A new approach to measuring financial contagion

Kee-Hong Bae*, G. Andrew Karolyi**, and René M. Stulz***

Abstract

contagion captures the co-incidence of extreme return shocks across countries within a region

the extent of contagion, its economic significance, and its determinants using a multinomial

1990s, we find that contagion, when measured by the co-incidence within and across regions of

changes, and conditional stock return volatility. Evidence that contagion is stronger for extreme

September 2001

* Associate Professor, College of Business Administration, Korea University
** Professor of Finance and Dean's Distinguished Research Professor, Fisher College of Business, Ohio State University
*** Professor of Finance and Reese Chair of Banking and Monetary Economics, Fisher College of Business, Ohio State University, Research Associate, National Bureau of Economic Research.

The authors are grateful to the Dice Center for Research on Financial Economics for support. We thank Tom Santner, Mark Berliner, Bob Leone, and Stan Lemeshow for useful discussions on methodology, Steve Cecchetti, Peter Christoffersen, Craig Doidge, Barry Eichengreen, Vihang Errunza, David Hirshleifer, Roberto Rigobon, Richard Roll, Karen Wruck and, especially, an anonymous referee and the editor, Cam Harvey, for comments. Comments from seminar participants at Hong Kong University of Science and Technology, Korea University, McGill University, Yale University, Michigan State University, Universiteit Maasstricht, Ohio State University, Rice University, Monte Verita Risk Management Conference (Ascona, Switzerland), Federal Reserve Bank of Chicago Annual Conference on Bank Structure and Competition, Global Investment Conference on International Investing (Whistler), and the NYSE Conference on Global Equity Markets in Transition (Hawaii) improved the paper.

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 valuations reflect future

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

[2] For a review of the difficulties in defining contagion, see Dornbusch, Park, and Claessens (2001). A recent book by Claessens and Forbes (2001) published this and over 20 other papers from a February 2000 World Bank/IMF conference, *International Financial Contagion: How it Spreads and How it Can be Stopped*. These papers include theoretical models (Pritsker, 2001; Schinasi and Smith, 2001), a conceptual contribution (Forbes and Rigobon, 2001), country case studies (De Gregorio and Valdes, 2001; Eichengreen, Hale, and Mody, 2001; Park and Song, 2001) and broad-based empirical studies (Kaminsky, Lyons, and Schmukler, 2001). Other important recent contributions include Eichengreen, Rose, and Wyplosz (1996), Masson (1999), Glick and Rose (1999), Kaminsky and Reinhart (2000), Allen and Gale (2000) and Kyle and Xiong (2001). Eichengreen, et al. (1996) estimate probit regressions to relate the occurrence of a currency crisis in a country to predictive variables. Though their seminal

economic activity, much of recent research attempts to learn about contagion by investigating whether equity markets move more closely together in turbulent periods. There are considerable statistical difficulties involved in testing hypotheses of changes in correlations across quiet and turbulent periods and recent investigations of this issue find at best mixed results.[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]

Investigations of contagion focus on asset return correlations, a linear measure of association, likely because most international asset pricing models start with a linear factor structure as a first principle. The factors are presumed to capture all of the important comovements in asset returns and are obtained empirically using factor analysis or principal components methods or simply by pre-specifying macroeconomic variables as instruments.[6] The problem with such investigations is that none of the concerns expressed about contagion seem to be based on a linear measure of association for returns. 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

---

analysis is a precursor of our approach, it is not focused on the probability of the joint occurrence of extreme events across countries.

[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, Sentana and Wadhwani (1995), Longin and Solnik (1995, 2001), and Karolyi and Stulz (1996).

[6] See Karolyi and Stulz (2001) for a survey of international asset pricing models.

appropriate 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 across countries, but this propagation is hidden in correlation measures by the large number of days when little of importance happens.

To address these concerns, a number of recent studies have extended models of international asset return correlations to allow for these observed threshold (large) and asymmetric (negative return) effects. Some researchers have employed multivariate extreme value theory from statistics (Longin and Solnik, 2001; Straetmans, 1998; Starica, 1999; Hartman, Straetmans and de Vries, 2001). Others have developed multivariate GARCH-M models allowing asymmetry (Bekaert and Wu, 2000; Ang and Chen, 2000), Poisson jumps (Das and Uppal, 1999), and even Hamiltonian regime-switching (Ang and Bekaert, 2000) in the joint dynamics of returns. By contrast, in this paper, we abandon the correlation framework that previous researchers have focused on to study contagion and direct our attention instead to the 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 the joint occurrences of large returns. We show that linear models cannot explain the patterns that we observe for large absolute value returns; that is, there are more frequent joint occurrences of large absolute value returns than linear models would predict. We then develop an econometric model of the joint occurrences of large absolute value returns using multinomial logistic regression.

In part, we are influenced in our choice of methodology by the extensive use of multinomial logistic analysis in epidemiology research on contagious diseases (Hosmer and Lemeshow, 1989). In epidemiology, 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* or more 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.

A second distinct advantage of this multinomial logistic analysis is that we can condition on attributes and characteristics of the exceedance event using control variables (or, covariates) measured with information available up to the previous day. We find that exchange rate changes, interest rate levels, and regional conditional volatility of equity market returns are statistically important covariates that help predict and explain exceedances in this model. It is important to note that these macroeconomic variables are similar to those that are often pre-specified as factors in models of international asset pricing (e.g., Ferson and Harvey, 1993, 1994; Dumas and Solnik, 1995; DeSantis and Gerard, 1997, 1998). However, our logistic regression model allows the factors to influence comovements in international returns nonlinearly by capturing extreme-return events. We define contagion within regions as the fraction of exceedance events that is not explained by our covariates (exchange rates, interest rates, market volatility). We find that 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.

A third advantage of our approach is that it enables us to consider contagion across regions as well as within regions. An earlier literature has 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 exceedances among countries in one region on the probability of observing exceedances among countries in other regions. More specifically, we

[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 (1998), Connolly and Wang (1999), Dumas, Harvey, and Ruiz (2000), and Ng (2000).

define contagion across regions as the fraction of the exceedance events in a particular region that is left unexplained by its own covariates but that is explained by the exceedances from another region. We find evidence of cross-regional contagion. Remarkably, the U.S. seems completely insulated from any Asian contagion, even during the Asian crisis in 1997. We show that contagion effects across regions cannot be explained by a linear returns-generating model.

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 also draws on extreme-value statistical theory that models the distribution of the tail observations ignoring the distribution of the other observations. In this paper, we draw 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 (EMDB, now owned by Standard and Poor's). 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 five years (1,305 time-series observations). To address this limitation, we extend the various series back to April 1992 by reconstructing the value-weighted indexes from individual stock prices in the respective markets from Datastream International and from information on the composition of the monthly IFC indices available from EMDB. This extended

[8] See Longin (1996), Danielsson and de Vries (1997), Longin and Solnik (2001) and, especially, recent applications to Asian markets by Kaminsky and Schmukler (1999) and Pownall and Koedijk (1999).

our sample to 2,283 time-series observations. All the conclusions in our paper hold whatever sample we use.

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.

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. Originally, the International Finance Corporation produced such indices for emerging markets; currently, these indices are produced by Standard and Poor's.[9] 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 December 29, 2000 (1,305 observations).

While the sample period does include the 1997 Asian crisis as well as the 1998 Russian crisis, we are concerned that the sample is too short and that it excludes another important crisis event, namely, the Mexican peso devaluation of December 1994. As a result, we proceed to construct value-weighted indexes of the stocks in the respective emerging markets using daily stock prices from Datastream International. Our effort is also facilitated by the availability of the monthly IFC indexes from the EMDB 2000 CD-ROM. Our index construction procedure follows a series of steps and checks. Every month, stocks in the EMDB Global Index for each market are identified and sorted by market capitalization (adjusted for the free-float if cross-holding data is provided). Stocks are included until 50 stocks are included or until the threshold of 90 percent of the EMDB Global Index capitalization is met. Daily returns are computed from daily log differences of a value-weighted portfolio of constituent stocks and both local currency and U.S. dollar-denominated (net of log difference of daily exchange rate) returns. Though we start the procedure as far back as December 1989, the official start date for all markets is April 1, 1992. We verify our selection and construction criteria by examining the statistical attributes of the index series and the correlations with the actual IFC indexes after December 31, 1995. Overall, the coverage in terms of market capitalization is well over 90 percent, even if the 50 stock limit is not met, due to the skewness of the composition in many of these emerging markets. Most correlations between the constructed and actual IFC indexes are well over 0.95 (median of 0.988) for all but three exceptional cases (Colombia, 0.88, India, 0.89, and Peru, 0.83) indicating the construction process is reasonably sound. We report only the results using our constructed indexes, but all the tests reported in this paper are estimated using the actual IFC indexes also.[10]

Table 1 provides sample statistics, including correlations for the full sample period, April 1, 1992 to December 29, 2000 (2,283 observations). Not surprisingly, the properties of the

---

[9] Detailed information can be obtained from *The IFC Indexes: Methodology, Definitions and Practices* (February, 1998, International Finance Corporation, Washington, DC) or Standard and Poor's *Emerging Market Data Base EMDB 2000™ Version 6.0* (CD-ROM).

indices vary dramatically across countries. China has the highest average daily return (0.087 percent), but Brazil has the highest daily return standard deviation (3.370 percent), almost four times that of the U.S. and Europe. The largest positive extreme return (58.708 percent) obtains for Pakistan whereas Peru experienced the largest negative extreme return (-41.908 percent). 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 0.30. Another cluster of moderately high correlations includes the markets of Southeast Asia (Philippines, Indonesia, Malaysia, and Thailand). 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 correlations between returns in Asia and Latin America separated by one day (upper triangular matrix) are roughly the same size as the same day correlations (lower triangular matrix).

Correlations have been much studied. 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.[11] We treat positive extreme returns separately from the negative extreme returns. In Table 2, we report our counts of the number of joint occurrences of extreme returns, or co-exceedances, within a region. The left side of the table focuses on negative return ("bottom tail") exceedances, and the

[10] These results are available from the authors upon request.

[11] Longin (1996), Longin and Solnik (2001), 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.

right side, on positive return ("top tail") exceedances.[12] 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 (top panel), the distribution of co-exceedances is mostly symmetric. There are five days with six or more countries in the bottom tail and seven days with six 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 five co-exceedances. In that case, there are 16 days with five countries in the bottom tail and only 6 days with five countries in the top tail. Indonesia was in the bottom tail for 14 of the 16 days with five countries and all five days with six or more countries. Malaysia was the next most regular participant in bottom tail co-exceedance events. During the Asian crisis, crisis countries (Thailand, Korea, Malaysia, and Indonesia) seem more likely to be in the 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 six or more Asian countries experience an exceedance on a given day. Surprisingly, the crisis countries do not always have larger negative returns on such days than non-crisis countries. The absolute value average return is higher for positive returns (7.47 percent) than for negative returns (-7.08 percent) on such days.

Though Latin America has only seven countries, there are seven days where all six or more countries are in the bottom tail at the same time and 28 days in total when four countries or more have extreme negative returns. This contrasts with the case for positive extreme returns in

[12] Since we count positive and negative return exceedances separately, both sides of the table should sum to the total of 2,283 days. That is, a bottom-tail (top-tail) outcome is treated as "0" when counting the number of co-exceedances in the top (bottom) tail, which explains their large number of around 1,500 for Asia and 1,700 for Latin America. Note that we count the total number of days with co-exceedances of a given number and identify which countries participate in those co-exceedance events and how often.

which there is only one day when six countries or more have returns in the positive tail. In Latin America and unlike Asia, therefore, there is clearer evidence of asymmetry in that co-exceedances of negative returns are more likely than co-exceedances of positive returns. Argentina, Chile, and Mexico are in each of the bottom-tail events with five one more co-exceedances; by contrast, Colombia has a disproportionately large number of single-country exceedances (73 out of 371 in total). Among top-tail co-exceedance counts, Colombia is again less likely to be involved with other Latin American countries, like Argentina, Chile, and Mexico but much more likely to experience a top-tail event alone (86 out of 448 in total).

We compare, but do not report, co-exceedance counts during the periods before and after the July 1997 devaluation of the Thai Baht for Asia and before and after the December 1994 devaluation of the Mexican peso. All but three of the Asian bottom-tail and all but one of the top-tail co-exceedances involving four countries or more (28 and 15, in total, respectively) take place after the devaluation of the Thai Baht. There are also clusters of large numbers of co-exceedances in Latin America but they are distributed more evenly over the period. Latin American co-exceedances involving four countries or more experiencing negative extreme returns take place in early 1994 (4 events) and around the December 1995 Mexican peso crisis (7 events), but two more clusters appear in July 1997 and, especially, in August 1998, the Russian default crisis period. The differences before and after the Thai Baht devaluation for Asia and around the Mexican peso and Russian default periods for Latin America reflect the same result as that observed by Forbes and Rigobon (1998, 2001) and others of an increase in correlations during the crisis periods. Indeed, such a result is difficult to interpret because, we should naturally see higher correlations once we condition on the occurrence of large returns. 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 existence 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 series of Monte Carlo simulation experiments.[13]

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 5,000 random realizations of the time series of 2,283 daily returns for the Asian countries. For each realization, 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 2. 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 5,000 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 three scenarios. The first scenario assumes that returns are jointly-distributed as multivariate Normal. The second scenario allows for the possibility of fatter tails with the multivariate Student-t distribution. The degrees of freedom equal 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). We explored a number of choices of K, but report only our analysis with K = 5.[14] One of the concerns expressed by Dornbusch et al. (2000), Baig and Goldfajn (1999), and Forbes and

[13] A new paper by Susmel (2001) also documents the unusually large number of extreme negative returns among Latin American index returns. His focus is on the implication of safety-first principles for U.S. investors who create a diversified portfolio using Latin American markets added to their purely domestic portfolio.

Rigobon (1998, 2001) 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. Neither of these two scenarios allows for the possibility of conditional heteroscedasticity in the index returns. Unfortunately, there are not many choices available to specify a parsimonious, yet reasonably general, structure with time-varying conditional volatility for a relatively large number of markets. One such parameterization is the multivariate generalized autoregressive conditional heteroscedasticity (GARCH) model of Ding and Engle (1994).[15] This Ding-Engle model constitutes our third scenario. Specifically, we estimate,

$$R_{it} = d_0 + e_{it} \qquad \underline{e}_t \mid W_{t-1} \sim N(0,H_t)$$

$$H_t = H_0 * (ii¢ - aa¢ - bb¢) + aa¢ * \underline{e}_{t-1}\underline{e}_{t-1}¢ + bb¢ * H_{t-1},$$

where R_{it} is the return on asset i between time $t-1$ and t, and W_{t-1}, the set of market-wide information available at $t-1$. δ_0 is a constant parameter and e_{it} and the associated N-vector, $\underline{e}_t$, are residuals that are conditionally distributed multivariate Normal with symmetric conditional covariance (N ´ N) matrix, H_t. In the law of motion equation for the conditional variances, i is an N-vector of ones, a, b are N-vectors of parameters (where $*$ is the Hadamard matrix product, element by element), and H_0 is an unobserved starting covariance matrix which we set equal to the sample covariance matrix of the returns. We estimate this system using maximum likelihood and the Berndt, Hall, Hall, and Hausman (1974) optimization algorithm for the 10 Asian and 7 Latin American markets and then simulate 5,000 random realizations given the estimated ($2N$ +

[14] A multivariate Student t distribution could potentially have a vector of degrees of freedom. Our choice to impose a single value for all returns series is restrictive. We thank the referee for this point.

[15] This model structure has been successfully applied by DeSantis and Gerard (1997, 1998) and, more recently, Ledoit, Santa-Clara, and Wolf (2001). The goal of their study, however, is to propose a numerically-feasible alternative "Diagonal-Vech" multivariate GARCH model. We thank the referee for pointing out this alternative conditional covariance structure.

1) parameters. It is important to note that the Ding-Engle model does not impose constant correlation, but rather guides the correlations in time by means of a constrained law of motion for the conditional volatilities.

