Contagion as Domino Effect in Global Stock Markets

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Abstract

This paper proposes a new approach for modeling extreme dependence between global stock markets. We explicitly define local, regional and global crashes and model the evolution of these crashes with an ordered logit model. Applying our approach to daily stock market returns of emerging and developed markets we find evidence for interdependence as well as contagion effects. Particularly, we find that interest rates, bond returns and volatility are important factors for the probabilities of observing the different types of stock market crashes. Contagion, on the other hand can be characterized as a domino effect, where local emerging market crashes evolve into regional or even global crashes. From a practical point of view, we show that an ordered logit model, including local and regional crashes, is able to predict global crashes better than a binary logit model for global crashes only.

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1 Introduction

Stock market crashes are one of the major risks that investors face. Although such crashes occur infrequently, their impact on the value of asset portfolios can be substantial. The October 1987 crash, for example, made stock prices decline by 20 percent or more in most developed markets around the globe. In emerging stock markets, crashes can be even more severe. In addition, as emerging stock markets are commonly quite susceptible to shocks, crashes occur more often in those markets. While many of these crashes are "local" and remain limited to an individual market, some spread to other emerging markets, resulting in regional stock market crashes. Some may even evolve into global crashes, where developed markets are also affected. The 1997 Asian crisis, for example, originated in Thailand, then infected other developing Asian countries and finally even financial markets in the United States and Western Europe were affected.

For investors as well as policy makers it is important to know whether crashes stay local, or whether a "domino pattern" occurs, with local crashes evolving via regional crashes into global crashes. If crashes remain local, they are relatively easy to hedge. However, if crashes spread regionally or even globally, hedging will be more difficult, as diversification opportunities rapidly diminish.

This study empirically examines how local emerging market crashes evolve into more severe crashes. We model the occurrence of local, regional and global crashes by means of an ordered logit model, making use of the fact that the different types of crashes have a natural ordering in terms of their severity. This allows us to consider multiple countries simultaneously and to investigate the transmission mechanism of crashes from local to regional and global levels. In particular, we test whether the occurrence of the different crash types can be linked to other financial variables, such as interest rates and currency depreciations. Furthermore, we investigate the presence of residual dynamics in the evolution of crashes after the removal of the effects of other financial variables.

We apply this approach to daily stock market prices for the US, Europe and several emerging markets in Latin America and Asia for the period from July 1996 to July 2007. We relate the occurrence of local, regional and global stock market crashes to information from the currency, stock and bond markets.

Our main results can be summarized as follows. First, we find that bond markets returns, interest rate levels and stock market volatility are important determinants of local, regional and global crashes, while currency changes are not. Higher interest rates and higher stock market volatility lead to higher probabilities of more severe crashes, while higher bond returns on average lead to lower crash probabilities. Second, we find evidence for residual dependence, which cannot be explained by the financial variables. Local, regional and global crashes on the previous day have substantial influence on today's probabilities of observing more severe crashes. This indicates that, like a domino pattern, probabilities of observing more severe crashes become higher when a crash occurred yesterday. Third, we do not find that the relation between the financial variables and crash likelihood depends on the type of crash that occurred the day before. Finally, we find that our model, allowing for different types of crashes including local and regional ones, leads to more precise estimates and is more successful in detecting and forecasting global crashes than a binomial model for global stock market crashes only.

We contribute to the literature in different ways. First, we explicitly distinguish between local, regional and global crashes. This adds to the approach of Bae et al. (2003) and to a lesser extent Cumperayot et al. (2006). For example, Bae et al. (2003) use the number of simultaneous extreme returns as dependent variable in a multinomial logistic regression model and find significant relationships with interest rates, changes in currencies and conditional stock market volatility. They however focus only on one continent at a time and do not investigate which part of the dependence can be attributed to reactions on shocks in other financial markets and which to residual dependence. We explicitly extent this study by including global crashes in our analysis. These global crashes are most important for investors and regulators, because diversification opportunities evaporate in this case.

