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This article proposes a new approach to evaluate contagion in financial markets. Our measure of contagion captures the coincidence of extreme return shocks across countries within a region and across regions. We characterize the extent of contagion, its economic significance, and its determinants using a multinomial logistic regression model. Applying our approach to daily returns of emerging markets during the 1990s, we find that contagion is predictable and depends on regional interest rates, exchange rate changes, and conditional stock return volatility. Evidence that contagion is stronger for extreme negative returns than for extreme positive returns is mixed.

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 markets economic crises have led to massive bailouts to quell contagion and have reduced support for free capital mobility.

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The International Monetary Fund (IMF) deputy managing director at the time, 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) to argue that "capital flows are characterized ... 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 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 [see Baig and Goldfajn (1999) and Forbes and Rigobon (2001)]. 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 correlation estimates are likely biased. A related literature demonstrates that, even though correlations change over time, it is difficult to explain changes in correlations.[3]

Perhaps the most important limitation of these investigations of financial contagion is that they focus on asset return correlations in the first place. None of the concerns expressed about contagion seem to be based on linear measures of association for macroeconomic or financial market events. In fact, 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

[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 more than 20 other articles from a February 2000 World Bank/IMF conference, *International Financial Contagion: How it Spreads and How it Can be Stopped*. These articles include theoretical models, a conceptual contribution, country case studies, and broad-based empirical studies. Other important recent contributions include Eichengreen, Rose, and Wyplosz (1996), Glick and Rose (1999), Masson (1999), Kaminsky and Reinhart (2000), Allen and Gale (2000), and Kyle and Xiong (2001). Eichengreen, Rose, and Wyplosz (1996) estimate probit regressions to relate the occurrence of a currency crisis in a country to predictive variables. Though their seminal 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, for instance, Erb, Harvey, and Viskanta (1995), King, Sentana, and Wadhwani (1995), Longin and Solnik (1995, 2001), and Karolyi and Stulz (1996). See also the recent survey by Karolyi and Stulz (2003).

negative returns to be contagious in a way that small negative returns are not. Correlations that give equal weight to small and large returns are not appropriate 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 volatilities and correlations to allow for these observed threshold (large absolute return) and asymmetric (negative return) effects. Some researchers have employed univariate and multivariate extreme value theory (EVT) from statistics [Longin (1996), Danielsson and de Vries (2000), Longin and Solnik (2001), Straetmans (1998), Starica (1999), Kaminsky and Schmuckler (1999), Pownall and Koedijk (1999), and Hartman, Straetmans, and de Vries (2001)]. Others have developed multivariate GARCH-M models allowing asymmetry [Ang and Chen (2002), Bekaert and Wu (2000)], Poisson jumps [Das and Uppal (2002)], and even Hamiltonian regime-switching [Ang and Bekaert (2002)] in the joint dynamics of returns. In contrast, in this article we abandon the correlation framework that previous researchers have focused on to study contagion and direct our attention instead to the large positive and negative return days. 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. In order to determine whether there are more frequent joint occurrences of large absolute value returns than expected, we calibrate these outcomes using Monte Carlo simulations of the joint returns-generating processes of international stock market returns with different assumptions about their structure. 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 model 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 or the preceding day.

An important advantage of this multinomial logistic analysis, especially relative to those based on EVT, is that we can condition on attributes and characteristics of the exceedance events 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 explain and predict exceedances in this model. 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.

Another 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.[4] 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 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 United States seems completely insulated from any Asian contagion, even during the Asian crisis in 1997.

To apply our approach, we construct daily index returns from stocks in the monthly investible indices of the International Finance Corporation (IFC indices) from April 1992 to December 1995 and then use the daily index returns provided by the IFC from January 1996 to December 2000 for 17 Asian and Latin American markets of the Emerging Markets Database (EMDB, now owned by Standard & Poor's). The sample period extends from April 1992 through December 2000. These returns are particularly well suited to our analysis because they correspond to the returns of portfolios that can be held by foreign investors.

The article proceeds as follows. In Section 1 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 2 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.

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[4] Important investigations of 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), Bae and Karolyi (1994), Lin, Engle, and Ito (1994), and Susmel and Engle (1994). More recent contributions include Ramchand and Susmel (1998), Ng (2000), Connolly and Wang (2003) and Dumas, Harvey, and Ruiz (2003).

In Section 3 we investigate contagion across regions. We conclude in Section 4.

1. Measuring Financial Contagion as Coexceedances

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 calibrate using Monte Carlo simulations whether the frequency of joint extreme returns within regions is consistent with various assumptions about the joint dynamics of returns.

1.1 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 (IFC) produced such indices for emerging markets; currently these indices are produced by Standard & Poor's.[5] We use the IFC indices from Asia and Latin America. To study the extent to which contagion affects the United States and Europe, we also use the S&P 500 index for the United States 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. Using these data, the sample of daily returns therefore starts on December 31, 1995, and ends on December 29, 2000 (1305 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 and is detailed in the appendix.

Table 1 provides sample statistics, including correlations for the full sample period—April 1, 1992, to December 29, 2000 (2283 observations). Not surprisingly, the properties of the indices vary dramatically across countries. China has the highest average daily return (0.087%), but Brazil has the highest daily return standard deviation (3.370%), almost four times that of the United States and Europe. The largest positive extreme return (58.708%) obtains for Pakistan, whereas Peru experienced the

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

Table 1
Summary statistics of daily returns on International Financial Corporation (IFC) emerging markets indices, April 1, 1992, to December 29, 2000

	CHN	KOR	PHI	TWN	INA	IND	MAL	PAK	SRI	THA	ARG	BRA	CHI	COL	MEX	PER	VEN	US	Europe
Mean (%)	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
Std. Dev. (%)	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 (%)	− 38.09	− 21.71	− 10.14	− 10.80	− 18.74	− 37.54	− 22.78	− 17.74	− 8.71	− 16.08	− 14.13	− 27.51	− 6.70	− 6.93	− 20.85	− 41.90	− 14.87	− 7.10	− 4.11
Maximum (%)	48.08	27.03	21.59	7.36	14.26	27.21	23.90	58.70	17.97	16.63	13.35	35.29	9.26	9.23	16.73	15.79	21.85	4.99	3.60
Correlations	CHN	KOR	PHI	TWN	INA	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
					0.12									*0.07*				*0.13*	*0.11*
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		
					0.05									*0.19*					
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	
					0.03									*0.23*					
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
					0.10									*0.19*					

Each index from the Emerging Market Database (EMDB) is adjusted to reflect accessibility of the market and individual stocks for foreign investors. Summary statistics include the mean, median, standard deviation, minimum, maximum, and correlations of daily index returns. EMDB countries include China (CHN), Korea (KOR), Philippines (PHI), Taiwan (TWN), India (INA), Indonesia (IND), Malaysia (MAL), Pakistan (PAK), Sri Lanka (SRI), Thailand (THA), Argentina (ARG), Brazil (BRA), Chile (CHI), Colombia (COL), Mexico (MEX), Peru (PER), and Venezuela (VEN). We also include daily returns of S&P 500 index for U.S. and Datastream International Europe index. The correlations in the upper right matrix are between daily returns of Asian indices in calendar time t and those of Latin America, United States, and Europe indices in calendar time $t - 1$. Averages of correlations are presented in italics and are associated with the block of correlations above and adjacent to the statistic.

largest negative extreme return (-41.908%). All IFC indices have a greater standard deviation than indices for the United States and 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 right matrix with average correlation of 0.07) are roughly the same size as the same day correlations (lower left matrix with average correlation of 0.05). But the correlations of returns in Asia and those of the United States lagged by one day are greater (average correlation of 0.13) than the contemporaneous correlations (average correlation of 0.03).