Table 3 reports the results separately for Asia (Panel A) and Latin America (Panel B). 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, regardless of the scenario. For example, we have five days where six or more countries in Asia have extreme negative returns. In our simulations, we generate an average of 0.61 days with the multivariate Normal scenario, 7.01 days on average in the multivariate Student t scenario, and only 1.16 with the multivariate GARCH scenario.[16] The simulation p-values indicate that the multivariate Normal scenario delivers not even one replication out of 5,000 in which five or more days of co-exceedances of negative returns of six countries occur. However, the multivariate GARCH and Student t scenarios do generate the actual number of co-exceedances in 4 percent and 86 percent of the replications, respectively. For co-exceedances of positive returns, the results are similar. In these cases, the sample has seven co-exceedances involving six countries or more and this count is larger than that generated by the multivariate Normal and GARCH scenarios (simulated p-value of 0.00 and 0.04), but it is not unusual for the Student t scenarios (p-value of 0.60).

The results for Latin America are harder to reconcile with the simulations than the results for Asia. In these experiments, the multivariate Normal and GARCH scenarios fails to generate any (simulated p-values of 0.00) observations of six or more co-exceedances of negative returns

[16] As a calibration exercise, we examined the skewness and kurtosis of the simulated returns from the three scenarios and compared them with the actual returns. Overall, the kurtosis implied by the multivariate Student t scenario for the marginal distributions of individual country index returns are reasonably close to the positive excess kurtosis in the actual returns. The skewness statistics were, however, typically much lower. For the multivariate GARCH and Normal scenarios, the skewness and kurtosis were even smaller than those of the Student t. For example, Peru's index returns display excess positive skewness (0.26) and positive kurtosis (6.89). The average skewness coefficients for the three simulated scenarios (Normal, Student t, GARCH) were 0.03, 0.28 and –0.05, respectively; the average kurtosis coefficients were 0.01, 5.79 and 2.48, respectively.

of which there are 7 in the actual sample. What is more surprising is that even the Student t scenario cannot deliver simulated co-exceedance counts as large as in the actual sample. By contrast, the number of positive tail co-exceedances in Latin America is not dramatically different from the simulated counts. There is only one co-exceedance event with six or more countries, so each of the scenarios are able to offer a reasonable number of realizations that meet this challenge. But, even the five co-exceedance events in which five Latin American countries experience returns in the top 5 percent tail occur in more than 2 percent of the replications for the multivariate Normal scenario, 8 percent for the multivariate GARCH scenario, and 75 percent for the multivariate Student t scenario. This asymmetry in co-exceedance events represents another challenge for a linear model of contagion.

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 a large fraction of the 5,000 replications) with a somewhat strong assumption about positive excess co-kurtosis in the Student t distribution (though not with the Normal or GARCH models). For Latin America, this is not the case for the bottom tail co-exceedance events for any scenario. 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, GARCH, 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 only a few applications of multivariate EVT to stock returns (Longin and Solnik, 2001; Straetmans, 1998; Starica, 1999; Hartman, Straetmans, and de Vries, 2001). But, even in these cases, 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, 2001). 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, 1983, 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 *b*s, 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,[17]

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

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 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. 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,

[17] Greene (2000, Chapter 19) warns about the limitations of using pseudo-R^2 for comparisons across models.

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

where x^* is the unconditional mean value of x. From this measure and following Greene (2000, Chapter 19), we compute the marginal change in probability for a given unit change in the independent covariate to test whether this change is statistically significantly different from zero.

We considered alternative estimation approaches for our problem. Because our multinomial logit model fails to account for the ordinal nature of our co-exceedance measure as the dependent variable, we may lose efficiency compared to an ordered logit model, which is explicitly designed to capture the ordering information. The ordered logit, also known as a proportional odds ordered logit model, requires the odds of adjacent categories, defined by different threshold or cutoff points along the ordinal scale, to have the same ratio for all independent variable combinations. As a result, there is only one set of coefficients estimated for the covariates instead of four sets separately for each outcome in the multinomial logit. However, this model implies that the odds of observing five co-exceedances instead of four are equivalent to the odds of observing three co-exceedances instead of two. Such a constraint will generate less efficient estimates if the odds are not proportional (Peterson and Harrell, 1990, Brant, 1990). With this concern in mind, we chose to feature the unordered multinomial logit; however, we do robustness tests described in Section 4 with the ordered logit model. Another alternative is the negative binomial model, which is a generalization of the Poisson regression model used mainly for count data. This model specifies that each observation is drawn from a Poisson distribution with an expected number of events per period that is related to independent variables, or covariates. The advantage of the negative binomial model is that it does not assume equality of the expected mean and variance. We hesitate to employ this model, as it is typically used in cross-sectional analysis and less often with time-series data (Greene, 2000, Section 19.9). However, Section 4 also provides a discussion of additional robustness tests with the negative binomial model.

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."[18]

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 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. The first panel shows estimates for Asia, the second panel, for Latin America. At the end of each table, we also report results for the binomial models for the U.S. and Europe. 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 66.84 percent that no Asian

[18] There are many examples of similar 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).

country has a bottom tail return. If bottom tail exceedances were independent, this probability would be 59.87 (or, 0.95^{10}) 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 23.22 percent. Since there are no covariates, these probabilities are the sample frequencies reported in Table 2. In column (2), we add the conditional volatility of the Asian index (h_{it}) as a covariate.[19] 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 numbers of joint occurrences. For instance, a one percent increase in the conditional volatility increases the probability of one exceedance by 0.058 percent and the probability of four or more occurrences by 0.009 percent. All the partial derivatives are significant at 5 percent level or better. The pseudo-R^2 is 5.09 percent.

In column (3), we add the average exchange rate change in the region (e_{it}) as well as the average interest rate level (i_{it}) in the region.[20] 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 (e_{it} rises), extreme returns are more likely. Further, if interest rates are higher, exceedances are more likely. Moreover, the magnitude of the partial derivatives for changes in e_{it} is two to three times larger than for the partial derivatives for h_{it}. In the case of interest rates, however, the significance of an increase in interest rates on the

---

[19] The conditional volatility is estimated from a univariate EGARCH(1,1) model to the value-weighted Asian and Latin American regional indexes, as created by IFC after 1995 and reconstructed back to April 1992 as described in Section 2.

[20] 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.

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 one, two, or four or more exceedances. Adding exchange rate changes and the level of interest rates almost doubles the pseudo-R^2 to 9.21 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 issue, we estimated, but do not report our models, in local currency returns. Our results are similar using local currency returns.[21]

When we look at the top-tail events (models 4 to 6 in Table 4), we find no evidence that co-exeedance events are less likely for positive extreme returns than 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).[22] 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 almost no information for positive co-exceedances. The pseudo-R^2s are much lower for positive returns than they are for negative

[21] We also recomputed our summary statistics for own currency returns and for the exchange rate returns alone. In the latter case, we do not observe the frequency of five or six or more country co-exceedances as we do with stock returns. For example, in Latin America, we observe one negative co-exceedance of five or more countries instead of 13 for U.S. dollar-denominated stock index returns.

[22] We estimate a logit model for all co-exceedances, positive or negative, and introduce a dummy variable covariate equal to one if the co-exceedance was positive. The Wald test that the coefficients on the dummy variable are jointly equal to zero is distributed as χ^2 with 3 degrees of freedom.

returns, so that our covariates are more successful at explaining co-exceedances 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 76.83 percent for Latin America, while it is 66.84 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 (β_{04} of –4.137 implies a probability of 1.23 percent). 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 co-exceedances 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 higher than the probability of no negative extreme return. There seems to be an asymmetry between positive and negative extreme returns in Latin America. Our test of equality 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. Specifically, 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 the 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 larger for positive tail events. Exchange rate and interest rate levels offer only weak explanatory power.[23] 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 events.

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

[23] 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 Deutschmark (Euro)-U.S. dollar bilateral exchange rate and the short rate in Germany as a proxy. All data are from Datastream International.

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 Asian 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 and Asia, less so for Europe, but are not significant 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 a 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 the next section.

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. To the extent that there is a fraction of the co-exceedances in Latin American that is left unexplained by its own covariates that can be explained by co-exceedances in Asia, we will interpret this as evidence of contagion. 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 1 percent level) for all but two-country co-exceedances. In evaluating the derivative of the exceedance probabilities ("Δ prob" in table) at the unconditional mean of the covariates, we note that an increase in the number of exceedances in Latin America increases the probability of all one-country and four-country-or-more exceedance outcomes in Asia for negative tail events. It seems surprising at first that the coefficient β_{53} is significant but its associated probability, P_4, is not, but this no doubt reflects the non-linear logistic mapping. Because the slope of the probability function depends on the covariates, the significance of this slope depends on the value of the covariates used to estimate the slope.

A concern with these results is that the number of exceedances in Latin America might proxy for an exceedance in the U.S. since Latin American markets are open at the same time as the U.S. market. 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 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 coefficients on the U.S. exceedance have significant coefficients, and the effect on the probability is larger than the effect from Latin America. In addition, the conditional volatility of the U.S. is helpful to predict exceedances in Asia. Interestingly, 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 1 percent level. Finally, the results from adding European exceedances and conditional volatility as covariates (models 3 and 6) are weaker than those obtained from adding U.S. covariates for negative returns and virtually negligible for positive returns. Comparing the regressions of Table 5 for Asia with those of Table 4, we see that the pseudo-R^2 is 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, at least for two-country and four-country-or-more co-exceedances. The results for conditional volatility are mixed and, possibly, negative, which suggests that there may be complex interaction effects among the conditional volatility processes of the different regions. The impact of the exceedance shocks from the U.S. and Europe are larger and more consistent than those from Asia. The effect of the conditional volatility from the U.S. is also strangely negative, though not from Europe. The pseudo-R^2s of the Latin American regressions increase 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 additional 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 little or no effect on the probability of a negative extreme return for the U.S. and none on 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 reaches 10 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 even weaker than 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 more insulated than the U.S. from contagion in Latin America, but more sensitive to contagion from Asia 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 2,283 returns (corresponding to the April 1, 1992 to December 29, 2000 period) for each country in Asia and Latin America using 1,000 replications using the historical variance-covariance matrix and assumptions about the joint returns generating process. As before, we propose the multivariate Normal, multivariate Student t (with five degrees of freedom) and the multivariate GARCH using the Ding and Engle (1994) specification. This time, however, the simulation is for all 17 countries in both regions. For each replication, we count co-exceedance events in both regions and estimate a simplified version of 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 multivariate Normal and Student t scenarios, we cannot explain the magnitude of these β_{1j} coefficients for negative extreme returns; the multivariate GARCH model has only moderate success in both tails. It is interesting to note that the β_{1j} coefficients associated with Y_{jt}^* co-exceedances from the other region for Asia yield typically negative values with the multivariate Normal and Student t. The multivariate GARCH yields positive coefficient estimates, but delivers simulation p-values of at most 5 percent for top tail exceedances and 16 percent for the bottom tails. The pseudo-R^2 in the simulations reach values as large as those in the actual data in at most 1 percent of the replications. For Latin America, the highest simulation p-value for any co-exceedance coefficient is 3 percent for the top tail in the multivariate GARCH scenario and 23 percent in the bottom tail, also for the multivariate GARCH scenario. Perhaps even more striking, the pseudo-R^2 is at least four times higher in the data than it is in any of the simulations.

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 5 using local currency returns. The results are virtually unchanged, except that the pseudo-R^2 are lower in Asia and Latin America. 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 multivariate GARCH 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.[24] 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 logit, or proportional odds, model and the negative binomial regression model, as discussed in Section 3. 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. Some propose diagnostic

[24] Another possible concern that we do not investigate with the alternative specifications using multi-day horizons and lagged covariates is with nonstationarity of the explanatory variables. Park and Phillips (2000) demonstrate the complications in the limit distributions for binary choice models with explanatory variables generated as integrated processes. The potential impact on multinomial logit models is an open question, however. We thank Richard Roll and our referee for pointing out this issue.

tests for ordered logit models relative to multinomial (unordered) logit models based on the differences in the log-likelihood values (Brant, 1990). One such test is referred to as a "likelihood ratio test." It is computed as $-2(L^o–L)$, where L^o (L) is the log-likelihood of the ordered (unordered) logit, which is distributed as a c^2 with $p(c\text{-}2)$ degrees of freedom, where c is the number of categories (c = 5, for Asia and Latin America) and p is the number of covariates (p=5, in our case). This diagnostic regularly rejects the ordered logit model in favor of the multinomial, with only one exception. Note that this diagnostic cannot be used as a formal measure of fit as the models are not nested. 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. 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 estimated for each covariate.[25] We replicate our tests for contagion across regions with this model (unreported) and find that our inferences about contagion effects are even stronger between Asia and Latin America and between the emerging market regions and Europe. Contagion from Asia and Latin America to the U.S. is measurably lower, however.

5. Conclusion

In this paper, we propose 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 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

[25] We tested the restriction in the multinomial logit models in Section 4.1 that 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.

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 with different scenarios according to what one would find if returns satisfied a multivariate Normal, Student t, and even GARCH distributions. 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 Normal, Student t, or GARCH. We also find that the number of joint occurrences of extreme returns within a region can be explained by 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 returns-generating model, even if the conditional volatility of returns varies over time. 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 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.

References

Allen, F., and D. Gale, 2000, Financial contagion, Journal of Political Economy 108, 1-34.

Ang, A., and G. Bekaert, 2000, International asset allocation with time-varying correlations, Review of Financial Studies, forthcoming.

Ang. A,, and J. Chen, 2000, Asymmetric correlation of equity portfolios, Journal of Financial Economics, forthcoming.

Bae, K.-H., and G. A. Karolyi, 1994, Good news, bad news and international spillovers of stock return volatility between Japan and the U.S., Pacific-Basin Finance Journal 2, 405-438.

Baig, T., and I. Goldfajn, 1999, Financial market contagion in the Asian crisis, IMF working paper, International Monetary Fund, Washington D.C.

Bekaert, G., and G. Wu, 2000, Asymmetric volatility and risk in equity markets, Review of Financial Studies 13, 1–42.

Berndt, E., B. Hall, R. Hall, and J. Hausman, 1974, Estimation and inference in nonlinear structural models, Annals of Economics and Social Measurement 4, 653-665.

Bhagwati, J., 1998, The capital myth, Foreign Affairs 77 (3), 7-12.

Boyer, B. H., M. S. Gibson, and M. Loretan, 1997, Pitfalls in tests for changes in correlations, International Finance Discussion Papers No. 597, Board of Governors of the Federal Reserve System, Washington, D.C.

Brant, R., 1990, Assessing proportionality in the proportional odds model for ordinal logistic regression, Biometrics 35, 1171-1178.

Calvo, G., 1996, Private Capital Flows to Emerging Markets after the Mexican Crisis, Institute for International Economics, Washington, DC.

Claessens, S., and K. Forbes, 2001, International Financial Contagion, Kluwer Academic Publishers, New York, NY.

Connolly, R., and A. Wang, 1999, International equity market comovements: Economic fundamentals or contagion, Rice University working paper.

Danielsson, J., and C. de Vries, 1997, Value-at-risk and extreme returns, London School of Economics working paper.

Das, S. and R. Uppal, 1999, The effect of systemic risk on international portfolio choice, UBC working paper.

DeGregorio, J., and R. Valdes, 2001, Crisis transmission: Evidence from the debt, Tequila and Asian flu crises, in Claessens, S., and K. Forbes, eds., International Financial Contagion, Kluwer Academic Publishers, New York, NY.

De Santis, G., and B. Gerard, 1997, International asset pricing and portfolio diversification with time-varying risk, Journal of Finance 52, 1881-1912.

De Santis, G., and B. Gerard, 1998, How big is the premium for currency risk?, Journal of Financial Economics 49, 375-412.

Ding, Z., and R. Engle, 1994, Large scale conditional covariance modeling, estimation and testing, University of California at San Diego working paper.