Second, we add to the ongoing debate on contagion and interdependence, as defined in

Dornbusch et al. (2000), by using a framework in which we allow for both types of spillovers. Interdependence means transmission of shocks resulting from the normal dependence between markets, such as trade links and geographical position. So, interdependence refers to the dependence that exists in all states of the world. Contagion, on the other hand, constitutes a dependence that exists only for large or extreme shocks to financial markets. Contrary to interdependence, this dependence does not exist in tranquil periods. Additionally, it cannot be linked to observed changes in macroeconomic or financial variables. Dornbusch et al. (2000) argue that this type of dependence is a result of "irrational" phenomena, such as financial panic, herd behavior and loss of confidence. We define contagion as the dependence that still exists, after correcting for interdependence that always hold. Thus, interdependence can be defined as the *expected* dependence while contagion is the *unexpected* dependence. Our research enables us to distinguish between contagion and interdependence in the occurrence and evolution of local, regional and global crashes.

Numerous other studies concerning interdependence and contagion are mostly based on bivariate analyses, and do not investigate dependencies at the global level. The most popular approach is based on correlations between returns in different markets (see King and Wadhwani (1990), Lee and Kim (1993), Loretan and English (2000), Forbes and Rigobon (2002)). A second approach attempts to model the volatility transmission mechanism by means of multivariate GARCH models (see Hamao et al. (1990), Longin and Solnik (1995) and Ng (2000)). Other studies use extreme value theory (see Kaminsky and Schmukler (1999), Longin and Solnik (2001), and Hartmann et al. (2004)) to avoid the problem that increased correlations in periods of turmoil may be mostly a result of increased volatility (Loretan and English (2000), Forbes and Rigobon (2002)). Rodriquez (2007) uses copulas to measure contagion and finds evidence for contagion based on changes in dependence of extreme returns. Fazio (2007) uses a bivariate framework to investigate the difference between interdependence and contagion for currencies. He concludes that contagion occurs only regionally and that interregional transmissions are mostly interdependence. Connolly and Wang (2003), also in a bivariate set-up, assess differences in interdependence and contagion for Japan, UK and the US, finding that comovements of the equity markets cannot be explained by public information on macroeconomic fundamentals, rejecting interdependence.

The paper proceeds as follows. In Section 2 we describe our data set, and provide the definition of a stock market crash as well as the classification into local, regional and global crashes. Section 3 discusses the methodology based on the ordered logit model. In Section 4 we discuss the empirical results concerning the dynamic patterns in the different types of crashes obtained by means of the ordered logit model. In Section 4 we also report several sensitivity tests to check the robustness of our results. Section 5 explores the economic relevance of our model compared to "standard" binomial crash models. We conclude in Section 6.

2 Data and Crash Classification

2.1 Data

We obtain country indices for the emerging stock markets from the IFC emerging market database (EMDB), currently produced by Standard & Poors. We include six countries from Latin America; Argentina, Brazil, Chile, Colombia, Mexico and Venezuela, as well as six countries from Asia: India, Korea, Malaysia, Philippines, Taiwan and Thailand. We also obtain the regional IFC indices for Latin America and Asia. For the United States and Europe we use MSCI equity indices. Although Europe exist of more countries rather than one, we do not consider local crashes in Europe for two reasons. First, the markets in Western Europe are highly integrated. Defining Europe as one market therefore seems appropriate. Second, the United States and Europe have the same characteristics using these definitions. We base our analysis on daily returns for the period from July 1, 1996 until July 30, 2007, giving a total of 2871 observations. All the data are provided by DataStream.