1.2 Exceedances and coexceedances

Correlations have been much studied. We focus instead on occurrences of extreme returns. At this point we arbitrarily define an extreme return, or exceedance, as one that lies either below (above) the 5th (95th) quantile of the marginal return distribution. Alternative definitions are used later.[6] 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 coexceedances, within a region on a particular day. The left side of the table focuses on negative return ("bottom tail") exceedances and the right side on positive return ("top tail") exceedances. We define a coexceedance count of i units for negative returns as the joint occurrence of i exceedances of negative returns on a particular day. The table is to be read in four parts for the top and bottom tails of the Asian (top panel) and Latin American (bottom panel) regional markets. In each part, the 2283 days in the sample period are divided into those in which there are no exceedances in any country (e.g., 1526 such days in Asia for negative extreme returns), only one country exceedance (e.g., 530 such days in Asia for negative extreme returns), and multicountry coexceedances. Note that we count not only the total number of days with

[6] Longin (1996), Kaminsky and Schmukler (1999), Pownall and Koedijk (1999), and Longin and Solnik (2001) employ conditional parametric or nonparametric 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.

Table 2
Summary statistics of (co-)exceedances for daily emerging market index returns, April 1, 1992, to December 29, 2000

	Mean return when ≥6 (%)	Number of negative (co-)exceedances							Number of positive (co-)exceedances							Mean return when ≥6 (%)
		≥6	5	4	3	2	1	0	0	1	2	3	4	5	≥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*
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*

A positive (negative) or "top-tail" ("bottom-tail") exceedance for daily index returns correspond to the subset of ordered returns that comprise the highest (lowest) five percent of all returns. Coexceedances represent joint occurrences of exceedances across country indices by day. A coexceedance of i means that i countries have an exceedance on the same day. Coexceedances are reported for $i = 1, \ldots, 5$ separately and for i equal to six or more as "≥ 6." For example, of 2283 trading days, there are 148 occurrences of negative or bottom-tail coexceedances for Asia with two countries only, and 27 of those occurrences include China as one of the two countries with bottom-tail coexceedances.

coexceedances of a given count, but we also identify which countries participate in those events and how often.

In Asia, the distribution of coexceedances is mostly symmetric between negative and positive extreme returns. 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 coexceedances. The one case where there is a substantial difference between the bottom-tail coexceedances and the top-tail coexceedances is for the category of five coexceedances. 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 5 days with six or more countries. Malaysia was the next most regular participant in bottom-tail coexceedance 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 noncrisis 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 noncrisis countries. The absolute value average return is higher for positive returns (7.47%) than for negative returns (– 7.08%) on such days.

Though Latin America has only seven countries, there are 7 days where 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 which there is only one day when six countries or more have returns in the positive tail. In Latin America, and unlike Asia, there is clearer evidence of asymmetry in that coexceedances of negative returns are more likely than coexceedances of positive returns. Argentina, Chile, and Mexico are in each of the bottom-tail events with five or more coexceedances; by contrast, Colombia has a disproportionately large number of single-country exceedances (73 out of 371). Among top-tail coexceedance 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 of 448).

We compare but do not report coexceedance 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 five of the Asian bottom-tail and all but one of the top-tail coexceedances involving four countries or more (38 and 30, in total, respectively) take place after the devaluation of the Thai Baht. There are also clusters of large numbers of coexceedances in Latin America but they are distributed more evenly over the period. Latin American coexceedances involving four countries or more experiencing negative extreme returns take place in early 1994 (four events) and around the December 1995 Mexican peso crisis (seven 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 (2002) 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 coexceedances can be explained by conditioning on large absolute value returns, we have to investigate what the distribution of coexceedances would be if correlations were constant during the sample period. To this end we perform Monte Carlo simulation experiments.[7]

1.3 Contagion versus coexceedances: 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's *t* distribution. Using that covariance matrix, we simulate 5000 random realizations of the time series of 2283 daily returns for the Asian countries. For each realization we identify the returns below (above) the 5th (95th) percent quantile returns for the bottom (top) tail of the return distributions and perform the same nonparametric count across countries by region as in Table 2. Doing so provides us with a distribution of exceedances and coexceedances. We use that distribution to calibrate the observed sample of coexceedances. The results are shown in Table 3 and for each scenario we report the simulated mean, standard deviation, 5% and 95% quantiles, and the simulated *p*-value of the 5000 replications.

The distribution of the coexceedances 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's *t* distribution. The degrees of freedom equal $N+K-1$, where

[7] 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.

Table 3
Monte Carlo simulation results of (co-)exceedances for daily emerging market returns

	Number of negative (co-)exceedances							Number of positive (co-)exceedances						
	≥ 6	5	4	3	2	1	0	0	1	2	3	4	5	≥ 6
Panel A: Asia														
Actual	5	16	22	36	148	530	1526	1507	546	148	51	18	6	7
Monte Carlo simulations														
A. Multivariate normality														
Simulated mean	0.61	2.79	12.05	46.07	170.15	595.60	1455.73	1450.26	598.08	172.03	46.84	12.33	2.84	0.62
Standard deviation	0.77	1.64	3.26	6.00	10.64	18.99	11.91	12.05	19.04	10.49	6.00	3.30	1.66	0.78
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														
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
5th quantile	0	0	3	22	96	424	1666	1662	426	97	22	4	0	0
95th 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

Table 3
(continued)

	Number of negative (co-)exceedances							Number of positive (co-)exceedances						
	≥ 6	5	4	3	2	1	0	0	1	2	3	4	5	≥ 6
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
5th quantile	0	2	11	34	95	313	1747	1742	315	95	34	11	3	0
95th 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
5th quantile	0	0	4	24	95	397	1674	1669	399	96	24	4	0	0
95th 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

Under the null hypothesis that national emerging market index returns in Asia and Latin America are drawn from a simulated return distribution, we employ a Monte Carlo simulation to evaluate the number of (co-)exceedances within each region. We compute the sample mean and the variance-covariance matrix of returns and generate 5000 random realizations. For each realization we compute the number of (co-)exceedances for a 5% threshold, as in Table 2. Summary statistics for the 5000 replications include the mean, standard deviation, 5% quantile, 95% quantile, and simulated p-value (the number of replications with coexceedances in a given category exceeding the actual number of coexceedances). Simulations are run under three different models of return distributions: a multivariate normal distribution, a multivariate t-distribution with five degrees of freedom, and a multivariate GARCH. The dynamics of variance and covariance matrix of returns for each region under the multivariate GARCH model is assumed to follow the specification proposed by Ding and Engle (1994).

N is the number of countries (10 for Asia, 7 for Latin America) and K is set to values ranging from 1 (significant positive excess cokurtosis) to 25 (little excess cokurtosis, approximating multivariate normal). We explored a number of choices of K, but report only our analysis for $K = 5$.[8]

One of the concerns expressed by Baig and Goldfajn (1999), Dornbusch, Park, and Claessens (2001), and Forbes and Rigobon (2001, 2002) is that contagion as measured by changes in cross-market correlations across quiet and turbulent periods can be biased by heteroscedasticity. Forbes and Rigobon (2002) 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).[9] This Ding and Engle model constitutes our third scenario. Specifically, we estimate

$$R_{it} = \delta_0 + \varepsilon_{it} \quad \varepsilon_t | \Omega_{t-1} \sim N(0, H_t)$$

$$H_t = H_0 * (\iota\iota' - \alpha\alpha' - \beta\beta') + \alpha\alpha' * \varepsilon_{t-1}\varepsilon'_{t-1} + \beta\beta' * H_{t-1},$$

where R_{it} is the return on asset i between time $t-1$ and t, and Ω_{t-1}, the set of marketwide information available at $t-1$. δ_0 is a constant parameter and ε_{it} and the associated N-vector, ε_t, are residuals that are conditionally distributed multivariate normal with symmetric conditional covariance $(N \times N)$ matrix, H_t. In the law of motion equation for the conditional variances, ι is an N-vector of ones, α and β 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 et al. (1974) optimization algorithm for the 10 Asian and 7 Latin American markets and then simulate 5000 random realizations given the estimated $(2N+1)$ parameters. It is important to note that the Ding and Engle model does not impose constant correlation,

[8] A multivariate Student's 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.