Dornbusch, R., Y.-C. Park, and S. Claessens, 2001, Contagion: How it spreads and how it can be stopped? in Claessens, S., and K. Forbes, eds., International Financial Contagion, Kluwer Academic Publishers, New York, NY.

Dumas, B., C. Harvey, and P. Ruiz, 2000, Are common swings in international stock returns justified by subsequent changes in national outputs, Duke University working paper.

Dumas, B. and B. Solnik, 1995, The world price of foreign exchange risk, Journal of Finance 50, 445-479.

Eichengreen, B., G. Hale, and A. Mody, 2001, Flight to quality, in Claessens, S., and K. Forbes, eds., International Financial Contagion, Kluwer Academic Publishers, New York, NY.

Eichengreen, B., A. Rose and C. Wyplosz, 1996, Contagious currency crises: First tests, Scandinavian Journal of Economics 98, 463-484.

Erb, C. B., C. R. Harvey, and T. E. Viskanta, 1995, Country risk and global equity selection, Journal of Portfolio Management 21, 74-83.

Eun, C. S., and S. Shim, 1989, International transmission of stock market movements, Journal of Financial and Quantitative Analysis 24, 241-256.

Engle, R. F., T. Ito, and W.-L. Lin, 1990, Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market, Econometrica 58, 525-542.

Ferson, W., and C. Harvey, 1993, The risk and predictability of international equity returns, Review of Financial Studies 6, 527-566.

Ferson, W., and C. Harvey, 1994, Sources of risk and expected returns in global equity markets, Journal of Banking and Finance 18, 775-803.

Forbes, K., and R. Rigobon, 1998, No contagion, only interdependence: Measuring stock market co-movements, Unpublished Working Paper, Sloan School of Management, MIT.

Forbes, K., and R. Rigobon, 2001, Measuring contagion: Conceptual and empirical issues, in Claessens, S., and K. Forbes, eds., International Financial Contagion, Kluwer Academic Publishers, New York, NY.

Gillespie, B., M. Halpern, and K. Warner, 1994, Patterns of lung cancer risk in ex-smokers, in N. Lange, et al., Case Studies in Biometry, John Wiley and Sons.

Glick, R., and A. K. Rose, 1999, Contagion and trade, Journal of International Money and Finance 18, 603-617.

Greene, W., 2000, Econometric Analysis, 4th edition, Macmillan Publishers.

Hamao, Y., R. W. Masulis, and Victor Ng, 1990, Correlations in price changes and volatility across international stock markets, Review of Financial Studies 3, 281-308.

Hartmann, P., S. Straetmans, C. de Vries, 2001, Asset market linkages in crisis periods, Universiteit Maastricht working paper.

Hosmer, D., and S. Lemeshow, 1989, Applied Logistic Regression, John Wiley and Sons.

International Finance Corporation, 1998, The IFC Indexes: Methodology, Definitions and Practices, (Emerging Markets Data Base, Washington D.C.).

Kaminsky, G., R. Lyons, and S. Schmukler, 2001, Mutual fund investment in emerging markets: An overview, World Bank Economic Review, forthcoming, and reprinted in Claessens, S., and K. Forbes, eds., International Financial Contagion, Kluwer Academic Publishers, New York, NY.

Kaminsky, G. L., and C. Reinhart, 2000, On crises, contagion and confusion, Journal of International Economics 51, 145-168.

Kaminsky, G. L., and S. L. Schmukler, 1999, What triggers market jitters?, Journal of International Money and Finance 18, 537-560.

Karolyi, G. A., and R. M. Stulz, 1996, Why do markets move together? An investigation of U.S.-Japan stock return comovements, Journal of Finance 51, 951-986.

Karolyi, G. A., and R. M. Stulz, 2001, Are assets priced locally or globally?, Ohio State University working paper.

King, M., E. Sentana, and S. Wadhwani, 1995, Volatility and links between national stock markets, Econometrica 62, 901-933.

King, M. A., and S. Wadhwani, 1990, Transmission of volatility between stock markets, Review of Financial Studies 3, 5-33.

Kyle, A. S., and W. Xiong, 2001, Contagion as a wealth effect, Journal of Finance 56, 1401-1440.

Ledoit, O., P. Santa-Clara, and M. Wolf, 2001, Flexible multivariate GARCH modeling with an application to international stock markets, UCLA working paper.

Lilien, G., and P. Kotler, 1992, Marketing Decision Making: A Model-Building Approach, Harper and Row.

Lin, W.-L., R. F. Engle, and T. Ito, 1994, Do bulls and bears move across borders? International transmission of stock returns and volatility, Review of Financial Studies 7, 507-538.

Longin, F. M., 1996, The asymptotic distribution of extreme stock market returns, Journal of Business 69, 383-408.

Longin, F. M., and B. Solnik, 1995, Is the correlation in international equity returns constant: 1970-1990?, Journal of International Money and Finance 14, 3-26.

Longin, F. M., and B. Solnik, 2001, Extreme correlations of international equity markets during extremely volatile periods, Journal of Finance 56, 649-676.

Maddala, G. S., 1983, Limited-dependent and Qualitative Variables in Econometrics, Cambridge University Press.

Masson, P., 1999, Contagion, Journal of International Money and Finance 18, 587-602.

McFadden, P., 1974, The measurement of urban travel demand, Journal of Public Economics 3, 303-328.

Ng., A., 2000, Volatility spillover effects from Japan and the U.S. to the Pacific-Basin, Journal of International Money and Finance 19, 207-233.

Park, J.Y., and P. C. B. Phillips, 2000, Nonstationary binary choice, Econometrica 68, 1249-1280.

Park, Y. C., and C. Y. Song, 2001, Financial contagion in the East Asian crisis, in Claessens, S., and K. Forbes, eds., International Financial Contagion, Kluwer Academic Publishers, New York, NY.

Peterson, B., and F. Harrell, Jr., 1990, Partial proportional odds models for ordinal response variables, Applied Statistics 39, 205-217.

Pownall, R. A., and K. G. Koedijk, 1999, Capturing downside risk in financial markets: The case of the Asian crisis, Journal of International Money and Finance 18, 853-870.

Pritsker, M., 2001, The channels for financial contagion, in Claessens, S., and K. Forbes, eds., International Financial Contagion, Kluwer Academic Publishers, New York, NY.

Ramchand, L., and R. Susmel, 1998, Volatility and cross-correlation across major stock markets, Journal of Empirical Finance 5, 397-416.

Rigobon, R., 1998, On the measurement of contagion, Unpublished Working Paper, Sloan School of Management, MIT, Cambridge, MA.

Schinasi, G., and T. Smith, 2001, Portfolio diversification, leverage and financial contagion, in Claessens, S., and K. Forbes, eds., International Financial Contagion, Kluwer Academic Publishers, New York, NY.

Starica, C., 1999, Multivariate extremes for models with constant conditional correlations, Journal of Empirical Finance 6, 515-553.

Stiglitz, J., 1998, Distinguished lecture on economics in government: The private uses of public interests: Incentives and institutions, Journal of Economic Perspectives 12, 3-22.

Straetmans, S., 1998, Extreme Financial Returns and their Comovements, Ph.D. dissertation, Erasmus Universiteit Rotterdam, Thesis Publishers, Amsterdam.

Susmel, R., 2001, Extreme observations and diversification in Latin American emerging equity markets, University of Houston working paper.

Susmel, R., and R. F. Engle, 1994, Hourly volatility spillovers between international equity markets, Journal of International Money and Finance 13, 3-26.

Table 1. Summary statistics of daily returns on International Financial Corporation (IFC) emerging markets indices, April 1, 1992 to December 29,
Each index from the Emerging Market Database (EMDB) is adjusted to reflect accessibility of the market and individual stocks for foreign investors.

China (CHN), Korea (KOR), Philippine (PHI), Taiwan (TWN), India (INA), Indonesia (IND), Malaysia (MAL), Pakistan (PAK), Sri Lanka (SRI), Thailand

S&P 500 index for US and
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	0.087	0.019	0.012	0.017	-0.030	0.002	0.021	0.037	0.016	-0.029	0.026	0.044	0.025	0.005	0.029	0.054	0.039	0.060	0.053
S.D. in percent	2.888	2.723	1.758	1.821	1.823	3.271	2.103	2.502	1.373	2.426	2.107	3.370	1.246	1.267	2.073	2.471	2.544	0.938	0.826
Median	0.000	0.000	0.000	0.000	0.000	0.006	0.001	0.000	0.000	-0.029	0.005	0.020	0.000	-0.013	0.003	0.001	0.000	0.033	0.089
Minimum	-38.094	-21.714	-10.145	-10.804	-18.747	-37.549	-22.789	-17.742	-8.716	-16.086	-14.132	-27.515	-6.706	-6.933	-20.853	-41.908	-14.872	-7.107	-4.117
Maximum	48.083	27.035	21.598	7.364	14.265	27.216	23.902	58.708	17.974	16.637	13.358	35.294	9.266	9.232	16.731	15.794	21.851	4.995	3.608
Correlation	CHN	KOR	PHI	TWN	INDIA	IND	MAL	PAK	SRI	THA	ARG	BRA	CHI	COL	MEX	PER	VEN	US	Europe
CHN	1.00										0.09	0.01	0.03	-0.01	0.07	0.05	-0.01	0.11	0.05
KOR	0.07	1.00									0.13	0.10	0.11	0.00	0.15	0.05	0.06	0.20	0.17
PHI	0.06	0.17	1.00								0.20	0.14	0.17	0.06	0.18	0.05	0.09	0.23	0.22
TWN	0.02	0.12	0.17	1.00							0.12	0.05	0.08	0.04	0.11	0.03	0.05	0.16	0.12
INA	0.05	0.10	0.09	0.04	1.00						0.05	0.04	0.06	0.01	0.04	0.02	-0.01	0.06	0.05
IND	0.04	0.15	0.36	0.13	0.06	1.00					0.13	0.09	0.14	0.05	0.13	0.07	0.07	0.16	0.12
MAL	0.04	0.18	0.28	0.16	0.08	0.36	1.00				0.10	0.06	0.09	-0.01	0.09	0.03	0.05	0.21	0.10
PAK	0.01	0.01	0.07	0.05	0.04	0.06	0.08	1.00			0.02	0.01	0.02	0.03	0.03	0.00	0.09	0.03	0.03
SRI	0.00	0.02	0.07	0.02	0.00	0.03	0.04	0.04	1.00		0.03	0.05	0.03	0.06	0.02	0.01	0.03	0.02	0.03
THA	0.10	0.25	0.36	0.15	0.10	0.33	0.38	0.07	0.07	1.00	0.16	0.10	0.13	0.04	0.13	0.06	0.06	0.18	0.16
ARG	0.03	0.10	0.07	-0.01	0.02	0.07	0.10	0.02	-0.02	0.10	1.00								
BRA	-0.01	0.09	0.05	0.02	0.06	0.05	0.05	0.03	0.01	0.07	0.39	1.00							
CHI	0.02	0.12	0.15	0.09	0.06	0.11	0.11	0.05	0.00	0.16	0.42	0.31	1.00						
COL	0.05	0.04	0.07	0.03	0.02	0.07	0.03	0.04	0.04	0.05	0.05	0.07	0.09	1.00					
MEX	0.01	0.12	0.11	0.04	0.04	0.06	0.10	0.06	-0.01	0.09	0.47	0.34	0.39	0.07	1.00				
PER	0.00	0.06	0.05	0.03	0.07	0.04	0.05	0.01	0.02	0.05	0.16	0.16	0.17	0.03	0.17	1.00			
VEN	0.06	0.08	0.07	0.03	0.02	0.08	0.07	0.00	0.00	0.08	0.17	0.14	0.17	0.08	0.18	0.06	1.00		
US	-0.02	0.08	0.07	0.01	0.02	0.02	0.01	0.01	0.01	0.04	0.39	0.27	0.29	0.05	0.40	0.11	0.09	1.00	
Europe	0.07	0.16	0.16	0.07	0.04	0.12	0.17	0.03	0.04	0.17	0.27	0.17	0.27	0.08	0.28	0.14	0.14	0.31	1.00

Table 2. Summary statistics of (co-) exceedances for daily emerging market index returns, April 1, 1992 to December 29, 2000.
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,…,5 separately and for i equal to six or more as >6. For example, of 2283 trading days, there are 148 occurrences of bottom tail co-exceedances for Asia with two countries only, and 27 of those occurrences include China with co-exceedances of a particular number. "Cum. %" cumulates the fraction of the total number of return observations (2283 days) by category.

		Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails							
	Mean return when > 6	> 6	5	4	3	2	1	0	0	1	2	3	4	5	> 6	Mean return when > 6
CHN	-7.56%	2	2	1	3	27	79	1526	1507	76	23	10	3	1	1	5.03%
KOR	-8.22%	4	10	6	15	35	44	1526	1507	41	33	21	8	5	6	8.05%
PHI	-6.72%	3	13	15	14	24	45	1526	1507	43	32	18	11	3	7	7.09%
TWN	-4.95%	4	4	6	6	33	61	1526	1507	66	24	15	4	1	4	6.11%
INA	-5.84%	3	5	5	10	28	63	1526	1507	61	34	8	5	3	3	3.61%
IND	-9.55%	5	14	14	11	35	35	1526	1507	42	27	23	13	4	5	18.52%
MAL	-6.17%	5	12	17	16	33	31	1526	1507	41	30	22	12	3	6	9.35%
PAK	-10.13%	4	3	6	4	30	67	1526	1507	61	34	9	4	3	3	3.82%
SRI	-3.76%	3	3	3	8	23	74	1526	1507	79	25	6	2	1	1	2.41%
THA	-7.85%	5	14	15	21	28	31	1526	1507	36	34	21	10	6	7	10.68%
Total	-7.08%	5	16	22	36	148	530	1526	1507	546	148	51	18	6	7	7.47%
Cum. %		0.22%	0.92%	1.88%	3.46%	9.94%	33.16%	100.00%	100.00%	33.99%	10.07%	3.59%	1.36%	0.57%	0.31%	
ARG	-8.96%	7	6	10	15	31	45	1754	1691	52	35	13	8	5	1	7.12%
BRA	-11.32%	6	6	12	17	27	46	1754	1691	58	31	13	7	4	1	10.81%
CHI	-4.79%	7	6	11	18	24	48	1754	1691	45	41	17	5	5	1	6.62%
COL	-3.66%	5	1	5	12	18	73	1754	1691	86	19	5	2	2	0	-
MEX	-7.56%	7	6	7	17	34	43	1754	1691	65	28	9	7	4	1	7.32%
PER	-5.84%	5	0	11	11	27	60	1754	1691	65	29	11	4	4	1	5.79%
VEN	-6.67%	6	5	4	12	31	56	1754	1691	77	25	7	3	1	1	7.37%
Total	-6.97%	7	6	15	34	96	371	1754	1691	448	104	25	9	5	1	7.51%
Cum. %		0.31%	0.57%	1.23%	2.72%	6.92%	23.17%	100.00%	100.00%	25.93%	6.31%	1.75%	0.66%	0.26%	0.04%	

exceedances for daily emerging market returns. Under the null hypothesis that national emerging market

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-) θ where equals five percent as in Table 2. Summary statistics for the 5000 replications include the mean, standard deviation, 5% quantile, and simulated p-value (the number of replications with co-exceedances in a given exceedances). Simulations are run under three different models of return distributions: a multivariate normal distribution, a multivariate t-distribution with the degree of freedom 5, and a multivariate GARCH. The dynamics of variance and covariance matrix under the

