{a}	-0.050^{c}	-8.704^{a}	-0.045
β_{11} (h_{it})	0.302^{a}	0.024^{b}	0.475^{a}	0.040^{a}	0.105	0.009	0.291^{a}	0.034^{b}	0.287^{b}	0.034^{c}	0.002	0.000
β_{12}	0.598^{a}	0.011^{b}	0.560^{a}	0.010^{c}	0.221	0.004	0.492^{a}	0.016^{b}	0.483^{a}	0.015^{c}	-0.047	-0.002
β_{13}	0.346	0.004	0.696^{a}	0.007	0.030	0.000	0.823^{a}	0.006^{c}	0.426^{c}	0.003	0.266	0.001
β_{14}	0.564^{a}	0.008^{b}	0.509^{a}	0.005	0.291	0.003	1.119^{a}	0.005	0.863^{a}	0.005^{c}	0.458^{b}	0.003
β_{21} (e_{it})	-0.288	-0.027	-0.297	-0.028	-0.406	-0.037	0.299	0.040	0.245	0.034	0.262	0.037
β_{22}	-0.653	-0.013	-0.315	-0.006	-0.420	-0.008	-0.197	-0.009	-0.331	-0.013	-0.384	-0.015
β_{23}	1.259^{c}	0.016	0.963	0.011	1.239^{b}	0.015	0.431	0.003	0.174	0.001	0.128	0.001
β_{24}	0.627	0.010	0.394	0.005	0.277	0.003	0.812	0.004	0.725	0.005	0.490	0.003
β_{31} (i_{it})	0.029	0.003	0.026	0.003	0.028	0.003	0.072^{a}	0.009^{b}	0.065^{a}	0.008^{b}	0.069^{a}	0.009^{b}
β_{32}	-0.097	-0.002	-0.130^{a}	-0.003	-0.145^{a}	-0.003	0.060	0.002	0.061^{a}	0.002	0.041	0.001
β_{33}	-0.031	0.000	-0.053	-0.001	-0.058	-0.001	-0.008	0.000	0.010	0.000	-0.099	-0.001
β_{34}	0.003	0.000	0.034	0.000	-0.040	0.000	0.217^{a}	0.001	0.142^{b}	0.001	0.112^{b}	0.001
β_{41}(h_{jt}^{*})	0.425^{c}	0.036	-0.055	-0.006	1.148^{a}	0.094^{b}	-0.499^{a}	-0.062^{c}	-0.394	-0.051	0.502	0.054
β_{42}	-0.239	-0.006	0.273	0.005	1.690^{a}	0.031^{c}	-0.430	-0.012	-0.397	-0.012	1.643^{a}	0.054^{b}
β_{43}	0.516	0.006	-0.547	-0.006	1.799^{b}	0.019	-0.132	0.000	0.928^{b}	0.008	2.844^{a}	0.014
β_{44}	0.972^{a}	0.014	0.817^{a}	0.010	2.074^{a}	0.020	-2.041^{a}	-0.009	-0.252	-0.001	1.295^{c}	0.006
β_{51} (Y_{jt}^{*})	0.121	0.008	-0.178	-0.029	1.284^{a}	0.104^{b}	0.243^{a}	0.028^{c}	0.329	0.027	0.491	0.057
β_{52}	0.692^{a}	0.013^{b}	2.719^{a}	0.052^{a}	1.892^{a}	0.035^{b}	0.445^{a}	0.014^{b}	2.062^{a}	0.068^{a}	0.957^{c}	0.030
β_{53}	0.470^{b}	0.006	3.058^{a}	0.033^{b}	2.368^{a}	0.026^{c}	0.666^{a}	0.005	2.186^{a}	0.016^{c}	1.694^{a}	0.008
β_{54}	0.448^{a}	0.006^{c}	3.565^{a}	0.042^{b}	3.500^{a}	0.034^{b}	0.913^{a}	0.004	2.220^{a}	0.014	2.301^{a}	0.012
Log-Likelihood	-523.481		-504.684		-503.544		-606.102		-605.650		-600.874	
Pseudo-R^2	9.11%		12.38%		12.84%		7.56%		7.63%		8.36%	