[9] This model structure has been successfully applied by De Santis and Gerard (1997, 1998), and more recently, Ledoit, Santa-Clara, and Wolf (2003). The goal of the Ledoit, Santa-Clara, and Wolf 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.

but rather guides the correlations in time by means of a constrained law of motion for the conditional volatilities. Readers should also be cautioned that the law of motion does not allow for the covariance asymmetry featured in recent work by Ang and Chen (2002), that could generate high coexceedance counts following large negative return shocks.

Table 3 reports the results separately for Asia (panel A) and Latin America (panel B). It is immediately apparent that we observe more coexceedances than one would expect for Latin America, but not necessarily for Asia. This is true regardless of the assumption about the structure of the joint returns-generating process. 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, 7.20 days on average in the multivariate Student's *t* scenario, and only 1.16 with the multivariate GARCH scenario.[10] The simulation *p*-values indicate that the multivariate normal scenario delivers not even one replication out of 5000 in which five or more days of coexceedances of negative returns of six or more countries occur. However, the multivariate GARCH and Student's *t* scenarios do generate the actual number of coexceedances in 4% and 86% of the replications, respectively. For coexceedances of positive returns, the results are similar. In these cases, the sample has seven coexceedances 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, respectively), but it is not unusual for the Student's *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 fail to generate any (simulated *p*-values of 0.00) observations of six or more coexceedances of negative returns of which there are seven in the actual sample. What is more surprising is that even the Student's *t* scenario cannot deliver simulated coexceedance counts as large as in the actual sample. By contrast, the number of positive-tail coexceedances in Latin America is not dramatically different from the simulated counts. There is only one coexceedance 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

[10] In order to check the validity of the 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's *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's *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's *t*, and GARCH) were 0.03, 0.28, and −0.05, respectively; the average kurtosis coefficients were 0.01, 5.79, and 2.48, respectively.

coexceedance events in which five Latin American countries experience returns in the top 5% tail occur in more than 2% of the replications for the multivariate normal scenario, 8% for the multivariate GARCH scenario, and 75% for the multivariate Student's t scenario. This asymmetry in coexceedance events represents another challenge for a model of contagion.

The bottom line from our simulation experiments is that it is more difficult to explain the distribution of coexceedances for Latin America than Asia. Our simulation evidence suggests that the frequency of bottom-tail and top-tail coexceedances in Asia can be generated (in a large fraction of the 5000 replications) with a somewhat strong assumption about positive excess cokurtosis in the Student's t distribution (though not with the normal or GARCH models). For Latin America, this is not the case for the bottom-tail coexceedance 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's 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.

2. Contagion within Regions

In this section we show how our approach is useful for understanding 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.

2.1 The logistic regression approach

Extreme value theory (EVT) has proposed three possible types of limiting distributions for minima or maxima of a variable which are 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) and nonparametric approaches. We know of only a few applications of multivariate EVT to stock returns [Straetmans (1998), Starica (1999), Hartman, Straetmans, and de Vries (2001), Longin and Solnik (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 coexceedances 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, chap. 2), Hosmer and Lemeshow (1989, chap. 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

$$P_i = G(\beta_i' x)/[1 + \sum_{j=1}^{m-1} G(\beta_j' x)], \tag{1}$$

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

$$\log L = \sum_{i=1}^{n} \sum_{j=1}^{m} I_{ij} \log P_{ij}, \tag{2}$$

where I_{ij} is an indicator variable that equals one if the ith observation falls in the jth category, and zero otherwise. Because P_{ij} is a nonlinear function of the β'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_ω, and restricted (constants only) likelihood, L_Ω, functions are compared:[11]

$$\text{pseudo}R^2 = 1 - [\log L_\omega / \log L_\Omega]. \tag{3}$$

In our application to coexceedances across countries within Asia and Latin America, we balance the need to have a model that is parsimonious 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 coexceedances. 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 coexceedances separately for positive and negative

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

extreme returns (though we test the importance of this distinction later). Finally, we compute the probability of a coexceedance of a specific level, P_i, by evaluating the covariates at their unconditional values,

$$P_i^* = \exp(\beta_i' x^*) \Big/ \left[1 + \sum_{j=1}^{m-1} \exp(\beta_j' x^*)\right], \tag{4}$$

where x^* is the unconditional mean value of x. From this measure and following Greene (2000, chap. 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.

Because it is often difficult to judge whether changes in probabilities of a given coexceedance 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 "coexceedance response curve."[12]

Note that our key hypotheses relate to the existence of contagion across regions as well as measuring contagion within regions. Specifically we will assess the importance of the coexceedance events within Asia and Latin America for the likelihood of an exceedance in the United States and Europe. To this end we will need to estimate a logistic regression model for the United States, 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.

2.2 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 and the second panel has estimates for Latin America. At the end of each table we also report results for the binomial models for the United States and Europe. Column (1) reports estimates of regressions for the bottom tails for Asia that provide us with estimates of probabilities of coexceedances.

[12] Our coexceedance response curve analysis is inspired by the epidemiology study by Gillespie, Halpern, and Warner (1994) which examines lung cancer deaths per year among ex-smokers and employs covariates such as age, gender, college attendance, smoker, and years since quitting for ex-smokers.

Table 4
Multinomial logit regression results for daily return coexceedances of emerging market indices, April 1, 1992, to December 29, 2000

	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%	
Latin America												
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
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	0.016					– 0.610[b]	– 0.021[b]
β_{31} (i_{it})					0.460[a]	0.018[a]					0.216	0.007
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%	

The number of coexceedances 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 coexceedances 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 the 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, chap. 19)] 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, chap. 2)]. The logit regression is estimated separately for positive (top-tail) and negative (bottom-tail) coexceedances.

[a], [b]Denotes significance levels at the 1% and 5%, respectively.

We find (not reported) that there is a probability of 66.84% that no Asian country has a bottom-tail return. If bottom-tail exceedances were independent, this probability would be 59.87% (or 0.95^{10}). 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%; for example, computed as the special case of the logistic function, $\exp(\beta_{01})/[1 + \sum_k \exp(\beta_{0k})]$. Since there are no covariates, these probabilities are the sample frequencies reported in Table 2; for example, 530 occurrences of single-country negative return exceedances in Asia during the 2283 days. In column (2) we add the conditional volatility of the Asian index (h_{it}) as a covariate.[13] 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 higher numbers of joint occurrences. For instance, a 1% increase in the conditional volatility increases the probability of one exceedance by 0.058% and the probability of four or more occurrences by 0.009%. All the partial derivatives are significant at the 5% level. The pseudo-R^2 is 5.09%.

In column (3), we add the average exchange rate change in the region (e_{it}) a well as the average interest rate level (i_{it}) in the region.[14] 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. Few of the interest rate coefficients are significant. The significant bottom-tail coefficients are positive, making it more likely that a negative exceedance will occur when interest rates are high. The two significant upper-tail coefficients are of opposite sign, which is puzzling. 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}. 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. The economic and statistical significance of exchange rate changes raises the question of whether the stock retun contagion we

[13] 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.

[14] Data on daily exchange rates relative to the U.S. dollar and mterest rates for each country are tamed from Datastream International. The interest rate series chosen is typically the short-term rate of interest available in Datastream with availability back to 1992. We computed simple equally-weighted average rate changes and average interest rates by region for these covariates.

measure is actually foreign exchange contagion since we measure returns in dollars. To examine this issue, we estimated our models in local currency returns, but do not report the results because they are similar to those we do report.