Panel A: Asia

		Number of (co-)								Number of (co-) exceedances in the top tails				
		5	4		2	1		0	1		3	4		> 6
Actual		16	22		148	530		1507	546		51	18		7
Monte Carlo Simulations														
Simulated Mean	0.61		12.05	46.07		595.60	1455.73		598.08	172.03		12.33	2.84	
Standard Deviation	0.77		3.26	6.00		18.99	11.91		19.04	10.49		3.30	1.66	
5th quantile	0	0	7	36	153	565	1436	1430	567	155	37	7	0	0
95th quantile	2	6	18	56	188	627	1475	1470	629	189	57	18	6	2
p-value	0.00	0.00	0.00	0.96	0.98	1.00	0.00	0.00	1.00	0.99	0.27	0.07	0.06	0.00
B. Multivariate t-distribution (degree of freedom = 5)														
Simulated Mean	7.20	12.37	28.52	64.86	153.75	415.81	1600.48	1595.28	418.52	155.01	65.43	28.96	12.50	7.30
Standard Deviation	2.56	3.31	4.83	7.07	10.89	18.64	14.09	14.19	18.47	11.03	7.09	4.84	3.35	2.55
5th quantile	3	7	21	54	136	385	1577	1572	388	137	54	21	7	3
95th quantile	12	18	37	77	172	447	1624	1619	448	173	77	37	18	12
p-value	0.86	0.17	0.93	1.00	0.72	0.00	1.00	1.00	0.00	0.75	0.99	0.99	0.99	0.60
C. Multivariate GARCH														
Simulated Mean	1.16	4.96	15.56	50.06	167.50	560.56	1483.20	1484.20	554.92	167.00	54.22	16.40	4.84	1.42
Standard Deviation	1.36	3.55	4.02	6.70	14.61	23.67	20.45	22.57	27.69	12.76	6.77	4.71	3.14	1.93
5th quantile	0	1	8	39	135	517	1448	1450	502	144	42	10	1	0
95th quantile	4	12	21	59	187	597	1519	1525	601	186	65	25	10	5
p-value	0.04	0.02	0.04	0.98	0.92	0.92	0.04	0.16	0.60	0.94	0.74	0.32	0.36	0.04

Panel B: Latin America

	Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails						
	>6	5	4	3	2	1	0	0	1	2	3	4	5	>6
Actual	7	6	15	34	96	371	1754	1691	448	104	25	9	5	1
Monte Carlo Simulations														
A. Multivariate Normality														
Simulated Mean	0.17	1.41	7.49	29.42	110.29	451.10	1683.12	1678.75	453.83	111.17	29.98	7.63	1.46	0.18
Standard Deviation	0.41	1.17	2.57	4.84	8.78	16.45	10.31	10.24	16.42	8.58	4.83	2.58	1.19	0.42
5^{th} quantile	0	0	3	22	96	424	1666	1662	426	97	22	4	0	0
95^{th} quantile	1	4	12	37	125	478	1700	1696	481	126	38	12	4	1
p-value	0.00	0.00	0.01	0.20	0.95	1.00	0.00	0.12	0.65	0.82	0.87	0.35	0.02	0.16
B. Multivariate t-distribution (degree of freedom = 5)														
Simulated Mean	1.79	6.09	17.27	42.93	109.67	339.36	1765.89	1761.56	342.15	110.49	43.40	17.39	6.18	1.83
Standard Deviation	1.31	2.38	3.85	5.69	8.93	16.21	11.48	11.73	16.40	9.20	5.81	3.86	2.41	1.35
5^{th} quantile	0	2	11	34	95	313	1747	1742	315	95	34	11	3	0
95^{th} quantile	4	10	24	52	125	366	1784	1781	370	126	53	24	10	4
p-value	0.00	0.58	0.76	0.95	0.95	0.03	0.86	1.00	0.00	0.77	1.00	0.99	0.75	0.84
C. Multivariate GARCH														
Simulated Mean	0.29	2.05	9.26	32.46	109.93	431.70	1697.31	1693.48	433.61	111.07	32.87	9.54	2.13	0.31
Standard Deviation	0.55	1.54	3.28	5.48	9.06	20.89	14.54	14.91	21.43	9.30	5.59	3.30	1.60	0.59
5^{th} quantile	0	0	4	24	95	397	1674	1669	399	96	24	4	0	0
95^{th} quantile	1	5	15	42	125	466	1722	1718	470	126	42	15	5	1
p-value	0.00	0.03	0.06	0.42	0.95	1.00	0.00	0.58	0.25	0.79	0.94	0.60	0.08	0.25

Table 4. Multinomial logit regression results for daily return co-exceedances of emerging market indices, April 1, 1992 to December 29, 2000. 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 $P_0 = 1 / [1 + \sum_k \exp(x'\beta_k)]$, 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, 2000, 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)	-1.058[a]	-0.124[a]	-1.453[a]	-0.191[a]	-1.312[a]	-0.170[a]	-1.015[a]	-0.118[a]	-1.259[a]	-0.160[a]	-1.240[a]	-0.174[a]
β_{02}	-2.333[a]	-0.117[a]	-2.984[a]	-0.146[a]	-3.096[a]	-0.148[a]	-2.321[a]	-0.117[a]	-2.839[a]	-0.140[a]	-2.186[a]	-0.098[a]
β_{03}	-3.747[a]	-0.051[a]	-4.865[a]	-0.051[a]	-6.613[a]	-0.058[a]	-3.386[a]	-0.064[a]	-4.281[a]	-0.067[a]	-3.865[a]	-0.057[a]
β_{04}	-3.569[a]	-0.057[a]	-4.951[a]	-0.052[a]	-6.208[a]	-0.048[a]	-3.884[a]	-0.046[a]	-5.360[a]	-0.036[a]	-6.037[a]	-0.032[a]
β_{11} (h_{it})			0.389[a]	0.058[a]	0.477[a]	0.077[a]			0.242[a]	0.033[a]	0.329[a]	0.048[a]
β_{12}			0.565[a]	0.026[a]	0.607[a]	0.026[a]			0.446[a]	0.021[a]	0.618[a]	0.029[a]
β_{13}			0.784[a]	0.008[a]	0.663[a]	0.005[a]			0.638[a]	0.010[a]	0.774[a]	0.011[a]
β_{14}			0.874[a]	0.009[a]	0.816[a]	0.006[a]			0.831[a]	0.006[a]	0.814[a]	0.004[a]
β_{21} (e_{it})					1.077[a]	0.158[a]					-1.003[a]	-0.150[a]
β_{22}					2.144[a]	0.102[a]					-1.774[a]	-0.082[a]
β_{23}					2.216[a]	0.017[a]					-1.872[a]	-0.025[a]
β_{24}					2.640[a]	0.019[a]					-2.351[a]	-0.011[a]
β_{31} (i_{it})					-0.021	-0.004					-0.006	0.000
β_{32}					-0.004	0.000					-0.078[b]	-0.004[b]
β_{33}					0.147[a]	0.001[b]					-0.053	-0.001
β_{34}					0.083	0.001					0.046	0.000
Log-Likelihood	-2113.85		-2006.21		-1919.16		-2139.16		-2056.82		-1998.90	
Pseudo-R^2				5.09%		9.21%				3.85%		6.56%

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)	-1.554[a]	-0.174[a]	-2.097[a]	-0.243[a]	-2.431[a]	-0.290[a]	-1.328[a]	-0.169[a]	-1.672[a]	-0.222[a]	-1.852[a]	-0.254[a]
β_{02}	-2.905[a]	-0.102[a]	-3.470[a]	-0.120[a]	-3.902[a]	-0.120[a]	-2.789[a]	-0.106[a]	-3.412[a]	-0.124[a]	-3.735[a]	-0.122[a]
β_{03}	-3.943[a]	-0.052[a]	-5.083[a]	-0.053[a]	-5.738[a]	-0.051[a]	-4.214[a]	-0.041[a]	-5.361[a]	-0.039[a]	-5.784[a]	-0.038[a]
β_{04}	-4.137[a]	-0.045[a]	-5.389[a]	-0.043[a]	-5.531[a]	-0.037[a]	-4.725[a]	-0.028[a]	-6.149[a]	-0.023[b]	-7.592[a]	-0.021[b]
β_{11} (h_{it})			0.363[a]	0.044[a]	0.345[a]	0.043[a]			0.237[a]	0.033[a]	0.232[a]	0.033[a]
β_{12}			0.374[a]	0.012[a]	0.359[a]	0.010[a]			0.390[a]	0.014[a]	0.408[a]	0.013[a]
β_{13}			0.614[a]	0.006[a]	0.604[a]	0.005[a]			0.586[a]	0.004[a]	0.600[a]	0.004[a]
β_{14}			0.647[a]	0.005[a]	0.651[a]	0.004[a]			0.657[a]	0.002[b]	0.665[a]	0.002[b]
β_{21} (e_{it})					1.177[a]	0.142[a]					-0.130	-0.006
β_{22}					1.914[a]	0.059[a]					-1.466[a]	-0.053[a]
β_{23}					1.962[a]	0.017[a]					-1.488[a]	-0.010[b]
β_{24}					2.048[a]	0.013[a]					-1.638[a]	-0.005[c]
β_{31} (i_{it})					0.014	0.002					0.012	0.002
β_{32}					0.008	0.000					0.018	0.001
β_{33}					0.018	0.000					0.024	0.000
β_{34}					-0.014	0.000					0.072[b]	0.000
Log-Likelihood	-1706.94		-1636.24		-1573.16		-1746.61		-1691.22		-1664.96	
Pseudo-R^2			4.14%		7.84%				3.17%		4.67%	
US												
β_{01} (constant)	-2.946[a]	-0.140[a]	-3.535[a]	-0.153[a]	-5.792[a]	-0.225[a]	-2.946[a]	-0.140[a]	-4.004[a]	-0.148[a]	-5.120[a]	-0.177[a]
β_{11} (h_{it})			0.570[a]	0.025[a]	0.427[a]	0.017[a]			0.921[a]	0.034[a]	0.892[a]	0.031[a]
β_{21} (e_{it})					0.409[c]	0.016[c]					-0.610[b]	-0.021[b]
β_{31} (i_{it})					0.460[a]	0.018[a]					0.216[c]	0.007[c]
Log-Likelihood	-452.76		-434.76		-424.88		-452.76		-399.13		-393.95	
Pseudo-R^2			3.98%		6.16%				11.85%		12.99%	
Europe												
β_{01} (constant)	-2.946[a]	-0.140[a]	-3.808[a]	-0.158[a]	-3.639[a]	-0.132[a]	-2.946[a]	-0.140[a]	-4.009[a]	-0.157[a]	-3.791[a]	-0.125[a]
β_{11} (h_{it})			1.049[a]	0.044[a]	1.046[a]	0.038[a]			1.250[a]	0.049[a]	1.186[a]	0.039[a]
β_{21} (e_{it})					0.922[a]	0.033[a]					-1.047[a]	-0.034[a]
β_{31} (i_{it})					-0.057	-0.002					-0.061	-0.002
Log-Likelihood	-452.76		-426.41		-408.07		-452.76		-412.92		-388.66	
Pseudo-R^2			5.82%		9.87%				8.80%		14.16%	

Table 5. Contagion test results of multinomial logit regression for daily return co-exceedances of emerging market indices, April 1, 1992 to December 29, 2000. 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)	-1.414[a]	-0.190[a]	-1.625[a]	-0.224[a]	-1.670[a]	-0.231[a]	-1.243[a]	-0.177[a]	-1.320[a]	-0.185[a]	-1.461[a]	-0.213[a]
β_{02}	-3.249[a]	-0.155[a]	-3.772[a]	-0.173[a]	-3.712[a]	-0.170[a]	-2.263[a]	-0.102[a]	-2.492[a]	-0.113[a]	-2.565[a]	-0.115[a]
β_{03}	-7.154[a]	-0.057[a]	-7.704[a]	-0.055[a]	-7.563[a]	-0.053[a]	-3.909[a]	-0.054[a]	-4.647[a]	-0.062[a]	-4.572[a]	-0.061[a]
β_{04}	-6.560[a]	-0.038[a]	-7.132[a]	-0.043[a]	-7.098[a]	-0.045[a]	-7.051[a]	-0.028[b]	-7.513[a]	-0.028[b]	-7.507[a]	-0.021[b]
β_{11} (h_{it})	0.446[a]	0.073[a]	0.357[a]	0.059[a]	0.352[a]	0.057[a]	0.353[a]	0.052[a]	0.284[a]	0.042[a]	0.243[a]	0.035[a]
β_{12}	0.553[a]	0.024[a]	0.427[a]	0.017[a]	0.445[a]	0.019[a]	0.654[a]	0.030[a]	0.523[a]	0.024[a]	0.504[a]	0.024[a]
β_{13}	0.575[a]	0.004[a]	0.475[a]	0.003[b]	0.500[a]	0.003[b]	0.852[a]	0.011[a]	0.629[a]	0.008[a]	0.656[a]	0.008[a]
β_{14}	0.794[a]	0.004[a]	0.670[a]	0.004[a]	0.647[a]	0.004[a]	0.796[a]	0.003[b]	0.645[a]	0.002[b]	0.777[a]	0.002[b]
β_{21} (e_{it})	1.082[a]	0.161[a]	0.997[a]	0.149[a]	1.054[a]	0.157[a]	-0.981[a]	-0.149[a]	-0.961[a]	-0.147[a]	-0.927[a]	-0.142[a]
β_{22}	2.156[a]	0.103[a]	2.048[a]	0.094[a]	2.147[a]	0.099[a]	-1.716[a]	-0.079[a]	-1.662[a]	-0.076[a]	-1.611[a]	-0.074[a]
β_{23}	2.298[a]	0.016[a]	2.166[a]	0.014[a]	2.222[a]	0.014[a]	-1.809[a]	-0.023[a]	-1.747[a]	-0.021[a]	-1.712[a]	-0.021[a]
β_{24}	2.720[a]	0.015[a]	2.574[a]	0.015[a]	2.632[a]	0.016[a]	-2.341[a]	-0.008[a]	-2.275[a]	-0.008[b]	-2.258[a]	-0.006[b]
β_{31} (i_{it})	-0.021	-0.004	-0.003	-0.002	-0.010	-0.003	-0.008	0.000	-0.001	0.001	0.001	0.001
β_{32}	-0.002	0.000	0.034	0.002	0.012	0.001	-0.080[b]	-0.004[b]	-0.057[c]	-0.003[c]	-0.064[b]	-0.004[c]
β_{33}	0.160[a]	0.001[b]	0.194[a]	0.001[b]	0.177[a]	0.001[b]	-0.060	-0.001	-0.004	0.000	-0.046	-0.001
β_{34}	0.077	0.001	0.129[b]	0.001[c]	0.117[b]	0.001[c]	0.076	0.000	0.114[c]	0.000	0.029	0.000
β_{41}(h_{jt}^*)	0.055	0.008	0.243[a]	0.038[a]	0.500[a]	0.080[a]	-0.052	-0.008	0.062	0.008	0.333[a]	0.052[b]
β_{42}	0.124[c]	0.006[c]	0.404[a]	0.018[a]	0.781[a]	0.034[a]	-0.063	-0.003	0.142	0.007	0.423[b]	0.018[c]
β_{43}	0.190[b]	0.001[c]	0.566[a]	0.004[b]	0.723[b]	0.004	-0.185	-0.003	0.241	0.003	0.879[a]	0.012[a]
β_{44}	-0.098	-0.001	0.231	0.001	0.600[c]	0.003	0.075	0.000	0.555[a]	0.002[b]	1.367[a]	0.004[c]
β_{51} (Y_{jt}^*)	0.157[b]	0.027[b]	0.670[a]	0.098[b]	0.402[c]	0.057	0.205[a]	0.029[b]	0.339	0.041	0.013	-0.014
β_{52}	0.012	-0.002	1.362[a]	0.062[a]	0.709[b]	0.031[c]	0.405[a]	0.019[a]	0.950[a]	0.046[b]	0.842[a]	0.046[a]
β_{53}	0.362[b]	0.003	1.884[a]	0.013[b]	1.989[a]	0.014[b]	0.673[a]	0.009[a]	1.728[a]	0.024[a]	0.728	0.010
β_{54}	0.889[a]	0.005[a]	2.610[a]	0.016[b]	1.988[a]	0.013[b]	0.834[a]	0.003[b]	1.567[a]	0.006[c]	1.443[a]	0.004[c]
Log-Likelihood	-1895.45		-1884.20		-1885.98		-1978.26		-1976.45		-1967.31	
Pseudo-R^2	10.31%		10.85%		10.76%		7.50%		7.59%		8.02%	
χ^2 (h_{jt}^*)	8.23[c]		21.14[a]		31.50[a]		5.90		12.74[b]		37.02[a]	
χ^2 (Y_{jt}^*)	38.25[a]		46.59[a]		29.57[a]		34.16[a]		24.97[a]		13.88[a]	