χ^2 (h_{jt}^{*})	8.917^{c}		6.783		19.213^{a}		11.65^{b}		9.185^{c}		19.700^{a}	
χ^2 (Y_{jt}^{*})	24.654^{a}		80.258^{a}		54.731^{a}		24.797^{a}		33.041^{a}		16.843^{a}	
US	From Asia		From Latin		From Europe		From Asia		From Latin		From Europe	
β_1 (constant)	-0.644	-0.028	-0.083	-0.002	-0.754	-0.028	-0.389	-0.015	-3.025	-0.111	-2.336	-0.086
β_2 (h_{it})	0.550^{b}	0.024^{c}	-0.404	-0.012	-0.024	-0.001	0.780^{a}	0.031^{a}	0.622^{b}	0.023^{c}	0.570^{b}	0.021^{c}
β_3 (e_{it})	-0.664	-0.029^{c}	-0.229	-0.007	-0.620	-0.023^{c}	-0.180	-0.007	-0.383	-0.014	-0.325	-0.012
β_4 (i_{it})	-0.582	-0.026	-0.645	-0.019	-0.613	-0.023	-0.841^{c}	-0.033^{c}	-0.250	-0.009	-0.422	-0.016
β_4 (h_{jt}^{*})	-0.045	-0.002	0.179	0.005	0.890^{b}	0.033^{c}	0.733^{a}	0.029^{b}	0.111	0.004	0.705	0.026
β_4 (Y^{*}_{jt})	0.175	0.008	0.969^{a}	0.029^{a}	2.054^{a}	0.077^{a}	-0.025	-0.001	0.625^{a}	0.023^{a}	1.642^{a}	0.060^{a}
Log-Likelihood	-170.544		-136.830		-156.799		-161.910		-154.384		-154.932	
Pseudo-R^2	2.38%		21.68%		10.25%		7.32%		11.63%		21.32%	
χ^2 (h_{jt}^{*})	0.020		0.872		4.019^{b}		5.668^{b}		0.484		2.509	
χ^2 (Y_{jt}^{*})	1.049		61.366^{a}		24.130^{a}		0.026		20.959^{a}		14.675^{a}	
Europe	From Asia		From Latin		From US		From Asia		From Latin		From US	
β_1 (constant)	-2.886^{b}	-0.081^{c}	-2.722^{b}	-0.083^{c}	-3.268^{a}	-0.104^{b}	-3.251^{a}	-0.078^{c}	-3.555^{a}	-0.092^{b}	-3.353^{a}	-0.086^{b}
β_2 (h_{it})	1.360^{a}	0.038^{a}	0.956^{c}	0.029^{c}	1.525^{a}	0.049^{a}	2.261^{a}	0.054^{a}	2.598^{a}	0.067^{a}	2.578^{a}	0.066^{a}
β_3 (e_{it})	-0.313	-0.009	-0.076	-0.002	-0.126	-0.004	0.170	0.004	0.138	0.004	0.151	0.004
β_4 (i_{it})	-0.552^{c}	-0.016^{c}	-0.418	-0.013	-0.365	-0.012	-0.610^{b}	-0.015^{b}	-0.490	-0.013^{c}	-0.532^{c}	-0.014^{c}
β_4 (h_{jt}^{*})	0.357	0.010	0.074	0.002	0.093	0.003	0.162	0.004	-0.120	-0.003	-0.106	-0.003
β_4 (Y^{*}_{jt})	0.524^{a}	0.015^{a}	0.639^{a}	0.020^{a}	1.928^{a}	0.062^{a}	0.318^{b}	0.008^{b}	0.267^{b}	0.007^{c}	0.706	0.018
Log-Likelihood	-147.339		-143.809		-148.060		-137.489		-138.882		-139.579	
Pseudo-R^2	15.66%		17.68%		15.25%		21.30%		20.50%		20.11%	
χ^2 (h_{jt}^{*})	1.242		0.165		0.103		0.246		0.609		0.158	
χ^2 (Y_{jt}^{*})	15.964^{a}		27.641^{a}		20.754^{a}		5.244^{b}		3.367^{c}		1.957	