When we look at the top-tail events (models 4–6 in Table 4), we find no evidence that coexceedance events are less likely for positive extreme returns than for negative extreme returns. A pairwise comparison of the coefficients in columns (1) and (4) cannot reject that the coefficients are equal (Wald chi-square statistic of 0.21, p-value of 0.65, not reported).[15] 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 a statistically important covariate for positive coexceedances.[16] 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 coexceedances. The pseudo-R^2s are much lower for positive returns than they are for negative returns, so that our covariates are more successful at explaining coexceedances 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 having no extreme return on a day is much higher for Latin America than it is for Asia. We estimate the probability of having no extreme return to be 76.83% for Latin America, while it is 66.84% 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%). 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 coexceedances 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 having no positive extreme return is higher than the probability of having no negative extreme return. Our test of equality for the probability of positive extreme return and

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[15] We estimate a logit model for all coexceedances, positive or negative, and introduce a dummy variable covariate equal to one if the coexceedance was positive. The Wald test that the coefficients on the dummy variable are jointly equal to zero is distributed as chi-square with three degrees of freedom.

[16] If high regional market volatility occurs because of high volatility in a common factor, it is not surprising that a large number of coexceedances arise.

negative extreme return coexceedances confirms the asymmetry for coexceedances of four or more extreme returns. Specifically coexceedances of four or more extreme returns are more likely for negative extreme returns than for positive extreme returns (Wald chi-square statistic of 3.17, p-value of 0.07, not reported).

We also include the United States and Europe in the third and fourth panels of Table 4. For the United States, 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.[17] The pseudo-R^2s are higher for the top tail than in any other regression. For Europe, there is clear evidence that an increase in the conditional volatility of returns increases the probability of tail events. The exchange rate coefficients are significant, but the interest rate coefficients are not. The pseudo-R^2s are substantially higher than those of the emerging market regions for the positive tail events.

Figure 1 illustrates the coexceedance response curves 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 coexceedances to the conditional volatility of Asian index returns. The different areas of the plot correspond to different coexceedance events. Clearly the probability of various coexceedances in Asia increases with the conditional volatility, but it does so nonlinearly. When the conditional volatility of Asian markets exceeds 3% or 4% per day, for example, the probability of two or more coexceedances reaches almost 45%. 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 extreme events. The two other figures are associated with the

[17] For the United States we employed the equally weighted average exchange rate for all countries in Asia and Latin America in the binomial tests as well as the daily Federal funds rate. For Europe we used the deutsche mark–U.S. dollar (or Euro–U.S. dollar) bilateral exchange rate and the short rate in Germany as a proxy. All data are from Datastream International.

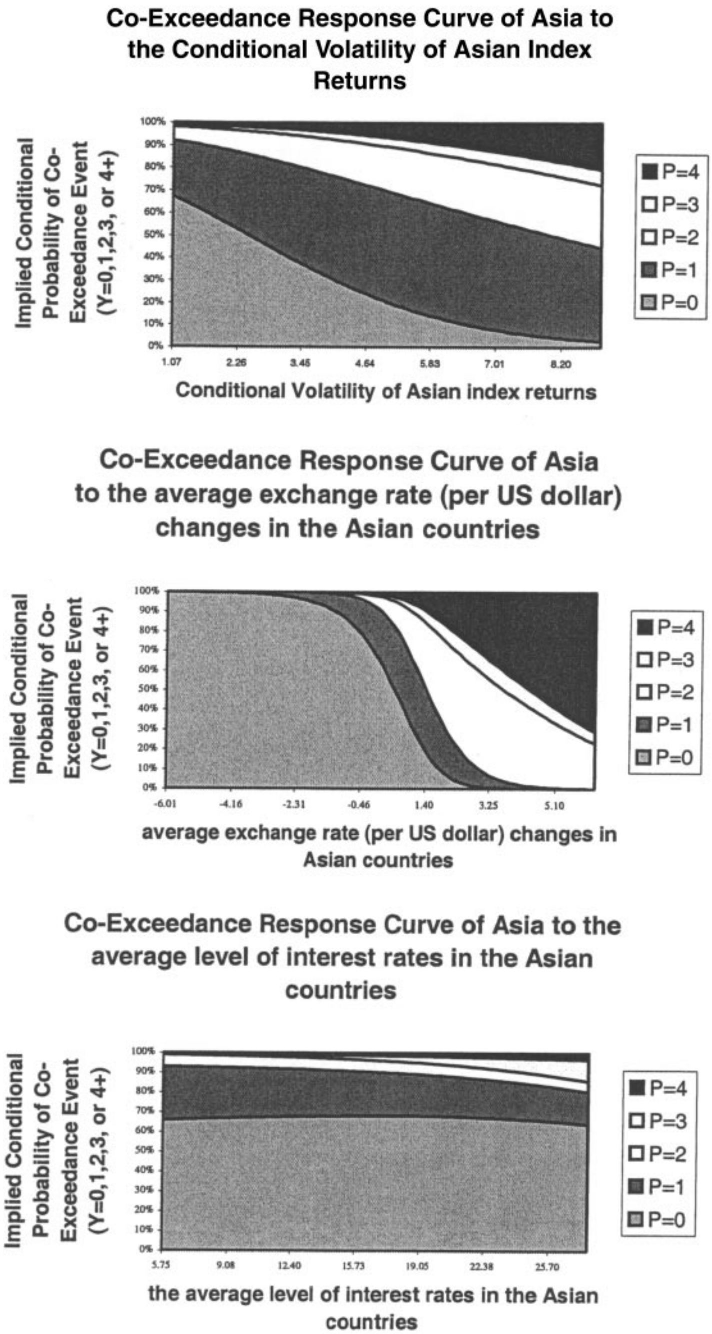

Figure 1
Coexceedance response curves of negative extreme returns in Asia

model for the exchange rate change and interest rate level covariates. Of interest is that the sensitivity of coexceedances 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 nonlinear. The response curve slope is relatively flat unless rather large average exchange rate depreciations of 1% or more per day occur, after which the probability of regional contagion (two or more coexceedances) rises to a maximum of 50% to 80%.

Two robustness checks follow. First, we provide a full set of Wald chi-square 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 coexceedances of four or more where negative coexceedances are more likely. Second, we also extended the analysis to incorporate some dynamics in coexceedances 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 coexceedances are statistically significant for Latin America and Asia, and less so for Europe, but are not significant for the exceedances in the United States. 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 coexceedance 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 that affect contagion within regions. We offer a number of sensitivity tests to address this concern in the next section.

3. Contagion Across Regions

In this section we investigate contagion across regions. The type of question we address is whether the number of coexceedances, or joint occurrences of extreme returns, of a given number in Asia can help predict the number of coexceedances or extreme returns in Latin America or in other regions. To the extent that there is a fraction of the coexceedances in Latin America that is left unexplained by its own covariates that can be explained by coexceedances in Asia, we will interpret this as evidence of contagion across regions. In the first part of the section, we answer this type of question using a base model. In the second part of the section, we explore alternate specifications, robustness tests, and calibration exercises.

3.1 The base model

To investigate the question we are interested in, we reestimate the models of Table 4 for Asia, Latin America, the United States, and Europe, respectively, but add two covariates related to coexceedances (Y^*_{jt}) and regional market volatility (h^*_{jt}) from each of the other regions during the preceding trading session that day (except for the United States and Latin American trading sessions, which are contemporaneous). Timing conventions are important since U.S. and Latin American markets open after the markets in Asia close. 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. As we are careful to condition on exceedance events or conditional volatility from the previous trading day, we interpret these results as evidence of predictability of contagion.