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)	-2.357[a]	-0.282[a]	-2.141[a]	-0.256[a]	-2.507[a]	-0.303[a]	-1.822[a]	-0.253[a]	-1.387[a]	-0.185[a]	-1.948[a]	-0.270[a]
β_{02}	-3.969[a]	-0.115[a]	-3.849[a]	-0.113[a]	-4.047[a]	-0.124[a]	-3.468[a]	-0.105[a]	-3.339[a]	-0.106[a]	-3.989[a]	-0.127[a]
β_{03}	-6.052[a]	-0.052[a]	-6.094[a]	-0.049[a]	-6.418[a]	-0.045[a]	-5.685[a]	-0.038[a]	-5.338[a]	-0.035[a]	-5.593[a]	-0.037[a]
β_{04}	-6.326[a]	-0.036[a]	-7.308[a]	-0.025[b]	-6.582[a]	-0.031[a]	-8.249[a]	-0.017[c]	-7.756[a]	-0.017[c]	-9.048[a]	-0.016[c]
β_{11} (h_{it})	0.368[a]	0.047[a]	0.435[a]	0.055[a]	0.322[a]	0.041[a]	0.280[a]	0.040[a]	0.358[a]	0.052[a]	0.213[a]	0.030[a]
β_{12}	0.359[a]	0.010[a]	0.444[a]	0.012[a]	0.324[a]	0.009[a]	0.530[a]	0.016[a]	0.546[a]	0.017[a]	0.370[a]	0.012[a]
β_{13}	0.559[a]	0.005[a]	0.642[a]	0.005[a]	0.551[a]	0.004[a]	0.634[a]	0.004[a]	0.738[a]	0.005[a]	0.606[a]	0.004[a]
β_{14}	0.548[a]	0.003[a]	0.649[a]	0.002[b]	0.567[a]	0.003[a]	0.722[a]	0.001[c]	0.745[a]	0.002[c]	0.562[a]	0.001[c]
β_{21} (e_{it})	1.144[a]	0.139[a]	1.086[a]	0.133[a]	1.165[a]	0.142[a]	-0.171	-0.014	-0.192	-0.017	-0.111	-0.005
β_{22}	1.909[a]	0.056[a]	1.878[a]	0.055[a]	1.916[a]	0.059[a]	-1.495[a]	-0.050[a]	-1.460[a]	-0.050[a]	-1.402[a]	-0.049[a]
β_{23}	1.985[a]	0.016[a]	1.946[a]	0.015[a]	2.002[a]	0.013[a]	-1.514[a]	-0.010[b]	-1.508[a]	-0.010[b]	-1.399[a]	-0.010[b]
β_{24}	2.121[a]	0.011[a]	2.123[a]	0.007[b]	2.128[a]	0.010[a]	-1.747[a]	-0.004[c]	-1.661[a]	-0.004[c]	-1.685[a]	-0.003
β_{31} (i_{it})	0.012	0.002	0.004	0.000	0.017[c]	0.002[c]	0.010	0.002	-0.005	-0.001	0.015[c]	0.002
β_{32}	0.011	0.000	0.006	0.000	0.013	0.000	0.010	0.000	0.003	0.000	0.027[c]	0.001
β_{33}	0.026	0.000	0.030	0.000	0.036	0.000	0.022	0.000	0.006	0.000	0.022	0.000
β_{34}	0.004	0.000	0.038	0.000	0.007	0.000	0.084[b]	0.000	0.077[c]	0.000	0.108[a]	0.000
β_{41}(h_{jt}^*)	-0.117[b]	-0.015[c]	-0.327[a]	-0.042[a]	0.012	0.001	-0.196[a]	-0.027[a]	-0.471[a]	-0.070[a]	0.040	0.006
β_{42}	-0.275[b]	-0.008[c]	-0.367[b]	-0.010[c]	0.063	0.002	-0.544[a]	-0.017[a]	-0.559[a]	-0.016[b]	0.067	0.002
β_{43}	0.058	0.001	-0.187	-0.001	0.103	0.001	-0.132	-0.001	-0.490[b]	-0.003	-0.349	-0.003
β_{44}	0.161	0.001	-0.044	0.000	0.417	0.002	-0.333	-0.001	-0.480[c]	-0.001	0.662[c]	0.001
β_{51} (Y_{jt}^*)	0.101	0.010	0.835[a]	0.097[a]	0.930[a]	0.114[a]	0.255[a]	0.037[a]	0.824[a]	0.116[a]	0.756[a]	0.108[a]
β_{52}	0.490[a]	0.015[a]	1.911[a]	0.057[a]	1.099[a]	0.032[b]	0.402[a]	0.012[b]	1.644[a]	0.052[a]	1.388[a]	0.044[a]
β_{53}	0.280	0.002	2.352[a]	0.019[a]	2.613[a]	0.019[a]	0.070	0.000	1.124	0.006	1.205[c]	0.007
β_{54}	0.513[a]	0.003[b]	3.899[a]	0.014[b]	2.757[a]	0.013[b]	0.848[a]	0.002	2.722[a]	0.006	2.145[a]	0.004
Log-Likelihood	-1555.18		-1522.99		-1541.19		-1640.94		-1637.00		-1646.92	
Pseudo-R^2	8.89%		10.78%		9.71%		6.05%		6.28%		5.71%	
χ^2 (h_{jt}^*)	11.69[b]		13.69[a]		1.81		24.45[a]		30.17[a]		4.94	
χ^2 (Y_{jt}^*)	25.29[a]		92.76[a]		63.17[a]		29.98[a]		37.10[a]		27.88[a]	
US	From Asia		From Latin		From Europe		From Asia		From Latin		From Europe	
β_1 (constant)	-5.842[a]	-0.224[a]	-6.577[a]	-0.205[a]	-5.911[a]	-0.215[a]	-5.150[a]	-0.178[a]	-5.453[a]	-0.170[a]	-5.059[a]	-0.163[a]
β_2 (h_{it})	0.370[a]	0.014[a]	0.437[a]	0.014[a]	0.170	0.006	0.884[a]	0.031[a]	1.043[a]	0.033[a]	0.930[a]	0.030[a]
β_3 (e_{it})	0.422[c]	0.016[c]	0.314	0.010	0.530[b]	0.019[b]	-0.611[b]	-0.021[b]	-0.591[b]	-0.018[b]	-0.745[a]	-0.024[a]
β_4 (i_{it})	0.455[a]	0.017[a]	0.558[a]	0.017[a]	0.451[a]	0.016[a]	0.219[c]	0.008[c]	0.247[b]	0.008[b]	0.199	0.006[c]
β_4 (h_{jt}^*)	0.020	0.001	-0.177[c]	-0.006[c]	0.347	0.013	-0.005	0.000	-0.204[b]	-0.006[b]	-0.258	-0.008
β_4 (Y^*_{jt})	0.185[c]	0.007[c]	0.914[a]	0.028[a]	1.551[a]	0.057[a]	0.045	0.002	0.678[a]	0.021[a]	1.756[a]	0.056[a]
Log-Likelihood	-423.01		-381.00		-409.55		-393.87		-378.28		-378.50	
Pseudo-R^2	6.57%		15.85%		9.54%		13.01%		16.45%		16.40%	
χ^2 (h_{jt}^*)	0.07		3.81[b]		2.50		0.00		5.72[b]		1.18	
χ^2 (Y_{jt}^*)	3.36[c]		90.36[a]		31.19[a]		0.17		33.37[a]		35.79[a]	
Europe	From Asia		From Latin		From US		From Asia		From Latin		From US	
β_1 (constant)	-4.311[a]	-0.133[a]	-3.609[a]	-0.121[a]	-4.017[a]	-0.129[a]	-4.258[a]	-0.128[a]	-3.781[a]	-0.120[a]	-4.187[a]	-0.131[a]
β_2 (h_{it})	0.958[a]	0.030[a]	0.983[a]	0.033[a]	1.031[a]	0.033[a]	0.987[a]	0.030[a]	1.044[a]	0.033[a]	0.896[a]	0.028[a]
β_3 (e_{it})	0.980[a]	0.030[a]	0.997[a]	0.033[a]	1.008[a]	0.032[a]	-1.120[a]	-0.034[a]	-1.081[a]	-0.034[a]	-1.073[a]	-0.034[a]
β_4 (i_{it})	-0.010	0.000	-0.083[c]	-0.003[c]	-0.023	-0.001	-0.025	-0.001	-0.083[c]	-0.003[c]	-0.013	0.000
β_4 (h_{jt}^*)	-0.007	0.000	-0.070	-0.002	-0.042	-0.001	0.067	0.002	0.035	0.001	0.251[c]	0.008[c]
β_4 (Y^*_{jt})	0.624[a]	0.019[a]	0.527[a]	0.018[a]	1.944[a]	0.062[a]	0.464[a]	0.014[a]	0.363[a]	0.012[a]	1.051[a]	0.033[a]
Log-Likelihood	-384.89		-395.68		-386.28		-376.02		-383.42		-380.56	
Pseudo-R^2	14.99%		12.61%		14.68%		16.95%		15.31%		15.95%	
χ^2 (h_{jt}^*)	0.01		0.88		0.07		0.81		0.30		3.42[b]	
χ^2 (Y_{jt}^*)	45.40[a]		27.39[a]		52.66[a]		21.85[a]		9.24[a]		11.14[a]	

Table 6. Monte Carlo simulation results of contagion tests using multinomial logit regression for daily return co-exceedances of emerging 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. Three different scenarios include: multivariate Normal, 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 5 and a multivariate GARCH following the specification of Ding and Engle (1994). For each scenario, we report the mean, standard deviation ("S.D."), minimum and maximum 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

		Multivariate Normal					Multivariate Student t (K=5)					Multivariate GARCH				
Coefficient	Actual	Mean	S.D.	Minimum	Maximum	p-val	Mean	S.D.	Minimum	Maximum	p-val	Mean	S.D.	Minimum	Maximum	p-val
Top tails																
β_{01}	-0.9979[a]	-0.9395	0.0226	-1.0094	-0.8929	0.99	-0.9410	0.0255	-1.0123	-0.8878	0.99	-0.9628	0.0209	-1.0192	-0.9020	0.94
β_{02}	-2.3211[a]	-2.2092	0.0470	-2.2997	-2.1121	1.00	-2.2145	0.0412	-2.3154	-2.1129	1.00	-2.2412	0.0400	-2.3112	-2.1521	1.00
β_{03}	-3.6755[a]	-3.4416	0.0806	-3.6523	-3.2359	1.00	-3.4405	0.0706	-3.6268	-3.3027	1.00	-3.4895	0.0795	-3.7306	-3.2957	0.99
β_{04}	-4.6293[a]	-4.1728	0.1161	-4.4618	-3.9657	1.00	-4.1672	0.1135	-4.4255	-3.8995	1.00	-4.2960	0.1296	-4.6660	-4.0710	0.97
β_{11} (Y^*_{jt})	0.1721[a]	0.0016	0.0643	-0.1347	0.1952	0.01	0.0053	0.0724	-0.1502	0.2024	0.01	0.0682	0.0584	-0.1086	0.2192	0.05
β_{12}	0.2848[a]	-0.0259	0.1382	-0.3582	0.2236	0.00	-0.0084	0.1169	-0.3498	0.2528	0.00	0.0672	0.1123	-0.2167	0.2414	0.00
β_{13}	0.5185[a]	-0.0462	0.2466	-0.9369	0.4390	0.00	-0.0426	0.2109	-0.5868	0.3941	0.00	0.0898	0.2196	-0.6595	0.5711	0.01
β_{14}	0.8274[a]	-0.0306	0.3321	-0.8626	0.5965	0.00	-0.0586	0.3905	-1.8337	0.5306	0.00	0.2734	0.2459	-0.3293	0.8239	0.00
Log-L	-2139.09	-2151.14	1.16	-2153.06	-2147.80	0.00	-2151.24	1.20	-2153.01	-2147.83	0.00	-2149.76	2.43	-2152.69	-2138.75	0.01
Pseudo-R^2	0.0070	0.0009	0.0006	0.0000	0.0020	0.00	0.0009	0.0007	0.0000	0.0020	0.00	0.0016	0.0011	0.0000	0.0070	0.01
Bottom tails																
β_{01}	-1.0923[a]	-0.8221	0.0428	-0.9385	-0.7052	1.00	-0.8648	0.0996	-1.5490	-0.7558	0.97	-0.9385	0.0472	-1.0679	-0.8035	1.00
β_{02}	-2.5219[a]	-2.0227	0.0718	-2.2597	-1.8659	1.00	-2.0558	0.0889	-2.5150	-1.8962	1.00	-2.2416	0.0722	-2.4148	-2.0777	1.00
β_{03}	-3.8226[a]	-3.3598	0.1520	-3.7154	-3.0688	1.00	-3.3424	0.1597	-3.7506	-3.0243	1.00	-3.4644	0.1291	-3.8054	-3.1389	1.00
β_{04}	-4.0033[a]	-4.4154	0.2786	-5.4394	-3.8925	0.08	-4.3604	0.2207	-4.8688	-3.9499	0.06	-4.3340	0.2189	-5.1291	-3.8659	0.02
β_{11} (Y^*_{jt})	0.1416[b]	-0.1418	0.0766	-0.3335	0.0498	0.16	-0.1028	0.1037	-0.3623	0.4466	0.02	0.0742	0.0682	-0.0858	0.2431	0.16
β_{12}	0.4362[a]	-0.3240	0.1402	-0.6394	-0.0353	0.00	-0.2400	0.1768	-0.6754	0.5223	0.01	0.1366	0.1037	-0.1202	0.3707	0.00
β_{13}	0.5569[a]	-0.4949	0.3006	-1.5998	0.1584	0.00	-0.4479	0.4288	-2.7325	0.7844	0.01	0.0989	0.2360	-0.8315	0.5270	0.00
β_{14}	0.7410[a]	-0.6511	0.5029	-1.8830	0.2924	0.00	-0.5518	0.5011	-1.6745	0.9447	0.01	0.0375	0.4237	-1.4413	0.6350	0.00
Log-L	-2109.16	-2154.39	5.80	-2164.91	-2131.43	0.00	-2155.67	11.24	-2168.92	-2063.62	0.01	-2158.76	4.87	-2170.68	-2147.67	0.00
Pseudo-R^2	0.0120	0.0034	0.0016	0.0000	0.0080	0.00	0.0031	0.0029	0.0000	0.0260	0.01	0.0017	0.0011	0.0000	0.0050	0.00

Table 6. Continued.