Table 8. Contagion test results of multinomial logit regression for daily return co-exceedances from conditional extreme returns, December 31, 1995 to May 14, 1999. Extreme returns are defined in terms of exceedances beyond a random threshold, θ, controlling for time-varying volatility. Specifically, the time-series of conditional volatilities, h_{it}, for each country index *i* at time *t* are obtained using EGARCH(1,1) model. Then, a return, r_{it}, is defined as extreme if $|r_{it}| > 1.65h_{it}$. The number of co-exceedances of daily returns is modeled as an ordered polychotomous variable and estimated using a multinomial logit regression model. P_j is defined as the probability that a given day is associated with j co-exceedances where j equals 0, 1, 2, 3, 4 or more (five categories). The multinomial logit regression model is given by

$$P_j = \exp(x'\beta_j) / [1 + \textstyle\sum_k \exp(x'\beta_k)]$$

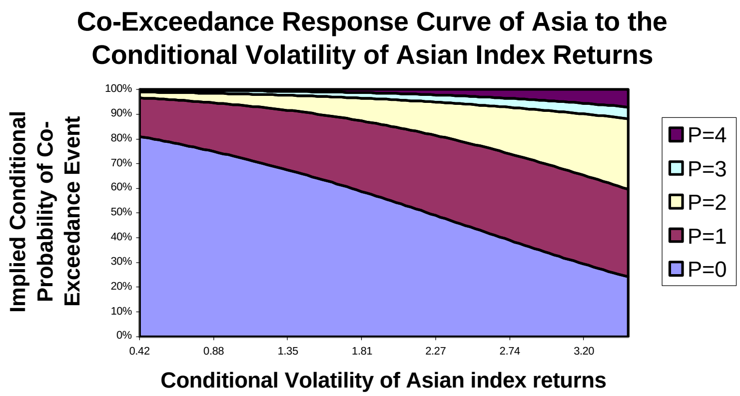
where β is the vector of coefficients, x, the vector of independent variables, and k equals 1 to 4. The probability that there are no (co-) exceedances equals $P_0 = 1 / [1 + \sum_{k=1,4}\exp(x'\beta_k)]$, which represents our base case. The independent variables, x, include those in Table 5. The conditional volatility is estimated as EGARCH(1,1) using the IFC investible regional index. Partial derivatives of probabilities with respect to the vector of independent variables are computed at the means of x and are reported next to the coefficient estimates. Goodness of fit is measured by McFadden's pseudo-R^2 equal to 1- (L_ω/L_Ω) where L_ω is the unrestricted likelihood, and L_Ω is the restricted likelihood (Maddala, 1983, Chapter 2). The logit regression is estimated separately for positive (top tail) and negative (bottom tail) co-exceedances. χ^2 (h_{jt}^*) and χ^2 (Y_{jt}^*) are Wald chi-squared tests for the restrictions that $\beta_{k1}= \beta_{k2}= \beta_{k3}=\beta_{k4}=0$ where k is 4 and 5, respectively. $^{a,\ b,\ c}$ denotes significance levels at the 1%, 5%, and 10%, respectively.

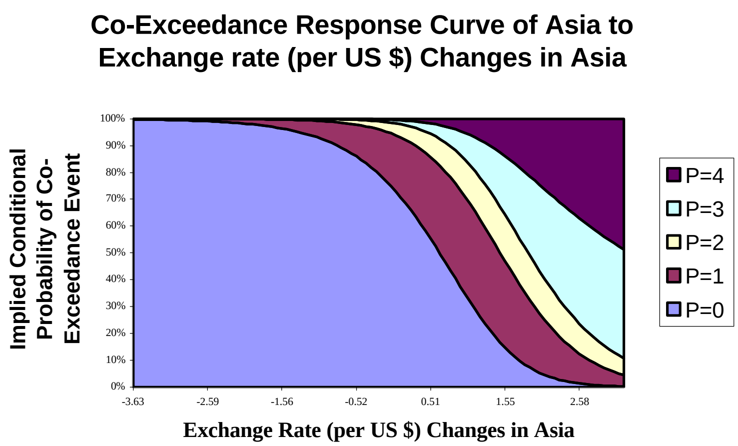
	Bottom tails						Top tails					
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.
Asia	From Latin		From US		From Europe		From Latin		From US		From Europe	
β_{01} (constant)	-1.717^{a}	-0.250^{a}	-1.854^{a}	-0.272^{a}	-1.690^{a}	-0.247^{a}	-0.100	0.026	0.339	0.109	-0.174	0.008
β_{02}	-2.743^{a}	-0.117^{a}	-2.884^{a}	-0.124^{a}	2.735^{a}	-0.118^{a}	-2.271^{a}	-0.086^{b}	-2.338^{a}	-0.093^{b}	-2.114^{a}	-0.078^{b}