The 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% level) for all but two-country coexceedances. In evaluating the derivative of the exceedance probabilities ("Δ prob") 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 while its associated change in probability is not, but this no doubt reflects the nonlinear 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 United States, since Latin American markets are open at the same time as the U.S. market. This turns out not to be the case. We reestimated our regressions, adding a variable that takes a value of one if the United States 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-square 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.

Table 5
Contagion test results of multinomial logit regression for daily return coexceedances of emerging market indices, April 1, 1992, to December 29, 2000

	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 America		From US		From Europe		From Latin America		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	−0.003	−0.064[b]	−0.004
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	0.117[b]	0.001	0.076	0.000	0.114	0.000	0.029	0.000
$\beta_{41}(h^*_{jt})$	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	0.006	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
β_{43}	0.190[b]	0.001	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	0.003	0.075	0.000	0.555[a]	0.002[b]	1.367[a]	0.004
β_{51} (Y^*_{jt})	0.157[b]	0.027[b]	0.670[a]	0.098[b]	0.402	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	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	1.443[a]	0.004
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	(0.08)	21.14	(0.00)	31.50	(0.00)	5.90	(0.21)	12.74	(0.01)	37.02	(0.00)
χ^2 (Y^*_{jt})	38.25	(0.00)	46.59	(0.00)	29.57	(0.00)	34.16	(0.00)	24.97	(0.00)	13.88	(0.01)

Latin America	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	– 7.756[a]	– 0.017	– 9.048[a]	– 0.016
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	0.745[a]	0.002	0.562[a]	0.001
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	– 1.661[a]	– 0.004	– 1.685[a]	– 0.003
β_{31} (i_{it})	0.012	0.002	0.004	0.000	0.017	0.002	0.010	0.002	– 0.005	– 0.001	0.015	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	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	0.000	0.108[a]	0.000
β_{41} (h^*_{jt})	– 0.117[b]	– 0.015	– 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	– 0.367[b]	– 0.010	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	– 0.001	0.662	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	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	(0.02)	13.69	(0.01)	1.81	(0.77)	24.45	(0.00)	30.17	(0.00)	4.94	(0.29)
χ^2 (Y^*_{jt})	25.29	(0.00)	92.76	(0.00)	63.17	(0.00)	29.98	(0.00)	37.10	(0.00)	27.88	(0.01)
US	From Asia		From Latin America		From Europe		From Asia		From Latin America		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	0.016	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	0.008	0.247[b]	0.008[b]	0.199	0.006
β_4 (h^*_{jt})	0.020	0.001	– 0.177	– 0.006	0.347	0.013	– 0.005	0.000	– 0.204[b]	– 0.006[b]	– 0.258	– 0.008
β_4 (Y^*_{jt})	0.185	0.007	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	(0.79)	3.81	(0.05)	2.50	(0.11)	0.00	(0.97)	5.72	(0.02)	1.18	(0.28)
χ^2 (Y^*_{jt})	3.36	(0.07)	90.36	(0.00)	31.19	(0.00)	0.17	(0.68)	33.37	(0.00)	35.79	(0.00)

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.
Europe	From Asia		From Latin America		From US		From Asia		From Latin America		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	−0.003	−0.023	−0.001	−0.025	−0.001	−0.083	−0.003	−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	0.008
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	(0.92)	0.88	(0.35)	0.07	(0.79)	0.81	(0.37)	0.30	(0.58)	3.42	(0.06)
c^2 (Y^*_{jt})	45.40	(0.00)	27.36	(0.00)	52.66	(0.00)	21.85	(0.00)	9.24	(0.00)	11.14	(0.00)

The number of coexceedances 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 coexceedances, 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 coexceedances 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 $1 - (L_\omega/L_\Omega)$, where L_ω is the unrestricted likelihood, and L_Ω is the restricted likelihood [Maddala (1983), chap. 2)]. The logit regression is estimated separately for positive (top-tail) and negative (bottom-tail) coexceedances. χ^2 (h^*_{jt}) and χ^2 (Y^*_{jt}) are Wald chi-square tests for the restrictions that $\beta_{k1} = \beta_{k2} = \beta_{k3} = \beta_{k4} = 0$ where k is 4 and 5, respectively, with p-values in parentheses.

[a], [b]Denotes significance levels at the 1% and 5%, respectively.

When we turn to contagion from the United States (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 United States is helpful to predict exceedances in Asia. Of interest is whether the United States 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 that both are significant at the 1% level. Finally, the results from adding European exceedances as covariates (models 3 and 6) are weaker than those obtained from adding U.S. covariates for negative returns, but they are still statistically significant. 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 (though, of course, it is not adjusted for degrees of freedom). 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 Asian markets close 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 coexceedances. 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 exceedance shocks from the United States and Europe have a larger and more consistent impact than those from Asia. The effect of the conditional volatility from the United States 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 United States and Europe in the third and fourth panels of Table 5. Asian extreme returns or conditional volatility have little effect on the probability of a negative extreme return for the United States and none on the probability of a positive extreme return for the United States. 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 United States are open, a concern is that contagion from Latin America is really contagion indirectly from the United States 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 coexceedance response curve plots in Figure 2 for Asia show how the conditional volatility and the number of extreme returns in Latin America, the United States, and Europe affects the probability of extreme returns in Asia. The plots for Latin America are given in Figure 3. 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%. 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 or more exceedances in Latin America is 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 from Asia to Latin America. Further, contagion affecting emerging markets is stronger than contagion affecting developed countries. Similar plots (not reported to save space) show that the United States is largely unaffected by coexceedances or conditional volatility from Asia. It is somewhat more dramatically affected by coexceedances in Latin America, but as discussed earlier, the relation between exceedances in Latin America and an exceedance in the United States is hard to interpret. Europe is more insulated than the United States from contagion in Latin America, but more sensitive to contagion from Asia than the United States.

3.2 Calibration, robustness tests, and alternative specifications

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 coexceedance patterns are just another manifestation of these correlations. To evaluate this hypothesis we extend the simulation experiment in Section 1.3 to evaluate our multinomial logistic regression model results. In this experiment we perform Monte Carlo simulations of 2283 daily returns (corresponding to the April 1, 1992, to December 29, 2000, period) for each country in Asia and Latin America using 1000 replications of the historical mean vector and variance-covariance matrix and assumptions about the joint returns-generating process. As before, we propose the multivariate normal, multivariate Student's 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 coexceedance 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 coexceedances in one region can be forecast with the number of coexceedances in another region. We only perform the experiments for contagion from Latin America to Asia and from Asia to Latin America.