Panel B. Latin America

Coefficient	Actual	Multivariate Normal Mean	S.D.	Minimum	Maximum	p-val	Multivariate Student t (K=5) Mean	S.D.	Minimum	Maximum	p-val	Multivariate GARCH Mean	S.D.	Minimum	Maximum	p-val
Top tails																
β_{01}	-1.5111[a]	-1.2950	0.0561	-1.4306	-1.1631	1.00	-1.3085	0.0631	-1.6141	-1.1688	0.99	-1.4399	0.0558	-1.5944	-1.2835	0.91
β_{02}	-2.7110[a]	-2.7141	0.0977	-3.0213	-2.4674	0.49	-2.7133	0.1124	-2.9524	-2.4331	0.51	-2.8213	0.1049	-3.1991	-2.5768	0.13
β_{03}	-4.7535[a]	-4.0880	0.1883	-4.7280	-3.7373	1.00	-4.0643	0.1933	-4.5798	-3.6080	1.00	-4.1155	0.2048	-4.6825	-3.6501	1.00
β_{04}	-5.4340[a]	-5.3402	0.4050	-6.4000	-4.4990	0.61	-5.1796	0.4028	-6.2207	-4.0149	0.78	-4.6838	0.2791	-5.7947	-3.9714	0.98
β_{11} (Y^*_{jt})	0.2492[a]	0.0105	0.0602	-0.1652	0.1519	0.00	-0.0081	0.0698	-0.2033	0.1402	0.00	0.0245	0.0592	-0.0974	0.1462	0.00
β_{12}	0.2451[b]	-0.0098	0.1234	-0.4040	0.2882	0.01	-0.0097	0.1108	-0.3839	0.1979	0.00	0.0479	0.1281	-0.2681	0.2914	0.03
β_{13}	0.6495[a]	-0.0221	0.2569	-0.8645	0.4219	0.00	-0.0237	0.2634	-0.8409	0.5091	0.00	0.1482	0.2188	-0.7469	0.6522	0.01
β_{14}	0.6776[a]	-0.1324	0.4947	-1.4267	0.8590	0.02	-0.2066	0.4785	-1.7440	0.6049	0.00	0.2931	0.2733	-0.6419	0.8231	0.04
Log-L	-1742.94	-1762.75	2.96	-1768.33	-1755.54	0.00	-1762.05	5.49	-1768.11	-1715.03	0.01	-1743.63	8.77	-1761.90	-1715.31	0.44
Pseudo-R^2	0.0090	0.0011	0.0010	0.0000	0.0050	0.00	0.0012	0.0009	0.0000	0.0040	0.00	0.0019	0.0013	0.0000	0.0060	0.00
Bottom tails																
β_{01}	-1.6103[a]	-1.2926	0.0543	-1.4348	-1.1461	1.00	-1.3072	0.0564	-1.6018	-1.1996	1.00	-1.4417	0.0599	-1.5872	-1.3050	1.00
β_{02}	-3.2254[a]	-2.7110	0.0913	-3.0467	-2.5071	1.00	-2.7160	0.0900	-2.9437	-2.4653	1.00	-2.8311	0.1129	-3.1328	-2.5414	1.00
β_{03}	-4.4007[a]	-4.0686	0.2370	-4.7494	-3.4718	0.92	-4.0372	0.2330	-4.6597	-3.5373	0.95	-4.0911	0.2112	-4.5028	-3.6877	0.90
β_{04}	-4.5927[a]	-5.3740	0.4168	-6.6869	-4.4885	0.01	-5.2349	0.3899	-6.1308	-4.1539	0.04	-4.6762	0.2473	-5.3794	-4.3007	0.43
β_{11} (Y^*_{jt})	0.0803	-0.0076	0.0731	-0.1856	0.2034	0.12	-0.0173	0.0651	-0.2117	0.0984	0.05	0.0240	0.0685	-0.1455	0.1909	0.23
β_{12}	0.4428[b]	-0.0048	0.1110	-0.2587	0.2211	0.00	-0.0021	0.1176	-0.4417	0.2386	0.00	0.0774	0.1245	-0.2319	0.3773	0.00
β_{13}	0.7189[a]	-0.0400	0.2754	-0.8836	0.5702	0.00	-0.0608	0.2970	-0.8508	0.6626	0.00	0.1450	0.2434	-1.0897	0.5832	0.00
β_{14}	0.6552[a]	-0.0663	0.4457	-1.4115	0.7589	0.03	-0.0778	0.5018	-1.5985	0.7888	0.10	0.2523	0.2368	-0.4480	0.7867	0.03
Log-L	-1678.13	-1762.33	2.99	-1768.31	-1752.78	0.00	-1762.30	4.39	-1768.34	-1730.22	0.00	-1744.92	7.78	-1761.69	-1719.66	0.00
Pseudo-R^2	0.0160	0.0012	0.0008	0.0000	0.0030	0.00	0.0012	0.0010	0.0000	0.0050	0.00	0.0019	0.0012	0.0000	0.0050	0.00

Table 7. Contagion test results of multinomial logit regression for daily return co-exceedances of emerging market indices using lagged conditioning variables, April 1, 1992 to December 29, 2000. 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 $1- (L_\omega/L_\Omega)$ 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)	-1.241[a]	-0.153[a]	-1.491[a]	-0.192[a]	-1.518[a]	-0.198[a]	-1.171[a]	-0.157[a]	-1.243[a]	-0.165[a]	-1.390[a]	-0.194[a]
β_{02}	-3.008[a]	-0.151[a]	-3.566[a]	-0.173[a]	-3.439[a]	-0.167[a]	-2.337[a]	-0.108[a]	-2.569[a]	-0.120[a]	-2.646[a]	-0.122[a]
β_{03}	-7.266[a]	-0.058[a]	-7.937[a]	-0.056[a]	-7.628[a]	-0.054[a]	-4.029[a]	-0.059[a]	-4.723[a]	-0.067[a]	-4.737[a]	-0.066[a]
β_{04}	-6.427[a]	-0.050[a]	-7.139[a]	-0.055[a]	-6.967[a]	-0.056[a]	-6.977[a]	-0.035[b]	-7.289[a]	-0.035[b]	-7.493[a]	-0.026[b]
β_{11} (h_{it})	0.404[a]	0.063[a]	0.312[a]	0.049[a]	0.307[a]	0.048[a]	0.315[a]	0.045[a]	0.250[a]	0.036[a]	0.209[a]	0.029[a]
β_{12}	0.531[a]	0.025[a]	0.408[a]	0.018[a]	0.431[a]	0.020[a]	0.600[a]	0.028[a]	0.475[a]	0.022[a]	0.456[a]	0.022[a]
β_{13}	0.457[a]	0.003[b]	0.349[a]	0.002[c]	0.392[a]	0.002[b]	0.805[a]	0.011[a]	0.598[a]	0.008[a]	0.613[a]	0.008[a]
β_{14}	0.704[a]	0.005[a]	0.571[a]	0.004[a]	0.563[a]	0.004[a]	0.794[a]	0.004[a]	0.665[a]	0.003[b]	0.772[a]	0.003[b]
β_{21} (e_{it-1})	0.246[c]	0.036	0.237[c]	0.035	0.252[c]	0.037	-0.410[a]	-0.060[b]	-0.388[a]	-0.057[b]	-0.341[b]	-0.050[b]
β_{22}	0.352[c]	0.016	0.346[c]	0.015	0.362[b]	0.016[c]	-0.875[a]	-0.043[a]	-0.861[a]	-0.042[a]	-0.773[a]	-0.038[a]
β_{23}	0.939[a]	0.007[a]	0.948[a]	0.007[a]	0.937[a]	0.007[a]	-0.575[b]	-0.007[c]	-0.531[b]	-0.006	-0.432[c]	-0.005
β_{24}	0.822[a]	0.006[a]	0.854[a]	0.006[a]	0.876[a]	0.007[a]	-0.801[a]	-0.003[b]	-0.770[a]	-0.003[b]	-0.672[a]	-0.002[c]
β_{31} (i_{it-1})	-0.033[c]	-0.007[c]	-0.012	-0.003	-0.021	-0.005	-0.015	-0.002	-0.008	-0.001	-0.006	0.000
β_{32}	-0.007	0.000	0.028	0.002	0.004	0.000	-0.071[b]	-0.004[b]	-0.048	-0.003	-0.055[c]	-0.003[c]
β_{33}	0.187[a]	0.002[b]	0.226[a]	0.002[b]	0.198[a]	0.002[b]	-0.044	-0.001	0.005	0.000	-0.029	0.000
β_{34}	0.114[b]	0.001[c]	0.168[a]	0.001[b]	0.149[a]	0.001[b]	0.086	0.001	0.113[c]	0.001	0.048	0.000
β_{41}(h_{jt}^*)	0.045	0.007	0.248[a]	0.038[a]	0.503[a]	0.079[a]	-0.042	-0.007	0.068	0.008	0.356[a]	0.055[b]
β_{42}	0.092	0.005	0.379[a]	0.017[a]	0.691[a]	0.032[a]	-0.049	-0.002	0.160	0.008	0.465[a]	0.020[b]
β_{43}	0.194[b]	0.002[c]	0.605[a]	0.004[b]	0.697[b]	0.004	-0.175	-0.003	0.265[c]	0.004	0.925[a]	0.013[a]
β_{44}	-0.165	-0.002	0.202	0.001	0.428	0.002	0.078	0.001	0.534[a]	0.003[b]	1.338[a]	0.005[b]
β_{51} (Y_{jt}^*)	0.158[b]	0.027[b]	0.720[a]	0.102[b]	0.425[c]	0.058	0.218[a]	0.031[b]	0.370	0.045	-0.010	-0.018
β_{52}	-0.014	-0.004	1.430[a]	0.068[a]	0.747[b]	0.034[c]	0.415[a]	0.019[a]	1.046[a]	0.051[a]	0.794[b]	0.044[b]
β_{53}	0.300[c]	0.002	1.981[a]	0.013[b]	2.028[a]	0.014[b]	0.689[a]	0.010[a]	1.770[a]	0.025[a]	0.711	0.010
β_{54}	0.842[a]	0.007[a]	2.624[a]	0.020[a]	2.095[a]	0.017[a]	0.829[a]	0.004[b]	1.470[a]	0.007[c]	1.495[a]	0.005[c]
Log-Likelihood	-1959.80		-1942.99		-1946.77		-2015.98		-2013.69		-2003.63	
Pseudo-R^2	7.71%		8.50%		8.32%		5.74%		5.85%		6.32%	
χ^2 (h_{jt}^*)	8.55[c]		22.90[a]		28.76[a]		5.04		13.57[c]		41.26[a]	
χ^2 (Y_{jt}^*)	36.01[a]		52.32[a]		35.71[a]		37.57[a]		28.15[a]		15.36[a]	

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)	-2.263[a]	-0.266[a]	-1.999[a]	-0.235[a]	-2.411[a]	-0.286[a]	-1.838[a]	-0.248[a]	-1.407[a]	-0.181[a]	-1.965[a]	-0.265[a]
β_{02}	-3.518[a]	-0.113[a]	-3.191[a]	-0.103[a]	-3.566[a]	-0.122[a]	-3.837[a]	-0.129[a]	-3.803[a]	-0.133[a]	-4.367[a]	-0.151[a]
β_{03}	-5.584[a]	-0.057[a]	-5.477[a]	-0.052[a]	-5.893[a]	-0.049[a]	-5.520[a]	-0.041[a]	-5.156[a]	-0.037[a]	-5.425[a]	-0.039[a]
β_{04}	-5.902[a]	-0.041[a]	-6.779[a]	-0.030[b]	-6.103[a]	-0.036[a]	-8.561[a]	-0.019[c]	-8.144[a]	-0.018[c]	-9.205[a]	-0.017[c]
β_{11} (h_{it})	0.367[a]	0.045[a]	0.442[a]	0.055[a]	0.319[a]	0.039[a]	0.266[a]	0.037[a]	0.343[a]	0.049[a]	0.198[a]	0.028[a]
β_{12}	0.386[a]	0.012[a]	0.492[a]	0.015[a]	0.345[a]	0.011[a]	0.445[a]	0.015[a]	0.444[a]	0.014[a]	0.297[a]	0.010[a]
β_{13}	0.569[a]	0.006[a]	0.671[a]	0.006[a]	0.562[a]	0.005[a]	0.617[a]	0.004[a]	0.733[a]	0.005[a]	0.602[a]	0.004[a]
β_{14}	0.552[a]	0.004[a]	0.657[a]	0.003[b]	0.572[a]	0.003[a]	0.682[a]	0.001[c]	0.706[a]	0.001[c]	0.542[a]	0.001[c]
β_{21} (e_{it})	0.317[b]	0.040[b]	0.294[b]	0.037[b]	0.355[a]	0.045[a]	0.159	0.024	0.096	0.014	0.192	0.029
β_{22}	0.303	0.009	0.303	0.009	0.363[c]	0.012	0.283[c]	0.010	0.284[c]	0.010	0.374[b]	0.013[b]
β_{23}	0.271	0.002	0.252	0.002	0.308	0.002	-0.343	-0.003	-0.461	-0.004	-0.356	-0.003
β_{24}	0.318	0.002	0.407	0.002	0.376	0.002	-0.808	-0.002	-1.046[b]	-0.003	-0.951[c]	-0.002
β_{31} (i_{it})	0.012	0.002	0.001	0.000	0.017[c]	0.002[c]	0.010	0.001	-0.005	-0.001	0.014	0.002
β_{32}	0.004	0.000	-0.010	0.000	0.005	0.000	0.030[c]	0.001[c]	0.027[c]	0.001[c]	0.046[a]	0.002[b]
β_{33}	0.022	0.000	0.018	0.000	0.030	0.000	0.015	0.000	-0.002	0.000	0.016	0.000
β_{34}	0.006	0.000	0.036	0.000	0.008	0.000	0.101[a]	0.000	0.094[b]	0.000	0.117[a]	0.000
β_{41}(h_{jt}^{*})	-0.128[b]	-0.015[c]	-0.372[a]	-0.046[a]	-0.007	-0.001	-0.187[a]	-0.026[a]	-0.453[a]	-0.067[a]	0.062	0.009
β_{42}	-0.351[a]	-0.012[b]	-0.556[a]	-0.018[b]	-0.074	-0.003	-0.454[a]	-0.016[a]	-0.418[a]	-0.012[c]	0.163	0.006
β_{43}	-0.010	0.000	-0.311	-0.002	-0.031	0.000	-0.133	-0.001	-0.516[b]	-0.003	-0.420	-0.004
β_{44}	0.093	0.001	-0.129	0.000	0.265	0.002	-0.267	0.000	-0.400	-0.001	0.647[c]	0.001
β_{51} (Y_{jt}^{*})	0.104	0.010	0.848[a]	0.096[a]	0.983[a]	0.118[a]	0.257[a]	0.037[a]	0.845[a]	0.117[a]	0.768[a]	0.107[a]
β_{52}	0.477[a]	0.017[a]	1.834[a]	0.062[a]	1.134[a]	0.037[b]	0.397[a]	0.013[b]	1.765[a]	0.061[a]	1.521[a]	0.052[a]
β_{53}	0.278	0.003	2.255[a]	0.021[a]	2.633[a]	0.022[a]	0.048	0.000	1.188	0.007	1.242[c]	0.008
β_{54}	0.515[a]	0.004[b]	3.774[a]	0.017[b]	2.777[a]	0.017[a]	0.837[a]	0.002	2.960[a]	0.006	2.353[a]	0.004
Log-Likelihood	-1610.69		-1575.66		-1595.47		-1658.16		-1651.72		-1658.96	
Pseudo-R^2	5.54%		7.59%		6.43%		5.14%		5.51%		5.09%	
χ^2 (h_{jt}^{*})	12.71[a]		20.69[a]		0.96		20.63[a]		9.185[c]		19.700[a]	
χ^2 (Y_{jt}^{*})	26.03[a]		94.31[a]		69.55[a]		29.95[a]		42.59[a]		33.17[a]	
US	From Asia		From Latin		From Europe		From Asia		From Latin		From Europe	
β_1 (constant)	-5.510[a]	-0.216[a]	-6.317[a]	-0.202[a]	-5.620[a]	-0.210[a]	-5.108[a]	-0.180[a]	-5.451[a]	-0.173[a]	-5.043[a]	-0.167[a]
β_2 (h_{it})	0.426[a]	0.017[a]	0.461[a]	0.015[a]	0.240[c]	0.009[c]	0.868[a]	0.031[a]	1.031[a]	0.033[a]	0.887[a]	0.029[a]
β_3 (e_{it})	-0.300	-0.012	-0.247	-0.008	-0.249	-0.009	-0.346	-0.012	-0.414	-0.013[c]	-0.317	-0.011
β_4 (i_{it})	0.383[a]	0.015[a]	0.501[a]	0.016[a]	0.385[a]	0.014[a]	0.217[c]	0.008[c]	0.249[b]	0.008[b]	0.205[c]	0.007[c]
β_4 (h_{jt}^{*})	0.017	0.001	-0.161[c]	-0.005[c]	0.353	0.013	0.003	0.000	-0.197[b]	-0.006[b]	-0.209	-0.007
β_4 (Y^{*}_{jt})	0.183[c]	0.007[c]	0.912[a]	0.029[a]	1.442[a]	0.054[a]	0.043	0.001	0.695[a]	0.022[a]	1.583[a]	0.052[a]
Log-Likelihood	-425.56		-383.03		-413.27		-396.08		-379.73		-382.45	
Pseudo-R^2	6.00%		15.39%		8.71%		12.51%		16.12%		15.52%	
χ^2 (h_{jt}^{*})	0.05		3.19[c]		2.64[c]		0.00		5.53[b]		0.81	
χ^2 (Y_{jt}^{*})	3.31[c]		91.17[a]		28.63[a]		0.15		34.76[a]		32.08[a]	
Europe	From Asia		From Latin		From US		From Asia		From Latin		From US	
β_1 (constant)	-4.201[a]	-0.153[a]	-3.546[a]	-0.139[a]	-3.944[a]	-0.149[a]	-4.237[a]	-0.154[a]	-3.841[a]	-0.145[a]	-4.228[a]	-0.157[a]
β_2 (h_{it})	0.931[a]	0.034[a]	0.972[a]	0.038[a]	1.000[a]	0.038[a]	1.034[a]	0.038[a]	1.075[a]	0.041[a]	0.919[a]	0.034[a]
β_3 (e_{it})	0.041	0.001	0.108	0.004	0.123	0.005	0.283[c]	0.010[c]	0.286[c]	0.011[c]	0.296[c]	0.011[b]
β_4 (i_{it})	0.011	0.000	-0.056	-0.002	0.002	0.000	0.001	0.000	-0.051	-0.002	0.015	0.001
β_4 (h_{jt}^{*})	-0.014	0.000	-0.076	-0.003	-0.040	-0.001	0.090	0.003	0.068	0.003	0.297[b]	0.011[b]
β_4 (Y^{*}_{jt})	0.580[a]	0.021[a]	0.466[a]	0.018[a]	1.777[a]	0.067[a]	0.383[a]	0.014[a]	0.283[b]	0.011[b]	0.804[a]	0.030[a]
Log-Likelihood	-405.32		-415.95		-407.12		-400.75		-406.67		-403.70	
Pseudo-R^2	10.47%		8.12%		10.07%		11.48%		10.17%		10.83%	
χ^2 (h_{jt}^{*})	0.03		0.98		0.07		1.54		1.30		5.11[b]	
χ^2 (Y_{jt}^{*})	40.96[a]		22.65[a]		45.80[a]		16.04[a]		5.80[b]		6.77[a]	