β_{03}	-6.251^{a}	-0.029	-4.441^{a}	-0.027	-6.660^{a}	-0.030	-5.486^{a}	-0.058^{c}	-5.095^{a}	-0.062^{b}	-5.312^{a}	-0.052^{c}
β_{04}	-6.956^{a}	-0.027	-7.141^{a}	-0.025	-7.627^{a}	-0.022	-6.183^{a}	-0.023	-6.317^{a}	-0.025	-5.471^{a}	-0.023
β_{11} (h_{it})	0.070	0.014	0.155	0.026	0.192	0.033	-0.176	-0.029	-0.131	-0.021	-0.398^{c}	-0.069
β_{12}	-0.070	-0.004	-0.006	-0.002	0.026	-0.001	-0.250	-0.008	-0.143	-0.004	-0.323	-0.008
β_{13}	-0.880	-0.005	0.174	0.001	-0.429	-0.002	-0.247	-0.002	-0.125	-0.001	-0.519	-0.004
β_{14}	-0.226	-0.001	0.793	0.003	0.341	0.001	-0.380	-0.001	-1.347	-0.005	-0.810	-0.003
β_{21} (e_{it})	0.918^{a}	0.133^{a}	0.916^{a}	0.132^{a}	0.923^{a}	0.135^{a}	-0.744^{a}	-0.121^{a}	-0.767^{a}	-0.124^{a}	-0.734^{a}	-0.120^{a}
β_{22}	1.640^{a}	0.072^{a}	1.615^{a}	0.072^{a}	1.639^{a}	0.072^{a}	-1.122^{a}	-0.036^{b}	-1.149^{a}	-0.037^{b}	-1.125^{a}	-0.036^{b}
β_{23}	2.685^{a}	0.012^{c}	2.370^{a}	0.014^{c}	2.640^{a}	0.012^{c}	-1.204^{a}	-0.011	-1.247^{a}	-0.012	-1.234^{a}	-0.010
β_{24}	2.615^{a}	0.010	2.459^{a}	0.008	2.594^{a}	0.007	-2.208^{a}	-0.008	-2.458^{a}	-0.009	-2.357^{a}	-0.009
β_{31} (i_{it})	0.015	0.002	0.017	0.003	0.007	0.001	-0.053	-0.010	-0.064^{b}	-0.011	-0.057^{c}	-0.009
β_{32}	0.001	0.000	0.005	0.000	-0.002	0.000	-0.059	-0.002	-0.072	-0.002	-0.114^{b}	-0.004
β_{33}	0.084	0.000	0.050	0.000	0.042	0.000	0.078	0.001	0.043	0.001	-0.002	0.000
β_{34}	0.068	0.000	0.052	0.000	0.025	0.000	0.060	0.000	0.077	0.000	-0.030	0.000
$\beta_{41}(h_{jt}^*)$	0.101	0.016	0.205	0.035	0.171	0.026	-0.074	-0.018	-0.330	-0.069	0.348	0.044
β_{42}	0.030	0.000	0.143	0.005	0.033	-0.001	0.269^{c}	0.011	0.509^{c}	0.023	1.348^{a}	0.048^{b}
β_{43}	0.541^{c}	0.003	-0.965	-0.007	1.634^{b}	0.008	0.281	0.003	0.536	0.007	1.990^{a}	0.019^{c}
β_{44}	0.587^{b}	0.002	0.153	0.000	1.508^{c}	0.005	0.245	0.001	1.357^{a}	0.006	2.075^{a}	0.008
β_{51} (Y_{jt}^*)	0.330^{a}	0.050^{b}	0.495	0.076	0.978^{a}	0.148^{b}	0.220^{b}	0.033	0.778	0.118	0.772^{b}	0.128^{b}
β_{52}	0.397^{a}	0.016^{c}	0.378	0.012	1.276^{a}	0.053^{c}	0.464^{a}	0.016^{c}	1.724^{a}	0.060^{c}	0.919	0.027
β_{53}	0.972^{a}	0.004	1.502	0.009	3.086^{a}	0.014	0.780^{a}	0.008^{c}	1.853^{c}	0.019	1.797^{b}	0.016
β_{54}	0.881^{a}	0.003	3.305^{a}	0.012	3.575^{a}	0.010	1.099^{a}	0.004	2.612^{b}	0.009	1.334	0.005
Log-Likelihood	-697.347		-705.028		-694.452		-716.500		-719.632		-716.018	
Pseudo-R^2	13.41%		12.45%		13.77%		10.89%		10.47%		10.92%	
χ^2 (h_{jt}^*)	6.850		2.448		6.289		5.426		13.746^{a}		25.653^{a}	
χ^2 (Y_{jt}^*)	27.957^{a}		18.042^{a}		33.401^{a}		24.378^{a}		11.434^{b}		10.021^{b}	