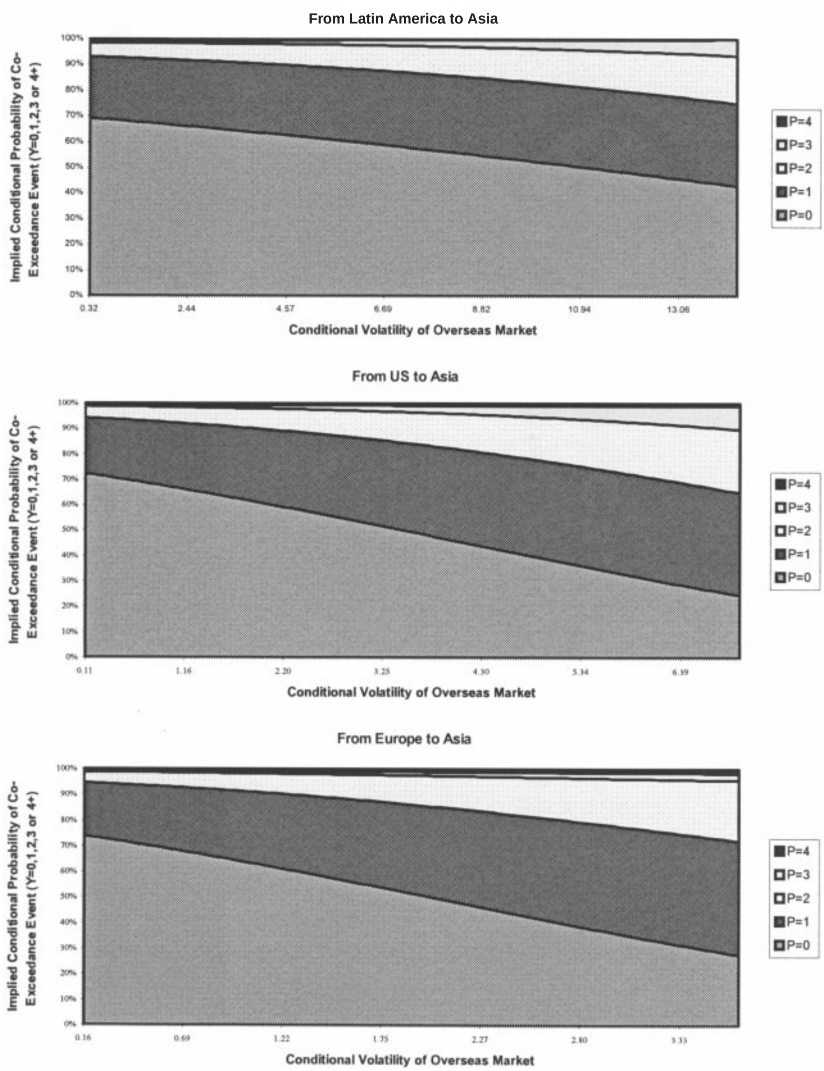

Figure 2
Coexceedance response curves of negative extreme returns in Asia to the conditional volatility and number of coexceedances of overseas market.

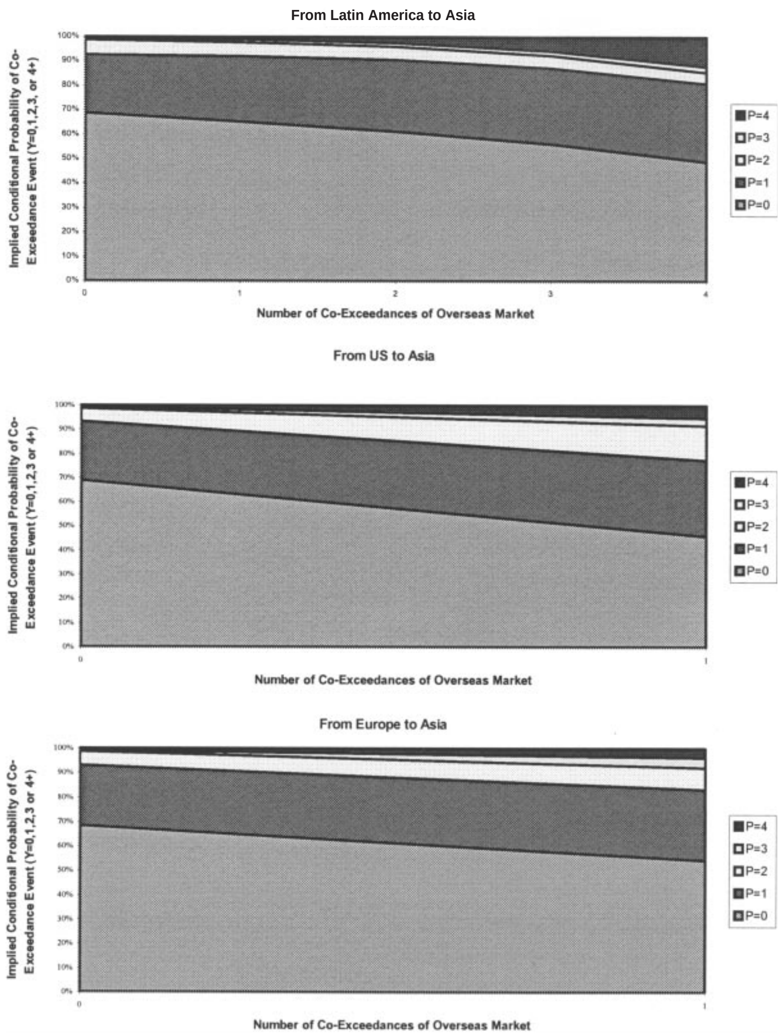

Figure 2
Continued

The results are available from the authors. Basically we cannot explain the coefficients on coexceedances from the other region for Asia or Latin America. For the multivariate normal and Student's t scenarios, we cannot explain the magnitude of the β_j coefficients associated with Y_{jt}^* coexceedances for positive or negative extreme returns. The multivariate GARCH model has only moderate success delivering simulation p-values of at most 5% for top-tail exceedances and 16% for the bottom tails. The pseudo-R^2 statistics in the simulations reach values as large as in the actual data in at most 1% of the replications. For Latin America, in particular, the highest simulation p-value for any coexceedance coefficient is 3% for the top tail in the multivariate GARCH scenario and 23% in the bottom tail also for the multivariate GARCH scenario. Perhaps even more striking for Latin America, the pseudo-R^2 is at least four times higher in the data than it is in any of the simulations.

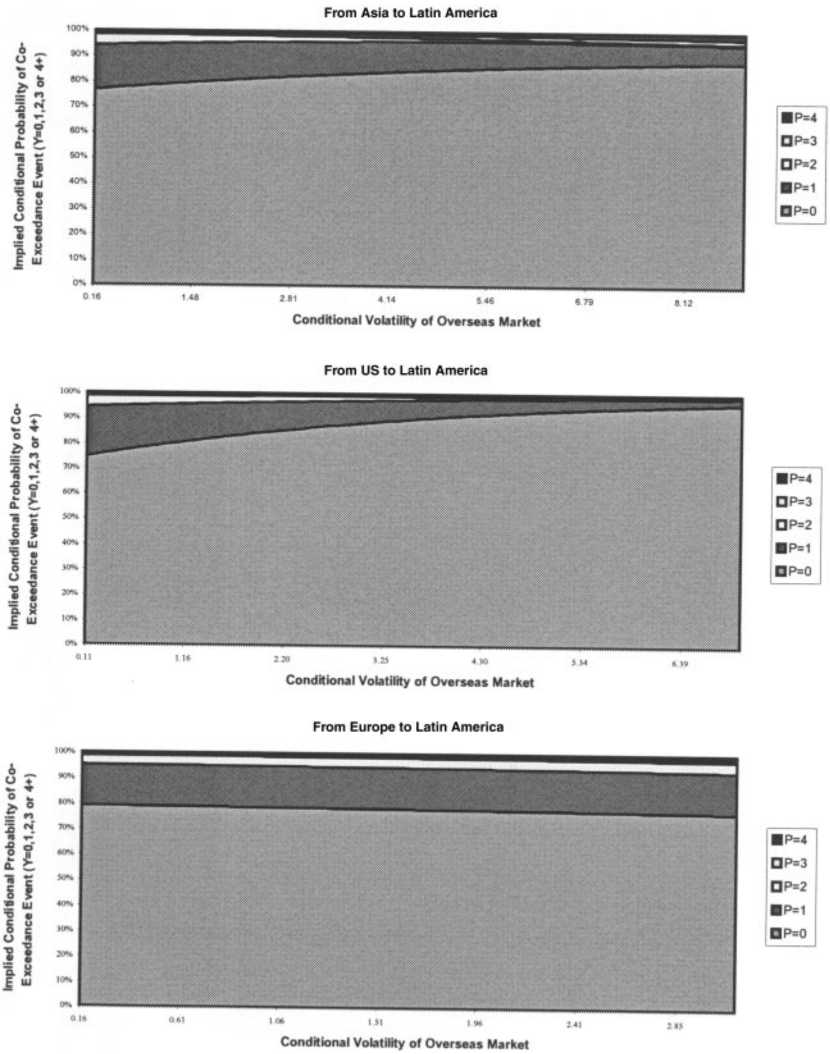

Figure 3
Coexceedance response curves of negative extreme returns in Latin America to the conditional volatility and number of coexceedances of overseas market