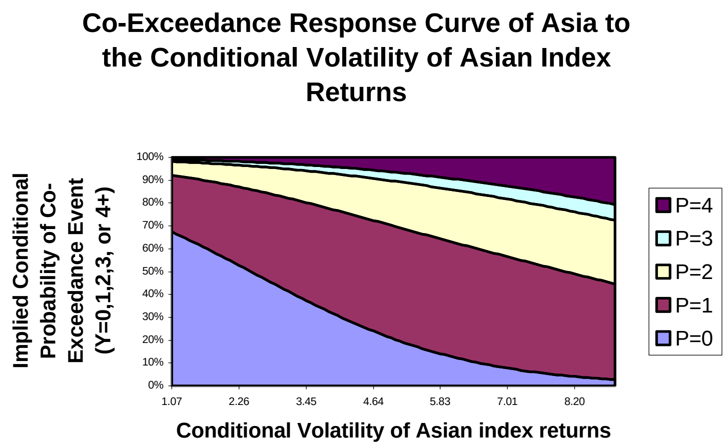
Table 8. Contagion test results of multinomial logit regression for daily return co-exceedances from conditional extreme returns, April 1, 1992 to December 29, 2000. Extreme returns are defined in terms of exceedances beyond a random threshold, θ, controlling for time-varying volatility. Specifically, 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 $P_j = \exp(x'\beta_j) / [1 + \sum_k \exp(x'\beta_k)]$, 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.

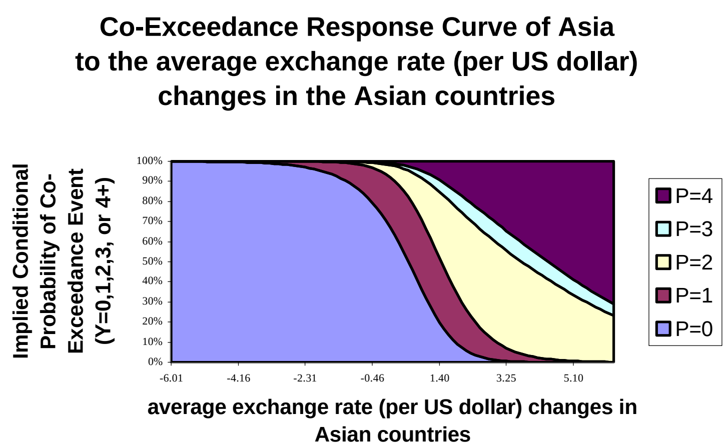
	Bottom tails						Top tails					
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.
Asia	From Latin		From US		From Europe		From Latin		From US		From Europe	
β_{01} (constant)	-1.312^a	-0.179^a	-1.463^a	-0.205^a	-1.393^a	-0.192^a	-0.992^a	-0.148^a	-0.976^a	-0.145^a	-1.110^a	-0.165^a
β_{02}	-2.912^a	-0.114^a	-2.862^a	-0.111^a	-2.738^a	-0.106^a	-1.507^a	-0.059^a	-1.440^a	-0.057^a	-1.760^a	-0.072^a
β_{03}	-6.393^a	-0.033^a	-6.515^a	-0.035^b	-6.636^a	-0.037^a	-4.597^a	-0.053^a	-5.017^a	-0.052^a	-4.728^a	-0.051^a
β_{04}	-4.961^a	-0.020^b	-4.775^a	-0.017^b	-5.295^a	-0.022^b	-4.490^a	-0.015^b	-4.230^a	-0.017^b	-4.423^a	-0.020^b
β_{11} (h_{it})	-0.025	-0.004	-0.075	-0.014	-0.042	-0.008	-0.099^c	-0.017^c	-0.103^c	-0.017	-0.149^a	-0.024^b
β_{12}	0.033	0.002	0.073	0.004	0.097	0.005	-0.124	-0.005	-0.147	-0.006	-0.272^b	-0.012^c
β_{13}	-0.197	-0.001	-0.082	0.000	-0.154	-0.001	-0.109	-0.001	-0.261	-0.003	-0.166	-0.001
β_{14}	0.215	0.001	0.352^c	0.001	0.195	0.001	0.459^b	0.002^c	0.374^b	0.002	0.325^c	0.002^c
β_{21} (e_{it})	0.788^a	0.115^a	0.781^a	0.114^a	0.780^a	0.114^a	-0.401^a	-0.054^c	-0.401^a	-0.053^c	-0.394^a	-0.051^c
β_{22}	1.396^a	0.053^a	1.318^a	0.050^a	1.307^a	0.050^a	-1.212^a	-0.055^a	-1.252^a	-0.059^a	-1.245^a	-0.058^a
β_{23}	1.796^a	0.009^a	1.746^a	0.009^a	1.743^a	0.009^a	-1.279^a	-0.014^a	-1.367^a	-0.013^a	-1.329^a	-0.014^a
β_{24}	1.643^a	0.006^b	1.678^a	0.006^b	1.591^a	0.006^b	-1.428^a	-0.004^b	-1.513^a	-0.006^b	-1.452^a	-0.006^b
β_{31} (i_{it})	-0.004	0.000	0.009	0.001	0.002	0.000	0.016	0.004	0.013	0.003	0.019	0.004
β_{32}	-0.018	-0.001	-0.013	-0.001	-0.017	-0.001	-0.062^c	-0.003^c	-0.071^c	-0.004^c	-0.054	-0.003
β_{33}	0.108	0.001	0.123^c	0.001	0.121^c	0.001	0.044	0.001	0.071	0.001	0.042	0.000
β_{34}	-0.064	0.000	-0.069	0.000	-0.020	0.000	-0.123	0.000	-0.117	-0.001	-0.117	-0.001
β_{41}(h_{jt}^*)	0.061	0.008	0.211^a	0.034^a	0.197^c	0.032	-0.064	-0.009	-0.071	-0.012	0.113	0.015
β_{42}	0.169^a	0.007^b	0.120	0.003	0.000	-0.002	-0.225^b	-0.011^c	-0.174	-0.008	0.243	0.011
β_{43}	0.206	0.001	0.352	0.002	0.801^b	0.004^c	0.119	0.002	0.460^b	0.005^b	0.583^b	0.006^c
β_{44}	0.019	0.000	-0.251	-0.001	0.128	0.000	-0.167	-0.001	-0.060	0.000	0.607	0.003
β_{51} (Y_{jt}^*)	0.143^c	0.021	0.363	0.047	0.680^a	0.101^a	0.151^b	0.021	0.678^a	0.109^a	0.255	0.044
β_{52}	0.131	0.004	0.894^b	0.035^b	0.809^b	0.029^c	0.413^a	0.018^a	0.788^b	0.030	-0.065	-0.008
β_{53}	0.831^a	0.004^b	2.210^a	0.012^b	1.965^a	0.010^b	0.382^c	0.004	1.864^a	0.018^b	1.305^a	0.015^b
β_{54}	0.863^a	0.004^b	2.590^a	0.010^b	2.238^a	0.009^b	1.127^a	0.004^b	2.578^a	0.010^b	0.934	0.004
Log-Likelihood	-1744.33		-1744.52		-1747.41		-1960.73		-1963.55		-1976.09	
Pseudo-R^2	3.78%		3.77%		3.61%		2.85%		2.71%		2.08%	
χ^2 (h_{jt}^*)	9.33^b		9.10^b		7.63		8.64^c		8.99^c		7.97^c	
χ^2 (Y_{jt}^*)	33.93^a		37.32^a		29.62^a		41.37^a		36.89^a		8.55^c	

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)	-1.975[a]	-0.243[a]	-1.907[a]	-0.236[a]	-2.063[a]	-0.258[a]	-1.261[a]	-0.154[a]	-0.969[a]	-0.114[a]	-1.265[a]	-0.154[a]
β_{02}	-4.225[a]	-0.090[a]	-4.479[a]	-0.092[a]	-4.180[a]	-0.090[a]	-3.193[a]	-0.110[a]	-2.576[a]	-0.086[a]	-3.183[a]	-0.113[a]
β_{03}	-4.872[a]	-0.024[a]	-4.870[a]	-0.022[b]	-5.363[a]	-0.023[b]	-5.251[a]	-0.039[a]	-5.957[a]	-0.046[a]	-5.631[a]	-0.042[a]
β_{04}	-6.546[a]	-0.027[b]	-6.953[a]	-0.023[b]	-7.126[a]	-0.020[b]	-6.244[a]	-0.016[b]	-5.543[a]	-0.019[b]	-6.586[a]	-0.017[b]
β_{11} (h_{it})	0.169[a]	0.022[a]	0.189[a]	0.025[a]	0.143[a]	0.019[a]	0.015	0.001	0.037	0.005	-0.021	-0.003
β_{12}	0.177[b]	0.003[c]	0.152[c]	0.003	0.185[b]	0.004[c]	0.052	0.002	0.112	0.004	-0.021	-0.001
β_{13}	0.095	0.000	0.207	0.001	0.053	0.000	0.147	0.001	0.022	0.000	0.070	0.001
β_{14}	0.217[b]	0.001	0.239[c]	0.001	0.167	0.000	0.431[a]	0.001[c]	0.389[a]	0.001[c]	0.307[a]	0.001[c]
β_{21} (e_{it})	0.976[a]	0.124[a]	0.991[a]	0.127[a]	1.005[a]	0.129[a]	-0.203	-0.019	-0.212	-0.023	-0.164	-0.014
β_{22}	1.602[a]	0.033[a]	1.639[a]	0.033[a]	1.571[a]	0.033[a]	-1.449[a]	-0.053[a]	-1.367[a]	-0.049[a]	-1.396[a]	-0.054[a]
β_{23}	1.499[a]	0.007[b]	1.483[a]	0.006[b]	1.459[a]	0.006[b]	0.355	0.004[c]	1.190[a]	0.011[a]	0.387[c]	0.004[c]
β_{24}	1.725[a]	0.007[b]	1.759[a]	0.006[b]	1.736[a]	0.005[b]	-1.839[a]	-0.005[c]	-1.650[a]	-0.006[c]	-1.753[a]	-0.005[c]
β_{31} (i_{it})	0.001	0.000	-0.001	0.000	0.005	0.001	-0.003	-0.001	-0.012	-0.002	-0.001	0.000
β_{32}	-0.001	0.000	0.012	0.000	0.001	0.000	0.011	0.000	-0.007	0.000	0.016	0.001
β_{33}	-0.056	0.000	-0.048	0.000	-0.039	0.000	0.043	0.000	0.063[b]	0.001[c]	0.050	0.000
β_{34}	0.013	0.000	0.032	0.000	0.023	0.000	-0.011	0.000	-0.011	0.000	0.007	0.000
β_{41}(h_{jt}^*)	-0.072	-0.011	-0.089	-0.014	0.074	0.008	-0.206[a]	-0.029[a]	-0.354[a]	-0.050[a]	-0.190	-0.030
β_{42}	0.138	0.003	0.286[c]	0.007[c]	0.267	0.006	-0.118	-0.003	-0.476[b]	-0.015[c]	0.120	0.006
β_{43}	0.325[b]	0.002[c]	0.061	0.000	0.825[b]	0.004	-0.341	-0.002	0.113	0.002	0.004	0.000
β_{44}	0.395[a]	0.002[b]	0.376	0.001	0.831[b]	0.002	-0.056	0.000	-0.107	0.000	0.647[c]	0.002
β_{51} (Y_{jt}^*)	0.260[a]	0.033[a]	0.840[a]	0.103[a]	0.762[a]	0.095[a]	0.185[b]	0.023[b]	0.374	0.040	0.492[b]	0.063[c]
β_{52}	0.462[a]	0.010[b]	2.057[a]	0.042[a]	1.425[a]	0.030[a]	0.503[a]	0.018[a]	1.650[a]	0.058[a]	0.943[a]	0.033[b]
β_{53}	0.579[b]	0.003[c]	2.818[a]	0.013[b]	2.668[a]	0.012[b]	0.162	0.001	1.878[a]	0.014[b]	1.347[b]	0.010
β_{54}	0.568[b]	0.002	3.354[a]	0.011[b]	3.464[a]	0.010[b]	0.923[a]	0.002[c]	1.573[b]	0.005	2.303[a]	0.006[c]
Log-Likelihood	-1426.14		-1411.04		-1414.26		-1627.55		-1635.25		-1638.95	
Pseudo-R^2	5.40%		6.41%		6.19%		3.20%		2.74%		2.52%	
χ^2 (h_{jt}^*)	21.98[a]		6.28		8.47[c]		12.69[a]		15.72[a]		5.54	
χ^2 (Y_{jt}^*)	26.08[a]		81.72[a]		69.08[a]		36.92[a]		42.60[a]		23.68[a]	
US	From Asia		From Latin		From Europe		From Asia		From Latin		From Europe	
β_1 (constant)	-3.901[a]	-0.170[a]	-4.381[a]	-0.162[a]	-4.241[a]	-0.170[a]	-3.377[a]	-0.152[a]	-3.886[a]	-0.160[a]	-3.362[a]	-0.151[a]
β_2 (h_{it})	-0.099	-0.004	-0.263	-0.010	-0.470[b]	-0.019[b]	0.084	0.004	0.039	0.002	0.081	0.004
β_3 (e_{it})	0.354	0.015	0.234	0.009	0.509[b]	0.020[b]	-0.693[a]	-0.031[a]	-0.657[a]	-0.027[a]	-0.738[a]	-0.033[a]
β_4 (i_{it})	0.189[c]	0.008[c]	0.214[b]	0.008[b]	0.214[b]	0.009[b]	0.063	0.003	0.098	0.004	0.057	0.003
β_4 (h_{jt}^*)	-0.021	-0.001	0.070	0.003	0.550[b]	0.022[b]	-0.022	-0.001	0.039	0.002	-0.029	-0.001
β_4 (Y^*_{jt})	0.107	0.005	0.844[a]	0.031[a]	1.665[a]	0.067[a]	0.035	0.002	0.638[a]	0.026[a]	0.452	0.020
Log-Likelihood	-428.86		-395.84		-414.80		-442.54		-425.16		-442.05	
Pseudo-R^2	0.71%		8.35%		3.96%		0.97%		4.86%		1.08%	
χ^2 (h_{jt}^*)	0.05		0.79		4.48[b]		0.06		0.12		0.01	
χ^2 (Y_{jt}^*)	0.63		73.84[a]		32.66[a]		0.07		39.84[a]		1.21	
Europe	From Asia		From Latin		From US		From Asia		From Latin		From US	
β_1 (constant)	-3.471[a]	-0.121[a]	-2.997[a]	-0.112[a]	-3.332[a]	-0.115[a]	-2.992[a]	-0.100[a]	-2.841[a]	-0.094[a]	-3.070[a]	-0.101[a]
β_2 (h_{it})	0.082	0.003	-0.091	-0.003	0.039	0.001	-0.549[b]	-0.018[b]	-0.501[c]	-0.017[b]	-0.816[b]	-0.027[b]
β_3 (e_{it})	1.011[a]	0.035[a]	1.040[a]	0.039[a]	1.095[a]	0.038[a]	-1.581[a]	-0.053[a]	-1.591[a]	-0.053[a]	-1.583[a]	-0.052[a]
β_4 (i_{it})	-0.043	-0.001	-0.086[c]	-0.003[c]	-0.038	-0.001	-0.030	-0.001	-0.053	-0.002	-0.005	0.000
β_4 (h_{jt}^*)	0.077	0.003	0.115[c]	0.004[c]	0.128	0.004	0.106	0.004	0.053	0.002	0.333[c]	0.011[c]
β_4 (Y^*_{jt})	0.770[a]	0.027[a]	0.587[a]	0.022[a]	2.367[a]	0.082[a]	0.253[b]	0.008[b]	0.304[b]	0.010[b]	0.989[a]	0.033[a]
Log-Likelihood	-402.84		-415.72		-399.25		-406.48		-407.02		-405.34	
Pseudo-R^2	10.44%		7.58%		11.24%		12.49%		12.37%		12.73%	
χ^2 (h_{jt}^*)	0.97		3.14[c]		0.45		1.79		0.45		2.87[c]	
χ^2 (Y_{jt}^*)	58.56[a]		28.56[a]		77.72[a]		4.65[b]		5.55[b]		7.76[a]	