Table 8. Continued.

	Bottom tails						Top tails					
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.
Latin	From Asia		From US		From Europe		From Asia		From US		From Europe	
β_{01} (constant)	-2.332[a]	-0.237[a]	-2.479[a]	-0.256[a]	-2.769[a]	-0.283[a]	-1.032[a]	-0.104	-1.372[a]	-0.152[c]	-1.709[a]	-0.195[b]
β_{02}	-3.354[a]	-0.057[c]	-3.341[a]	-0.054[c]	-3.006[a]	-0.047	-4.086[a]	-0.152[a]	-3.893[a]	-0.138[a]	-4.729[a]	-0.172[a]
β_{03}	4.300[a]	-0.047[c]	-4.644[a]	-0.047[c]	-4.541[a]	-0.043[c]	-4.703[a]	-0.023	-4.646[a]	-0.031	-4.567[a]	-0.023
β_{04}	-7.356[a]	-0.035	-6.968[a]	-0.028	-8.015[a]	-0.021	-5.935[a]	-0.037	-5.841[a]	-0.039	-5.638[a]	-0.022
β_{11} (h_{it})	-0.192[c]	-0.019	-0.228	-0.024	-0.598[a]	-0.062[a]	-0.165	-0.021	-0.388[a]	-0.053[b]	-0.686[a]	-0.088[a]
β_{12}	-0.598[c]	-0.011	-0.391	-0.007	-0.338	-0.005	-0.204	-0.007	-0.179	-0.004	-0.747[a]	-0.024
β_{13}	-0.234	-0.002	-0.382	-0.004	-0.940[a]	-0.009	-0.711[c]	-0.004	-0.479	-0.003	-1.299[b]	-0.006
β_{14}	-0.677[b]	-0.003	-0.306	-0.001	-1.618[a]	-0.004	0.305[c]	0.002	0.252	0.002	-0.031	0.001
β_{21} (e_{it})	1.963[a]	0.200[a]	1.975[a]	0.205[a]	2.192[a]	0.223[a]	-1.892[a]	-0.241[a]	-2.081[a]	-0.268[a]	-2.165[a]	-0.277[a]
β_{22}	2.817[a]	0.048[c]	2.588[a]	0.042[c]	2.535[b]	0.040	-2.069[a]	-0.067[c]	-2.215[a]	-0.070[b]	-2.312[a]	-0.075[b]
β_{23}	3.573[a]	0.039[c]	3.722[a]	0.037[c]	4.293[a]	0.041[c]	-3.873[a]	-0.019	-3.080[a]	-0.019	-3.668[a]	-0.018
β_{24}	5.186[a]	0.025	4.896[a]	0.019	5.622[a]	0.014	-2.063[c]	-0.011	-2.148[b]	-0.012	-2.923[b]	-0.011
β_{31} (i_{it})	0.015	0.002	0.016	0.002	0.015	0.002	0.019	0.002	0.021	0.002	0.024	0.003
β_{32}	-0.029	-0.001	-0.026	-0.001	-0.031	-0.001	0.094[a]	0.004[c]	0.095[a]	0.003[c]	0.100[a]	0.004[c]
β_{33}	-0.031	0.000	-0.039	0.000	-0.073	-0.001	-0.041	0.000	-0.019	0.000	-0.073[c]	0.000
β_{34}	0.083	0.000	0.066	0.000	0.022	0.000	0.046	0.000	0.047[b]	0.000	-0.013	0.000
β_{41}(h_{jt}^{*})	0.254[c]	0.025	0.423	0.044	1.570[a]	0.163[a]	-0.591[a]	-0.080[b]	0.073	0.012	0.964[a]	0.119[b]
β_{42}	0.685	0.012	0.291	0.004	-0.012	-0.005	-0.293	-0.008	-0.352	-0.014	1.410[a]	0.048
β_{43}	0.504	0.005	1.056[b]	0.011	3.049[a]	0.030[c]	1.156[a]	0.007	0.837	0.006	3.398[a]	0.018
β_{44}	1.276[b]	0.006	0.538	0.002	4.671[a]	0.012	-0.284	-0.001	0.021	0.000	1.614[a]	0.006
β_{51} (Y_{jt}^{*})	0.228[b]	0.023[c]	1.397[a]	0.142[b]	1.095[a]	0.109[b]	0.190[c]	0.021	0.409	0.034	0.104	0.013
β_{52}	0.238	0.004	2.671[a]	0.045[b]	2.200[a]	0.037[b]	0.476[a]	0.017[b]	2.393[a]	0.087[a]	0.933[c]	0.037