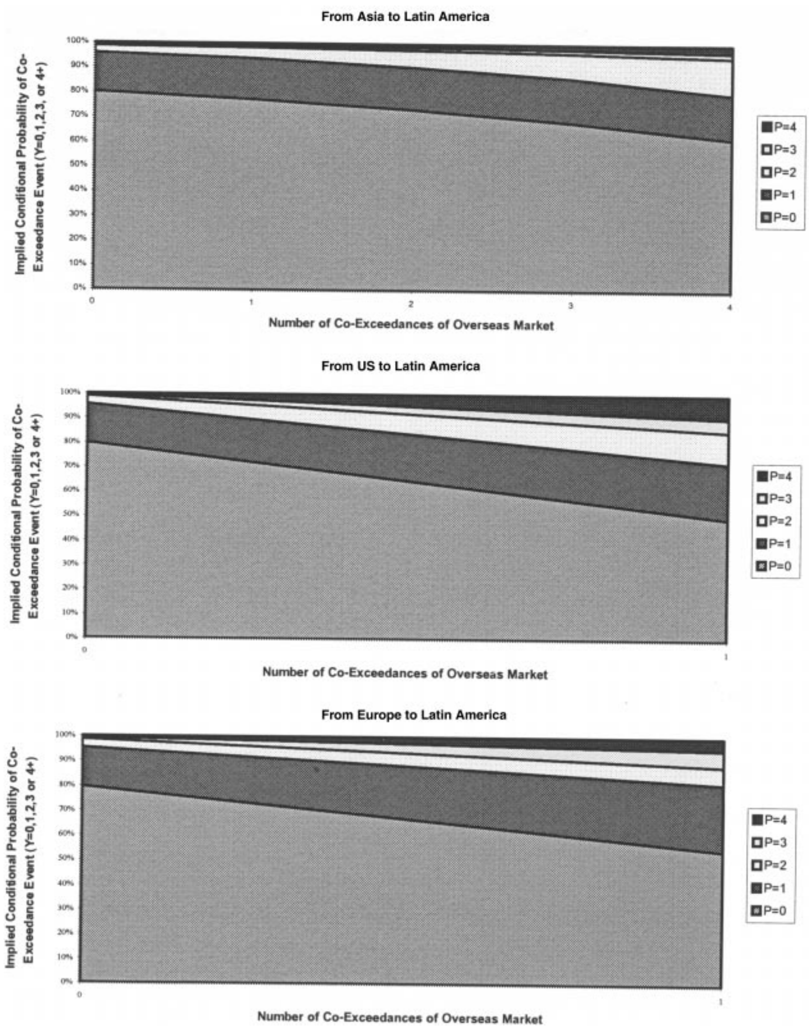

Figure 3
Continued

We consider a battery of robustness checks. We reestimated our multinomial logistic regressions with Monday dummies. These dummies are insignificant. We also reestimated 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 6 we report our contagion tests using lagged conditioning variables. Though it is an in-sample experiment, it allows us to investigate further the predictability of contagion. We see immediately that the pseudo-R^2 falls. However, the significance of yesterday's coexceedances from the other regions is not less than the significance of same day coexceedances. The table provides evidence that contagion across regions is predictable and that the number of coexceedances 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 7 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 coexceedances. However, coexceedances in one region still provide useful information in predicting coexceedances in another region. For instance, the number of coexceedances in Latin America helps explain the number of coexceedances 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 reestimate (not reported) the base model regression, but use exceedances computed over three days instead of over one day as regressors. That is, a coexceedance 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 coexceedances within a region. Overall, the results are similar to those of the base case in Table 5 for Asia, but weaker for Latin America.[18] Finally, we define exceedances by the 2.5% quantile rather than the 5% 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 coexceedance responses to Table 5, but inference tests lose power.

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[18] Another possible concern that we do not investigate with the alternative specifications using multiday horizons and lagged covariates is with nonstationarity of the explanatory variables. Park and Phillips (2000) demonstrate the complications in the limiting 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 this out.

Table 6
Contagion test results of multinomial logit regression for daily return coexceedances of emerging market indices using lagged conditioning variables, April 1, 1992, to December 29, 2000

	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 America		From US		From Europe		From Latin America		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	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	0.036	0.237	0.035	0.252	0.037	−0.410[a]	−0.060[b]	−0.388[a]	−0.057[b]	−0.341[b]	−0.050[b]
β_{22}	0.352	0.016	0.346	0.015	0.362[b]	0.016	−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	−0.531[b]	−0.006	−0.432	−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
β_{31} (i_{it-1})	−0.033	−0.007	−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	−0.003
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	0.168[a]	0.001[b]	0.149[a]	0.001[b]	0.086	0.001	0.113	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	0.605[a]	0.004[b]	0.697[b]	0.004	−0.175	−0.003	0.265	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	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	0.415[a]	0.019[a]	1.046[a]	0.051[a]	0.794[b]	0.044[b]
β_{53}	0.300	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	1.495[a]	0.005
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	(0.07)	22.90	(0.00)	28.76	(0.00)	5.04	(0.28)	13.57	(0.01)	41.26	(0.00)
χ^2 (Y^*_{jt})	36.01	(0.00)	52.32	(0.00)	35.71	(0.00)	37.57	(0.00)	28.15	(0.00)	15.36	(0.00)

Latin America	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	−8.144[a]	−0.018	−9.205[a]	−0.017
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	0.706[a]	0.001	0.542[a]	0.001
β_{21} (e_{it-1})	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	0.012	0.283	0.010	0.284	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	−0.002
β_{31} (i_{it-1})	0.012	0.002	0.001	0.000	0.017	0.002	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	0.001	0.027	0.001	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	−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	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	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	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	(0.01)	20.69	(0.00)	0.96	(0.92)	20.63	(0.00)	9.19	(0.06)	19.70	(0.00)
χ^2 (Y^*_{jt})	26.03	(0.00)	94.31	(0.00)	69.55	(0.00)	29.95	(0.00)	42.59	(0.00)	33.17	(0.01)

US	From Asia		From Latin America		From Europe		From Asia		From Latin America		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	0.009	0.868[a]	0.031[a]	1.031[a]	0.033[a]	0.887[a]	0.029[a]
β_3 (e_{it-1})	−0.300	−0.012	−0.247	−0.008	−0.249	−0.009	−0.346	−0.012	−0.414	−0.013	−0.317	−0.011
β_4 (i_{it-1})	0.383[a]	0.015[a]	0.501[a]	0.016[a]	0.385[a]	0.014[a]	0.217	0.008	0.249[b]	0.008[b]	0.205	0.007
β_4 (h^*_{jt})	0.017	0.001	−0.161	−0.005	0.353	0.013	0.003	0.000	−0.197[b]	−0.006[b]	−0.209	−0.007
β_4 (Y^*_{jt})	0.183	0.007	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	(0.92)	3.19	(0.07)	2.64	(0.10)	0.00	(0.99)	5.53	(0.02(	0.81	(0.37)
χ^2 (Y^*_{jt})	3.31	(0.00)	91.17	(0.00)	28.63	(0.00)	0.15	(0.69)	34.76	(0.00)	32.08	(0.01)