Figure 1. Co-Exceedance response curve of Asia.





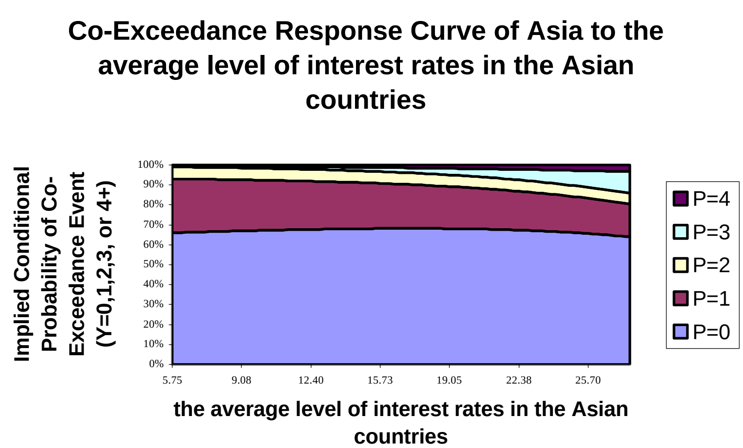


Figure 2. Co-Exceedance response curve of Asia to the conditional volatility and the number of co-exceedances of overseas market.

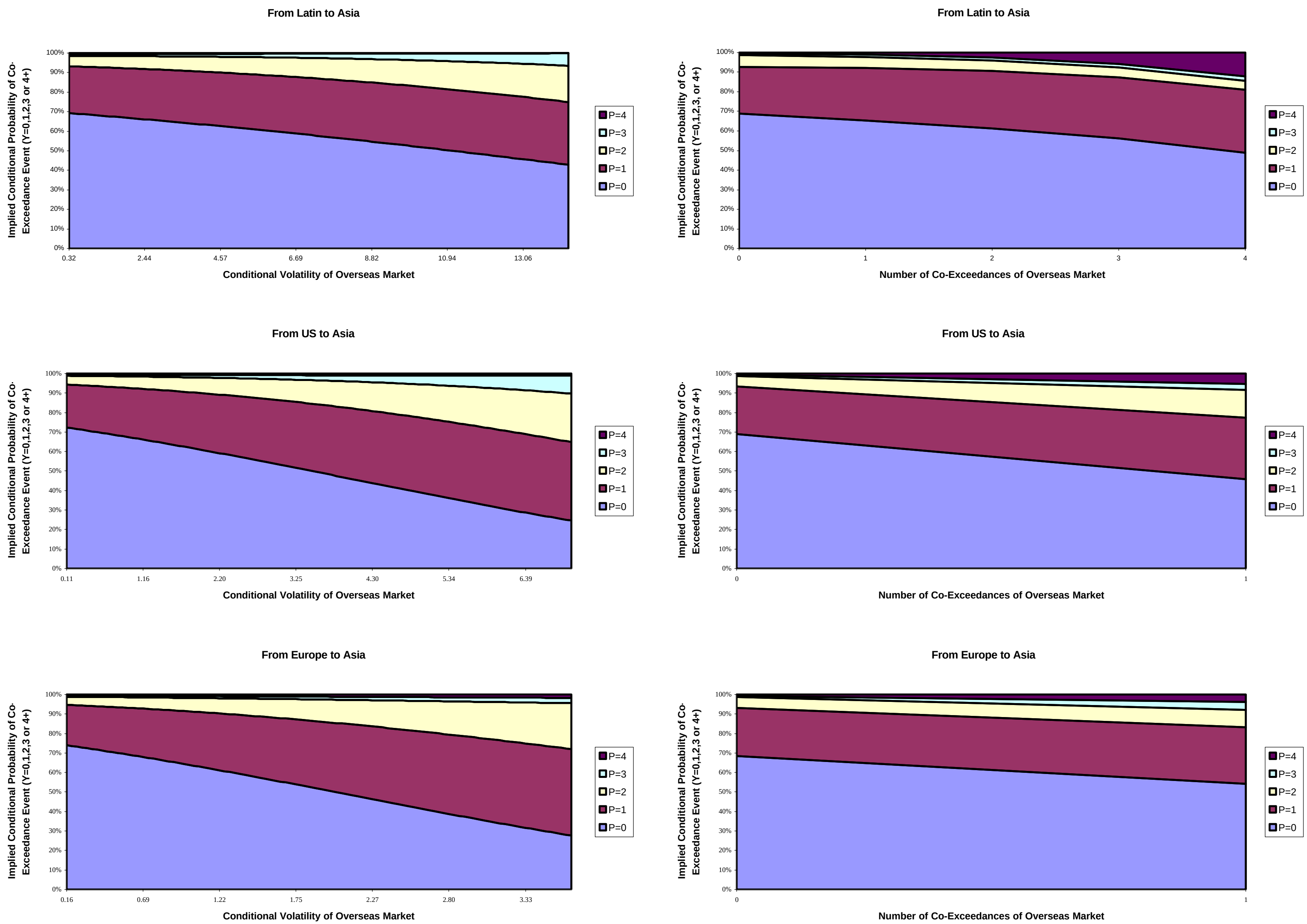


Figure 3. Co-Exceedance response curve of Latin to the conditional volatility and the number of co-exceedances of overseas market.

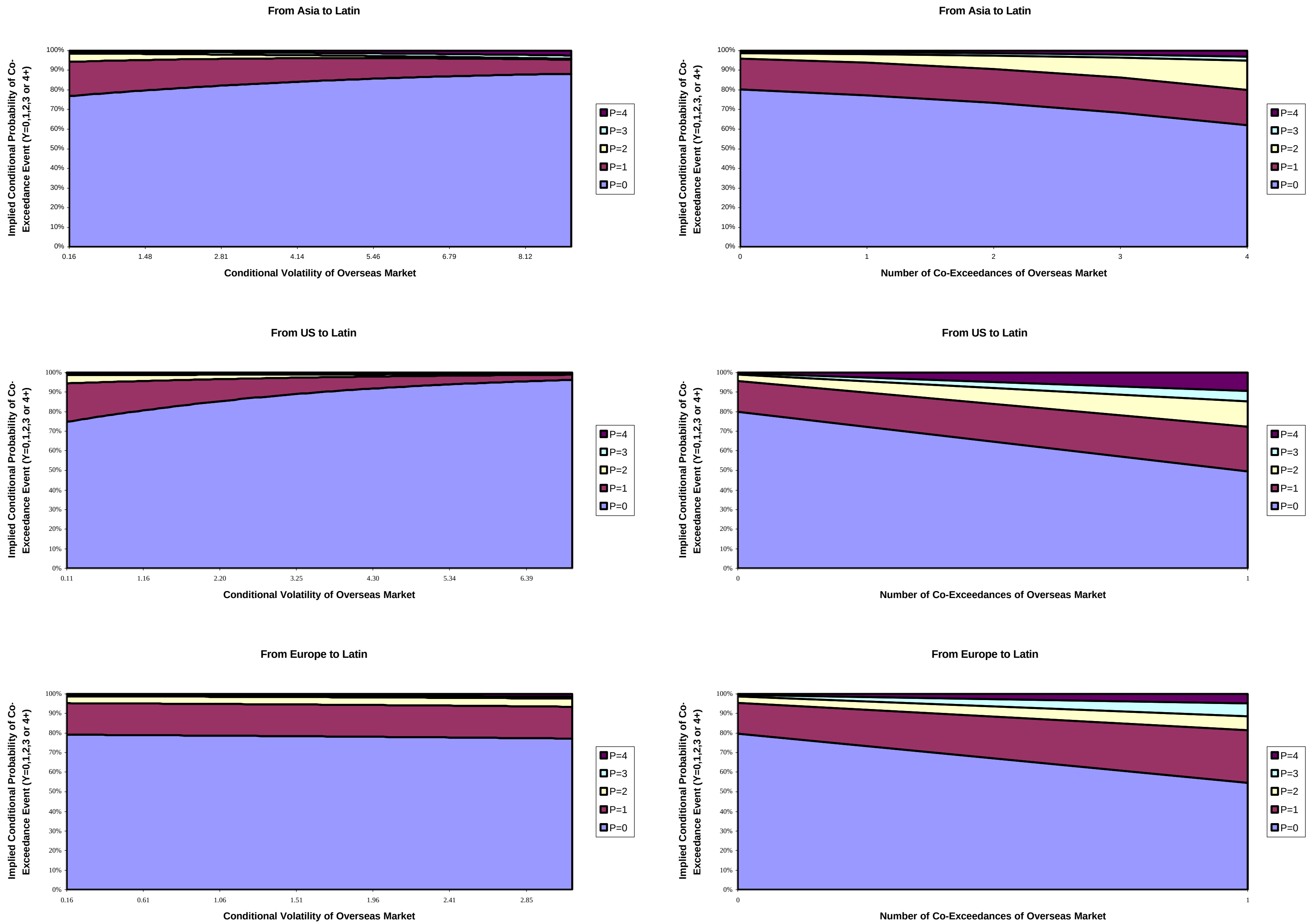


Figure 4. Co-Exceedance response curve of US to the conditional volatility and the number of co-exceedances of overseas market.

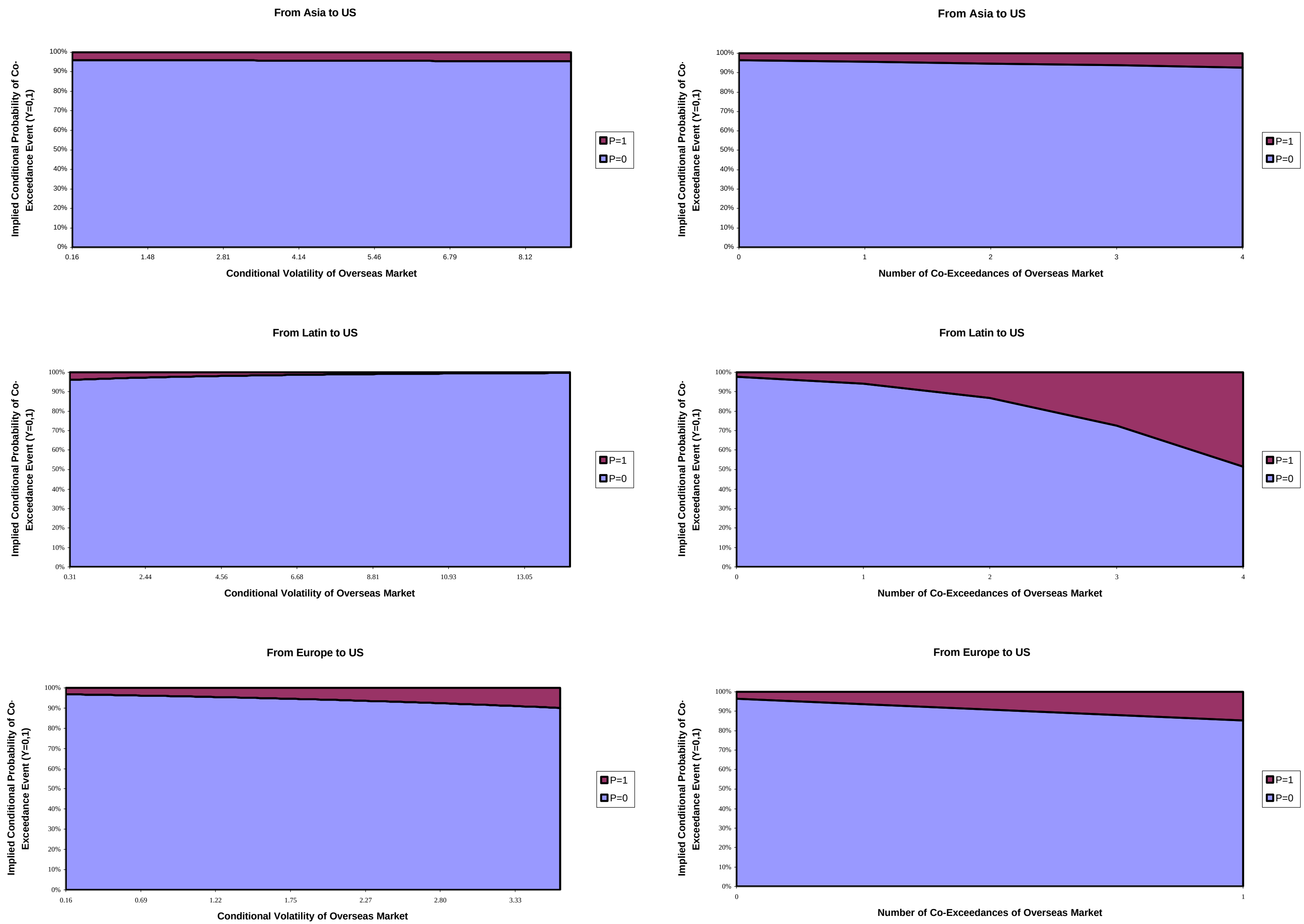


Figure 5. Co-Exceedance response curve of Europe to the conditional volatility and the number of co-exceedances of overseas market.