β_{53}	0.607[a]	0.007[c]	3.087[a]	0.031[b]	1.825[a]	0.017	0.859[a]	0.004	3.077[a]	0.021[c]	1.820[a]	0.010
β_{54}	0.551[b]	0.003	4.041[a]	0.016	3.186[a]	0.008	0.727[a]	0.004	2.444[b]	0.016	-9.240[b]	-0.043
Log-Likelihood	-527.476		-513.919		-506.847		-621.423		-625.432		-624.926	
Pseudo-R^2	8.42%		10.77%		11.99%		5.23%		5.61%		4.69%	
χ^2 (h_{jt}^{*})	7.701[c]		6.729		38.794[a]		13.793[a]		3.633		17.322[a]	
χ^2 (Y_{jt}^{*})	12.929[a]		52.751[a]		39.805[a]		20.200[a]		26.270[a]		11.142[b]	
US	From Asia		From Latin		From Europe		From Asia		From Latin		From Europe	
β_1 (constant)	-6.511[a]	-0.201[a]	-6.467[a]	-0.137[b]	-7.005[a]	-0.182[a]	-2.721	-0.054	-2.469	-0.043	-3.539	-0.059
β_2 (h_{it})	-0.181	-0.006	-1.129	-0.024	-1.070[c]	-0.028[c]	-0.664	-0.013	-1.255	-0.022	-1.419[b]	-0.024[b]
β_3 (e_{it})	0.710	0.022[c]	0.587	0.012	0.786[c]	0.020[c]	-0.096	-0.002	-0.032	-0.001	-0.446	-0.007
β_4 (i_{it})	0.731	0.023[c]	0.650	0.014	0.713	0.019	-0.172	-0.003	-0.160	-0.003	-0.014	-0.002
β_4 (h_{jt}^{*})	-0.590	-0.018	0.208	0.004	0.999[c]	0.026[c]	0.289	0.006	0.390	0.007	1.992[a]	0.033[a]
β_4 (Y^{*}_{jt})	0.138	0.004	1.007[a]	0.021[a]	2.138[a]	0.056[a]	0.608[a]	0.012[a]	0.821[a]	0.014[a]	2.344[a]	0.039[a]
Log-Likelihood	-130.784		-108.730		-122.132		-94.862		-90.260		-89.497	
Pseudo-R^2	0.77%		5.62%		2.70%		0.98%		2.01%		2.19%	
χ^2 (h_{jt}^{*})	2.104		0.516		3.145[c]		0.411		2.527		11.468[a]	
χ^2 (Y_{jt}^{*})	0.390		53.275[a]		21.213[a]		9.237[a]		21.038[a]		17.953[a]	
Europe	From Asia		From Latin		From US		From Asia		From Latin		From US	
β_1 (constant)	-2.329[c]	-0.101[c]	-1.551	-0.065	-2.166[c]	-0.096	-0.014	0.000	0.320	0.012	0.121	0.004
β_2 (h_{it})	-0.393	-0.017	-1.338[c]	-0.056[c]	-0.169	-0.007	-2.041[a]	-0.073[a]	-1.348	-0.048	-1.916[a]	-0.067[b]
β_3 (e_{it})	-0.072	-0.003	0.057	0.002	0.190	0.008	-1.444[a]	-0.051[a]	-1.437[a]	-0.052[a]	-1.444[a]	-0.051[a]
β_4 (i_{it})	-0.194	-0.008	-0.263	-0.011	-0.198	-0.009	-0.456[c]	-0.016[c]	-0.497[c]	-0.018[c]	-0.489[b]	-0.017[c]
β_4 (h_{jt}^{*})	0.149	0.006	0.338	0.014	0.034	0.001	0.286	0.010	-0.215	-0.008	0.199	0.007
β_4 (Y^{*}_{jt})	0.629[a]	0.027[a]	0.738[a]	0.031[a]	2.332[a]	0.103[a]	0.211	0.007	-0.049	-0.002	1.651[a]	0.058[b]
Log-Likelihood	-170.489		-168.126		-169.912		-161.056		-161.664		-159.040	
Pseudo-R^2	2.41%		3.76%		2.74%		7.81%		7.46%		8.97%	
χ^2 (h_{jt}^{*})	0.230		2.364		0.006		0.744		0.434		0.171	
χ^2 (Y_{jt}^{*})	20.793[a]		28.887[a]		29.761[a]		1.125		0.041		7.630[a]	