[Insert Table 1 around here]

Table 1 provides summary statistics of the log daily stock returns for the full sample period, July 1996 - July 2007. Within the emerging market countries the annualized average returns vary widely, ranging from a minimum of -7% in Thailand to a maximum of 16% in Mexico. The annualized volatilities also show large variation across countries. For example, the Chilean stock market has a volatility of 17% only, while the volatility in Korea is much larger and equal to 42%. For most countries volatility exceeds 25%, indicating the relatively large investment risk typical for emerging markets. For many of the emerging markets that we consider kurtosis is also substantially higher than for the developed markets, suggesting that extremely large returns occur relatively more often. Interestingly, skewness is negative for the Latin American countries, while it is positive for the Asia market except India. The lowest return in the sample was observed on 29 November 2002, when the Venezuelan index lost 46% of its value. We see that the maximum returns can also vary from moderate (Chile, India, Taiwan) to very high (Venezuela, Korea, Malaysia, Philippines). The regional indices show that emerging markets are riskier than developed markets, while the average returns perhaps are not as high as might be expected to compensate for this higher risk. This can be explained by the 1997 Asian crisis and the 1998 Russian debt crisis, which considerably depressed emerging market returns. Average yearly returns computed over the period 1999 - 2007 are equal to 21, 13, 2 and 5 % for Latin America, Asia, the US and Europe, respectively, which are more in line with their respective volatilities.

The entries below the main diagonal in the bottom part of table 1 are the linear correlations between contemporaneous daily returns. For the regional indices, we observe that the correlations between the US, Europe and Latin America are of the same order of magnitude around 0.50. The correlations between Asia and the other regions are lower, especially the correlation between the US and Asia (0.09). This lower correlation mainly is a result of different trading times of stock markets around the globe. As trading on a given calendar day starts in Asia, then moves to Europe, and ends in the United States, information from the

European and (especially) the US stock markets cannot affect the Asian market on the same day, such that these correlations (mostly) measure the effect of the Asian market on Europe and the US. The reverse effect can be measured by means of the correlation between today's returns in Asia and yesterday's returns in Europe and the US, which are equal to 0.29 and 0.38, respectively.

The correlations between individual countries in the emerging market regions are somewhat lower on average. The average correlations between countries within Latin America and Asia are equal to 0.29 and 0.24, respectively, while the average cross-correlation (the correlation between the countries in Asia and Latin America) is only 0.12. We do note, though, that the correlations between the four largest Latin American markets (Argentina, Brazil, Chile and Mexico) are considerably higher at around 0.50, comparable to the correlation among developed markets. The correlations between the individual emerging market and US or European indices also are quite low, indicating a weak dependence between these markets.

2.2 Crash definition and classification

Following Bae et al. (2003), a stock market crash in a given country is said to occur when the daily return lies below the lower 5th percentile of the empirical return distribution. A local crash occurs when one to three[1] individual emerging markets experience a crash, while the respective regional indices do not. A regional crash in Latin America or Asia occurs when either the regional index crashes, or when four or more country indices in the specific emerging market region crash. This definition enables us to observe a regional crash in the emerging markets when four or more small countries crash. If we do not include this additional regional crash occurrence, results can be driven by large countries such as Argentina, Brazil, Korea, Taiwan and Thailand. Regional crashes in the United States and Europe occur when the corresponding MSCI indices encounter a crash. We define a global crash as the

[1]Results hardly change when we vary this number between three to six markets.

simultaneous occurrence of two or more regional crashes, of which at least one is in a developed region. Because of the different stock market trading hours we also define a global crash when the United States or Europe encounter a crash on day t, followed by a crash in Asia on day t + 1.

Based on the definitions given above, from the total sample period of 2871 days we find 1842 days with no crashes, while on 616 days a local emerging market crash occurs. On 271 days we observe a regional crash, and finally a global crash occurs on 142 days of the sample We find that regional crashes occur little more often than once every two weeks and global crashes occur about once a month. Although the latter seems quite frequent, crashes occur in clusters resulting in relatively short periods with several global crashes, followed by relatively longer periods with hardly any global crash. To examine whether these numbers are high or low we compute the numbers of crashes we expect if all markets were independent. Because for all indices we know that the crash probability is equal to 5%, these probabilities for the different crashes can be computed analytically. This results in 1260 days with no crash, and 1066, 497, 48 local, regional and global crashes respectively. Comparing these numbers to the actual numbers of crashes of different type in the sample shows that the crash risk involved with investing in equity markets is indeed rather large. Although the total number of days with a crash is lower, global stock market crashes, which are the most troublesome for investors, occur 3 times more often than would be expected if all markets were independent.