Table 6
(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.
Europe	From Asia		From Latin America		From US		From Asia		From Latin America		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-1})	0.041	0.001	0.108	0.004	0.123	0.005	0.283	0.010	0.286	0.011	0.296	0.011[b]
β_4 (i_{it1})	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	(0.86)	0.98	(0.320	0.07	(0.79)	1.54	(0.21)	1.30	(0.25)	5.11	(0.02)
χ^2 (Y^*_{jt})	40.96	(0.00)	22.65	(0.00)	45.80	(0.00)	16.04	(0.00)	5.80	(0.02)	6.77	(0.01)

The number of coexceedances 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 coexceedances, where j equals 0, 1, 2, 3, 4 or more (five categories). The multinomial logit regression model is given by $P_j = \exp(x'\beta_j)/[1 + \Sigma_k \exp(x'\beta_k)]$, where β is the vector of coefficients, x is the vector of independent variables, and k equals 1 to 4. The probability that there are no (co-)exceedances equals $P_0 = 1/[1 + \Sigma_k \exp(x'\beta_k)]$ 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, chap. 2)]. The logit regression is estimated separately for positive (top-tail) and negative (bottom-tail) coexceedances. χ^2 (h^*_{jt}) and χ^2 (Y^*_{jt}) are Wald chi-square tests for the restrictions that $\beta_{k1} = \beta_{k2} = \beta_{k3} = \beta_{k4} = 0$, where k is 4 and 5, respectively, with p-values in parentheses.

[19] [a], [b]Denotes significance levels at the 1% and 5%, respectively.

Table 7
Contagion test results of multinomial logit regression for daily return coexceedances from conditional extreme returns, April 1, 1992 to December 29, 2000

	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 America		From US		From Europe		From Latin America		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	−0.017	−0.103	−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
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	0.001	0.195	0.001	0.459[b]	0.002	0.374[b]	0.002	0.325	0.002
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	−0.401[a]	−0.053	−0.394[a]	−0.051
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	−0.003	−0.071	−0.004	−0.054	−0.003
β_{33}	0.108	0.001	0.123	0.001	0.121	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	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	−0.174	−0.008	0.243	0.011
β_{43}	0.206	0.001	0.352	0.002	0.801[b]	0.004	0.119	0.002	0.460[b]	0.005[b]	0.583[b]	0.006
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	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	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	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	(0.05)	9.10	(0.06)	7.63	(0.11)	8.64	(0.07)	8.99	(0.06)	7.97	(0.09)
χ^2 (Y^{*}_{jt})	33.93	(0.00)	37.32	(0.00)	29.62	(0.00)	41.37	(0.00)	36.89	(0.00)	8.55	(0.07)

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 America	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	0.152	0.003	0.185^b	0.004	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	0.001	0.167	0.000	0.431^a	0.001	0.389^a	0.001	0.307^a	0.001
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	1.190^a	0.011^a	0.387	0.004
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	-1.650^a	-0.006	-1.753^a	-0.005
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	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	0.007	0.267	0.006	-0.118	-0.003	-0.476^b	-0.015	0.120	0.006
β_{43}	0.325^b	0.002	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	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
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	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	1.573^b	0.005	2.303^a	0.006
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	(0.00)	6.28	(0.18)	8.47	(0.08)	12.69	(0.01)	15.72	(0.00)	5.54	(0.24)
χ^2 (Y^*_{jt})	26.08	(0.00)	81.72	(0.00)	69.08	(0.00)	36.92	(0.00)	42.60	(0.00)	23.68	(0.01)

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	0.008	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	(0.82)	0.79	(0.37)	4.48	(0.03)	0.06	(0.81)	0.12	(0.73)	0.01	(0.92)
χ^2 (Y^*_{jt})	0.63	(0.43)	73.84	(0.00)	32.66	(0.00)	0.07	(0.79)	39.84	(0.00)	1.21	(0.27)
Europe	**From Asia**		**From Latin America**		**From US**		**From Asia**		**From Latin America**		**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	− 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	− 0.003	− 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	0.004	0.128	0.004	0.106	0.004	0.053	0.002	0.333	0.011
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	(0.32)	3.14	(0.08)	0.45	(0.50)	1.79	(0.18)	0.45	(0.50)	2.87	(0.09)
χ^2 (Y^*_{jt})	58.56	(0.00)	28.56	(0.00)	77.72	(0.00)	4.65	(0.03)	5.55	(0.02)	7.76	(0.01)

Extreme returns are defined in terms of exceedances beyond a threshold that varies over time with the conditional volatility of regional market returns. 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 coexceedances, 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 coexceedances, where j equals 0, 1, 2, 3, 4 or more (five categories). The multinomial logit regression model is given by $P_j = \exp(x'\beta_j)/[1 + \Sigma_k \exp(x'\beta_k)]$, 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 $P_0 = 1/[1 + \sum_k \exp(x'\beta_k)]$, where k equals 1 to 4, 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 $1 - (L_\omega/L_\Omega)$, where L_ω is the unrestricted likelihood, and L_Ω is the restricted likelihood [Maddala (1983, chap. 2)]. The logit regression is estimated separately for positive (top-tail) and negative (bottom-tail) coexceedances. χ^2 (h^*_{jt}) and χ^2 (Y^*_{jt}) are Wald chi-square tests for the restrictions that $\beta_{k1} = \beta_{k2} = \beta_{k3} = \beta_{k4} = 0$, where k is 4 and 5, respectively, with p-values in parentheses.

[a], [b] Denotes significance levels at the 1% and 5%, respectively.

Finally, we consider alternative estimation approaches for our problem. Because our multinomial logit model fails to account for the ordinal nature of our coexceedance 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 coexceedances instead of four are equivalent to the odds of observing three coexceedances instead of two. Such a constraint will generate less-efficient estimates if the odds are not proportional [Brant (1990), Peterson and Harrell (1990)]. With this concern in mind, we chose to feature the unordered multinomial logit. However, in unreported results, we replicated our contagion tests across regions using the ordered model and found that our inferences about the coexceedance variable Y_j^* (coefficients and marginal effects) and the pseudo-R^2 were consistent and very similar. Some propose diagnostic 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 chi-square with $p(c-2)$ 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.

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)]. 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.[19] We

[19] 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 coexceedances 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.

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 United States is measurably lower, however.

Our multinomial logistic regression model results for contagion within and across regions are not simply manifestations of the correlations of returns in those markets, even if we allow for returns-generating processes with excess kurtosis and time-varying volatility. The findings are robust to specifications with seasonal dummies, lagged conditioning information, local currency (versus U.S. dollar) denominated returns, multiday horizons for exceedance counts, and even conditional measures of extremes based on conditional volatility. We also explore other econometric methods including ordered logit, proportional odds, and negative binomial regression models. If anything, these alternative specifications likely strengthen our main findings on the existence of contagion effects across regions.

4. Conclusion

In this article we propose a new approach to the study of financial contagion. The key presumption of our approach is that contagion is a phenomenon associated with extreme returns: 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 of our tests. One must be careful not to let inferences be dominated by a few datapoints. As a result, we choose to focus on counts of coincidences 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 were distributed as multivariate normal, Student's t, and even with GARCH effects. We find that we have too many cases where large negative returns occur in most countries of a region. 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's 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 joint returns-generating model with normal or fat tails or 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 article 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 United States 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 article would be well suited for such analyses. There is a long tradition that focuses on modeling the properties of extreme returns. A factor model might capture both the properties of extreme returns and of other returns. It would be a challenge to develop a model that would capture the nonlinearities that we emphasize, but such a model could provide useful insights about the contagion quantified in this article.

Appendix

Every three 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% 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% 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 0.988) for all but three exceptional cases (Colombia, 0.88; India, 0.89; 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 article are estimated using the actual IFC indexes also. Further details on the scope of coverage and components is available from the authors upon request.

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