Figure 1. Co-Exceedance response curve of Asia.





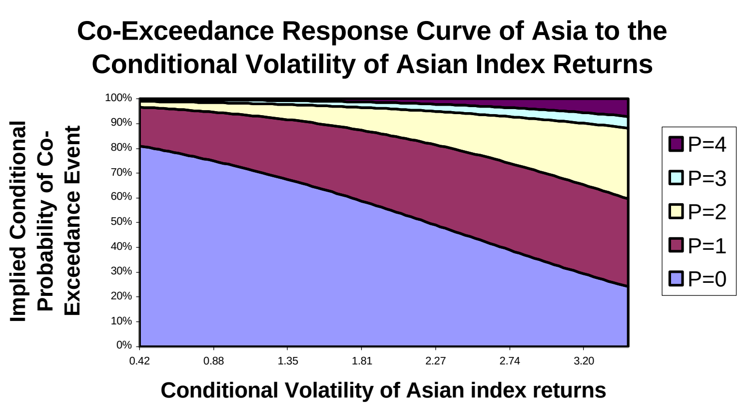


Figure 2. Co-Exceedance response curve of Asia to the conditional volatility and the number of co-exceedances of overseas market.

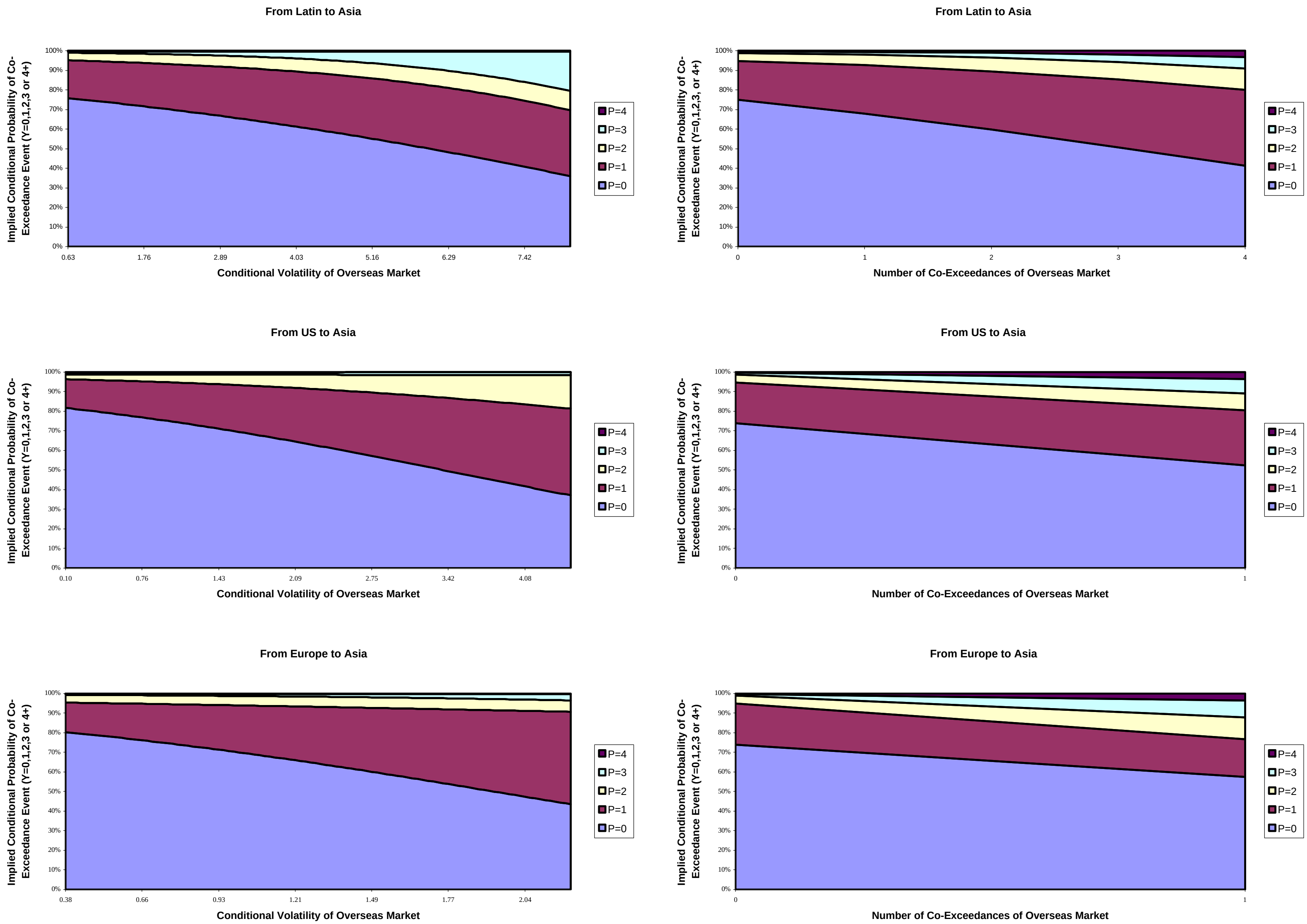


Figure 3. Co-Exceedance response curve of Latin to the conditional volatility and the number of co-exceedances of overseas market.