The entries above the main diagonal in the lower part of table 1 are conditional probabilities of observing a crash in a specific country, given the occurrence of a crash in another country. These probabilities give insight into the tail dependence of the stock market returns. By construction, the same number of crashes occur for all individual markets, and therefore these probabilities are also symmetric. For the regional indices we find that the probability of observing a crash given that another region encounters a crash is around 0.30 on average. For the individual markets in both Latin America and Asia we find substantial variation in these conditional probabilities, although most are between 0.10 and 0.20. To put these numbers into perspective, note that if all markets were independent these conditional probabilities would be equal to 0.05. Hence, the empirical conditional probabilities show that there is substantial dependence in the occurrence of crashes across countries and regions.

2.3 Crash Dynamics

We close this section by documenting some stylized facts on the dynamic properties of the different types of crashes. In particular, we introduce a diagnostic measure which sheds light on how crashes evolve. We call this measure the crash transition matrix. The ij-th entry of this transition matrix is equal to the probability of observing a state $i = 0, 1, 2, 3$, given that on the previous day state $j = 0, 1, 2, 3$ occurred. The numbers 0, 1, 2 and 3 correspond to no crash and local, regional and global crashes, respectively.

[Insert Table 2 around here]

The empirical crash transition matrix is shown in Panel A of table 2. Several interesting conclusions emerge. First, for both regional and global crashes we find increasing probabilities of occurrence, conditional on the occurrence of a crash on the previous day. The probabilities of observing a global crash, for example, increase from 0.03 when no crash occurred on the previous day, via 0.06 to 0.11 following the occurrence of a local or regional crash, respectively. This suggests that most global crashes do not occur abruptly but rather evolve out of prior local or regional crashes. Similarly, the probabilities of observing a crash (no matter what type) tomorrow increases from 0.28 when no crash occurs today via 0.43 and 0.55 to 0.73 when a global crash occurs today. Second, crashes of a given type are persistent, in the sense that the probability that a certain crash continues is very much higher than the probability of occurrence of the same type of crash on two consecutive days if these were independent. For example, the empirical probability that a global crash continues is 20%, which is more than 80 times as large as the probability of $(\frac{142}{2871})^2$ =0.24 % of observing two consecutive days with a global crash if these occurrences were independent. The same holds for local and regional crashes. Third, crashes die out gradually as indicated by the relatively high probabilities that a regional crash occurs tomorrow following a global crash today, or a local crash following a regional crash.

Forbes and Rigobon (2002) show that increased correlations between returns in different stock markets in times of extreme downturns can be attributed to the increase in volatility during these periods. To examine whether our results for the crash dynamics are not driven by volatility only, we compute the crash transition matrices using crash definitions based on standardized returns[2]. Panel B of Table 2 shows this matrix, and we observe that the results are even stronger than for the normal returns. Therefore we conclude that in our setting the dependence between markets is not affected by time-varying levels of return volatility.

Our final approach to obtain more insight into the crash dynamics is based on a bootstrap procedure. To examine whether the crash dependencies are mainly driven by correlations or whether there are specific crash dependencies we employ the stationary bootstrap of Politis and Romano (1994). The advantage of this bootstrap method over the standard i.i.d. bootstrap is the possibility of taking into account autocorrelations of the stock returns, which is relevant for the emerging markets in our sample. This is managed by not drawing the next observation in the bootstrap sample completely at random, but to take the next observation in the natural ordening with a specific probability (p) and a random observation otherwise. The optimal value of p can be determined using the method of Politis and White (2004)[3]. For our data this turns out to be $p = 0.50$[4]. If the transmission mechanism of crashes were mainly driven by linear correlations, then the optimal stationary bootstrapped matrix should approximate the empirical crash transition matrix.

[2]We use the sample volatility over the past year to standardize the returns. For the standardized returns, we find 1833, 621, 289 and 128 days with no, local, regional and global crash, respectively.

[3]This method minimizes the mean squared errors of the variances and autocovariances of the stationary bootstrapped data, given that the first draw is random.

[4]We computed the optimal values of p for the four regional indices and then took the average. The individual values of p for the sample returns are 0.73, 0.83, 0 and 0.42, for Latin America, Asia, USA and Europe respectively. For the standardized returns these are 0.71, 0.82, 0 and 0.46.

Panel C show the average transition matrices based on 10,000 bootstrap samples of 2871 observations, corresponding with the length of the empirical return series. Again we observe higher probabilities for regional and global crashes when a crash occurred on the previous day. However, the pattern is less clear than for the original data. For the transitions between regional and global crashes the differences between the original and the bootstrapped contagion transition matrix becomes particularly large. For instance, the probability of observing a regional crash today and a global crash tomorrow decreases from 0.11 to 0.07. Further, the probability that a global crash continues is now 0.11, compared to 0.20 for the empirical probability. This indicates that there are indeed higher-order dependencies in the dynamic patterns of crashes, especially concerning the more severe crashes. Again, using standardized returns has hardly any influence on the results (see panel D).

2.4 Explanatory variables

In explaining the occurrence of crashes we use variables representing information from the currency market, the fixed income market, and short-term interest rates. For the currency market we take the average exchange rate changes in Latin America and in Asia. These variables are constructed by taking the equally weighted average of the daily log changes in the currencies of all countries in the region against the US Dollar. We expect a positive effect on the probability of more severe crashes as depreciations lead to a lower value of the stock index.

To investigate whether shocks in the bond market lead to increased dependence we include daily returns on well diversified regional bond portfolios. These portfolios consist of bonds with long and short maturities, issued by sovereign and quasi-sovereign entities. We expect bond returns to have a negative effect, because positive bond returns indicate economic stability.

We also include two variables associated with extreme events in the the currency and bond markets. Extreme currency depreciations are those depreciations above the upper 5th percentile of the empirical distribution of currency returns. For the bond market the extreme observations are those below lower 5th percentile. The variables are then defined as the sum over the regions and the past five days of extreme events. We add these two variables to capture possible overreaction to bad news, not captured by the other currency and bond variables.

The third group of variables consist of three-month interbank interest rates.[5] Interest rates are on average negatively correlated with stock market returns. High interest rate levels thus are expected to increase the crash probabilities.

In addition to these variables reflecting information from other financial markets, we consider the use of volatility on the stock market itself to explain the occurrence of crashes. To obtain a volatility measure we take the RiskMetrics approach with decay parameter $\lambda = 0.94$, (see JPMorgan and Reuters (1994))[6]. We compute the daily volatility on each of the regional stock market indices described in Section 2.1. An higher volatility increases the probability of extreme negative returns, and therefore we expect a positive relation between volatility and the crash probabilities.

Finally, to test for dynamics in the evolution of crashes, we also include dummy variables of crashes on the previous day, as suggested by the contagion transition matrix. Positive effects of local, regional or global dummies would induce higher probabilities of observing a specific crash, if this type of crash has occurred in the previous period.

Table 3 shows that the correlations between the different groups of variables are low and often insignificant[7]. This indicates that the different groups of variables provide different and complementary information. Within the different groups some correlations are higher, for instance among the interest rate levels. The only correlation which is at a level that may give rise to concerns about possible multicollinearity problems is that between the US and

[5]For some emerging market countries we use the one-month interbank interest rate, as the three month interbank interest was not available

[6]Riskmetrics volatility is computed as $\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1 - \lambda) u_{t-1}^2$, where u_{t-1} is the demeaned stock market return on the previous day.