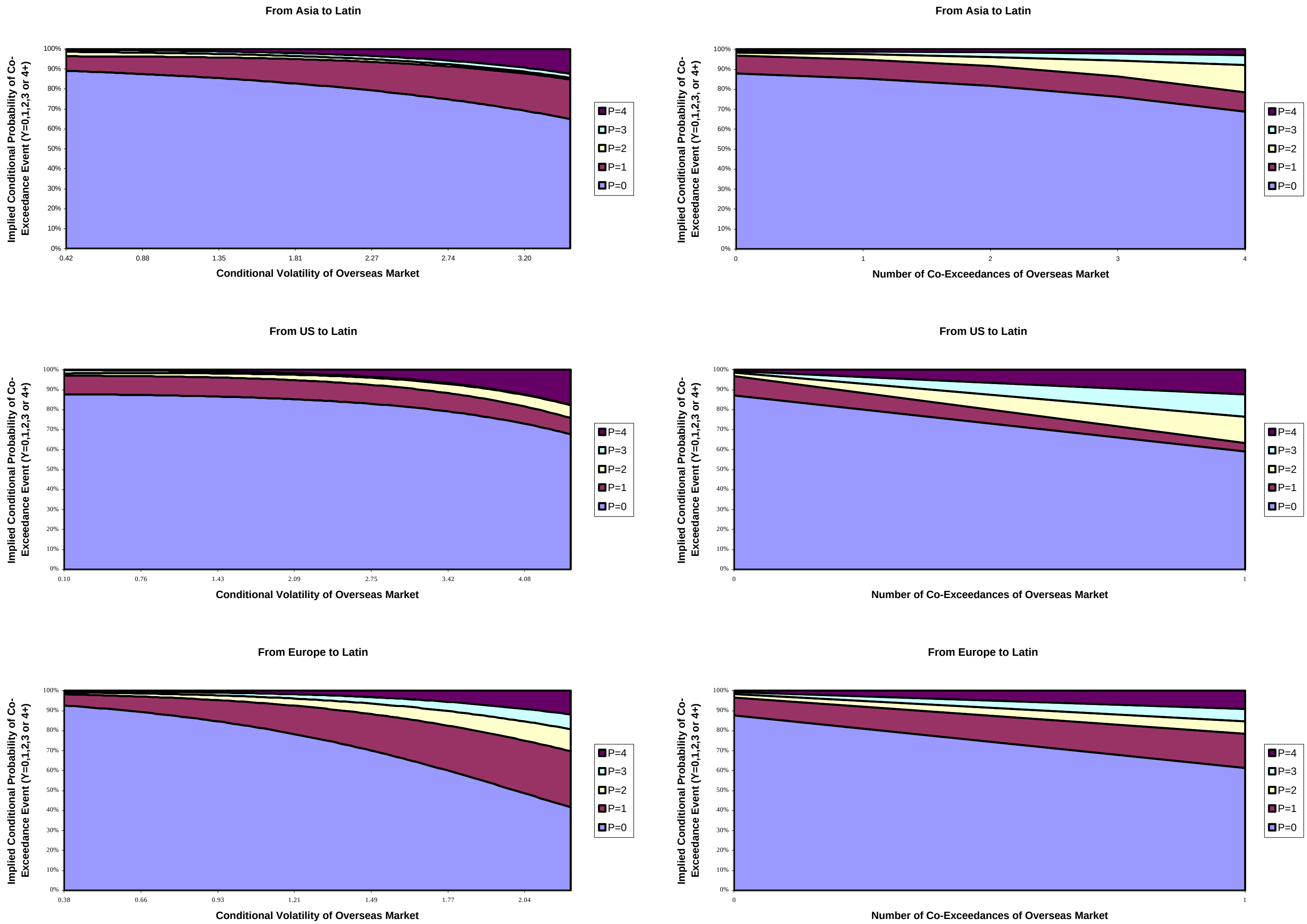


Figure 4. Co-Exceedance response curve of US to the conditional volatility and the number of co-exceedances of overseas market.

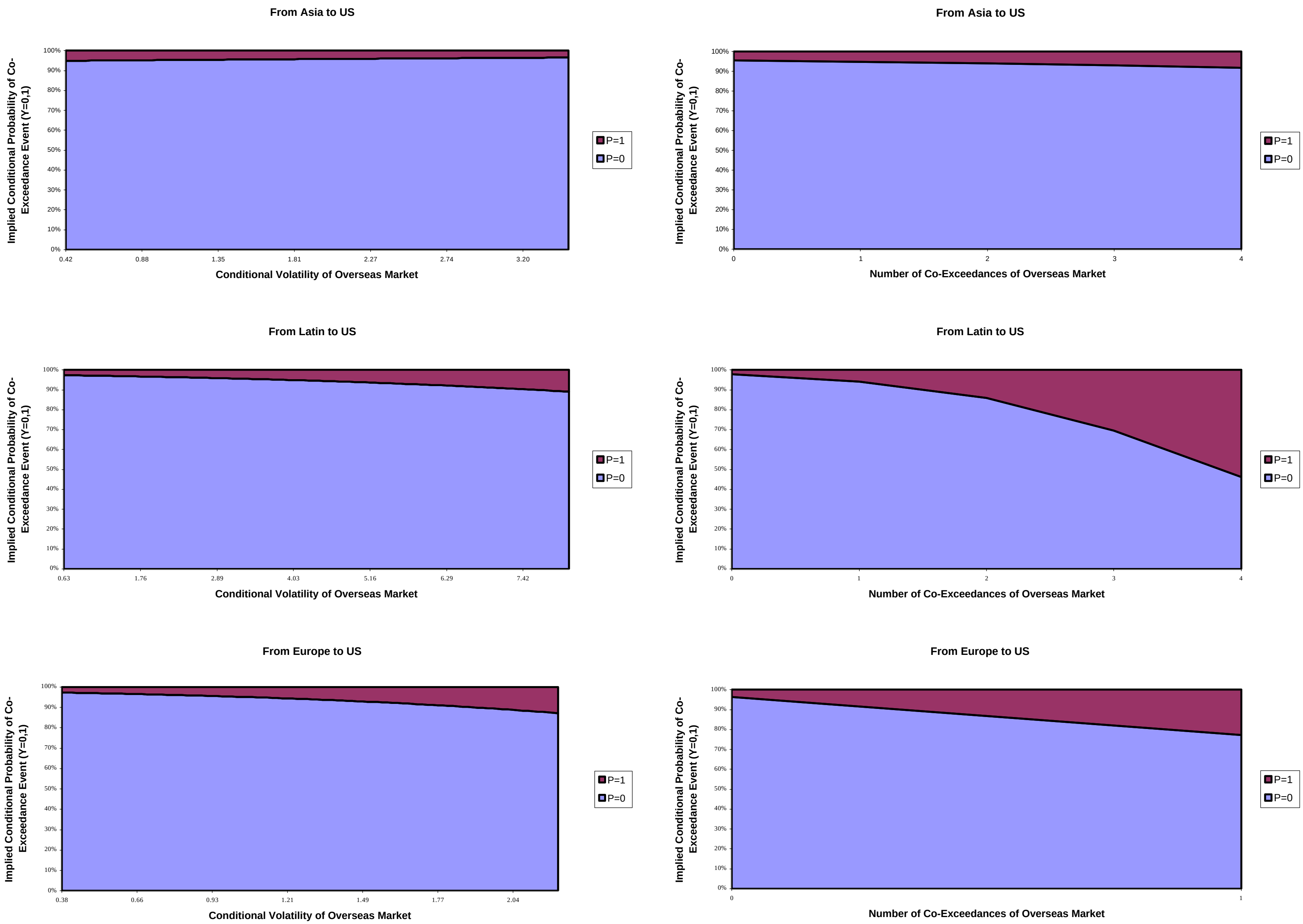


Figure 5. Co-Exceedance response curve of Europe to the conditional volatility and the number of co-exceedances of overseas market.