[7]the 5 percent critical values for significance of the correlation coefficients based on a sample of $N = 2871$, are -0.04 and 0.04.

European equity volatility at 0.82.

The explanatory variables are from JP Morgan for the fixed income related variables, and from Reuters for the currencies. All the data are provided by DataStream. We stress that all explanatory variables are included in the ordered logit model discussed in the next section with a lag of one day, such that our models are predictive in nature.

3 Methodological framework

We propose to model the evolution of local, regional and global crashes within the framework of ordered logit regressions. The type of crash at time t can be seen as the outcome of a discrete choice process, and given that the different crash types have a natural ordering in terms of their severity, the ordered logit model seems appropriate for our modeling purposes

We denote the observed crash on day t as y_t, taking the values 0, 1, 2 and 3 when no crash, or a local, regional or global crash occurs, respectively. The ordered logit model is easiest understood by introducing a latent variable, y_t^* . The observed crash y_t is related with the latent variable y_t^* in the following way:

$$\begin{aligned} y_t = 0 \quad &\text{if} \quad \alpha_0 < y_t^* < \alpha_1 \\ y_t = j \quad &\text{if} \quad \alpha_{j-1} < y_t^* < \alpha_j \quad , \quad j = 2 \dots m-1 \\ y_t = m-1 \quad &\text{if} \quad \alpha_{m-1} < y_t^* < \alpha_m \end{aligned} \tag{1}$$

where in our case $m = 4$. The α_j for $j = 0, \dots, m$ are the m threshold variables, where we define $\alpha_0 = -\infty$ and $\alpha_4 = \infty$. In the ordered logit model the latent variable y_t^* is assumed to be linearly related to a vector of explanatory variables x_t, that is $y_t^* = x_t'\beta + \varepsilon_t$, with ε_t assumed to follow a standardized logistic distribution. In our case, the vector x_t consists of the variables reflecting information from other financial markets, stock market volatility and the previous crash dummies. Using the link between y_t and y_t^* as specified above, the probability of observing a crash of type j at time t is given by:

$$p_{tj} = P[y_t = j] = \Lambda(\alpha_j - x_t'\beta) - \Lambda(\alpha_{j-1} - x_t'\beta), \tag{2}$$

where Λ is a logistic function. The ordered logit model can be estimated straightforwardly using maximum likelihood, where the log likelihood for a sample of t time series observations is given by

$$\ell(\beta, \alpha_1, \alpha_2, \alpha_3) = \sum_{t=1}^{T} \sum_{j=1}^{m} I[y_t = j] \log(p_{tj}) \tag{3}$$

where $I[y_t = j] = 1$ if observation t was of type j, and zero otherwise. Standard errors of the estimates are obtained by taking the square root of the diagonal elements of the inverse of the information matrix. In line with other studies using models with limited dependent variables, we use the pseudo-R^2 of McFadden (1974) as a measure of fit of the model. If the loglikelihood of the unrestricted model is denoted by ℓ_1 and the log-likelihood of a restricted model which only includes the threshold parameters by ℓ_0, then the pseudo-R^2

$$R^2 = 1 - \frac{\ell_1}{\ell_0} \tag{4}$$

We also perform likelihood ratio tests on the individual and joint significance on the explanatory variables in our model. As the marginal effect of variables in a non linear model are not constant, we examine the economic significance with the use of probability response curves. These curves show the probabilities of observing a crash of type j at time t as a function of a specific variable in the vector of regressors x_t.

4 Empirical Results

4.1 Base Model

Table 4 reports the estimation results of the ordered logit model for local, regional and global stock market crashes. Panel A shows the coefficient estimates, the loglikelihood and the pseudo-R2 of the regression. Panel B provides results on likelihood ratio tests for the joint significance of variables within a specific group.

[Insert Table 4 around here]

The first and most important result is that we find evidence for interdependence as well for contagion. The evidence for interdependence follows from the significant relationships between the crash probabilities and the different groups of explanatory variables. Part of the occurrence of local, regional and global stock market crashes can thus be attributed to dependencies with other financial variables that hold in all states of the markets. The individual and joint significance of the previous crash dummies indicates that part of the evolution of crashes cannot be explained by the dependence between stock and other markets that also holds in tranquil periods, suggesting the presence of contagion effects.

Second, as we find significant relations within the different groups of financial market variables, we conclude that interdependence occurs through different channels. The variables within the group of bond returns, interest rate levels and volatilities are all jointly significant at the 5 percent significance level.[8] The positive coefficient estimates of the interest rate level and volatility variables are in line with our expectations. Higher interest rates significantly increase the probabilities of stock market crashes. Increased volatilities also make extreme returns, and thus crashes, more probable. The coefficient estimates for

[8] We also considered two relative interest rates: the day-on-day change between two interest rate levels and the difference of the current interest rate level from its three month moving average. For both these variables there were no significant results. The same holds for extreme changes in interest rates. Results are not shown here to save space, but are available upon request.

the variables in these two groups all show the same sign, indicating that our hypothesis concerning these variables is confirmed for all regions. For the bond portfolio returns we find mixed evidence. For Latin America, Asia and Europe the estimates show the expected sign, but not for the US. The positive sign for the US bond return indicates that US bonds are regarded as a safe haven investment. The currency change variables are both insignificant, indicating no relation between the crash probabilities and currency changes in the emerging market regions.

The contagion coefficients related to the previous day crash dummies are individually and jointly highly significant. This supports our hypothesis that limited crashes have a strong tendency to evolve into more severe crashes. The local crash dummy estimate, for example, indicates that the occurrence of a local crash significantly increases the probability of observing a local, regional or global crash the next day. The results for regional and global crashes are even stronger. Particularly important is the joint significance of the past crash dummies and volatility variables. As discussed before, by definition there are more crashes in times of high volatility. As volatilities are also persistent and highly correlated between regions, regional and even global crashes can be expected to occur more frequently when volatility is high than in periods of low volatility. The patterns we observe in the crash transition matrix in Table 2 could therefore also be the result of the comovement in volatility in global stock markets. The significance of the previous crash variables clearly indicates the presence of dependence in the evolution of crashes that goes beyond this volatility effect, and thus provides evidence for contagion effects.

The coefficient estimate for the extreme currency depreciation indicator is highly significant, while it is not significant for extreme bond returns. As the average currency returns are not significant this implies that a stock market reaction only occurs when the emerging market currencies are adjusted downwards with a substantial magnitude. We also interpret this relation as some form of contagion from the currency market to stock markets: As this relation is only there in crisis periods it cannot qualify as interdependence.

Further, for the estimates of the threshold parameters α_j we use a Wald test to determine whether each α_j is significantly different from its adjacent thresholds α_{j-1} and α_{j+1}. We find that this is indeed the case and therefore the distinction between the four crash types seems appropriate. Finally, the pseudo-R2 is equal to 0.07, which is comparable to other studies predicting crashes. This indicates that the explanatory variables have some predictive power with respect to crashes.

4.2 Probability response curves

Although the coefficient estimates in ordered logit regressions can be interpreted based on their significance and signs, they cannot be used to assess the marginal effects of the variables on the crash probabilities as the model is highly nonlinear. To examine these marginal effects, and thereby the economic importance of our results, we therefore use probability response curves. These curves show the probabilities of the different types of crashes for different levels of a specific explanatory variable z. Varying the value of this variable from its minimum to maximum, we compute the probabilities of observing a type of crash for all T observations of the remaining explanatory variables $x|z$ and obtain the averages.

[Insert Figure 1 around here]

Figure 1 reports the probability response curves for all individual variables. Additionally, it shows a selected number of joint effects for the interest rate and equity volatility variables. The graphs show that the effects of the different variables on the crash probabilities are also economically important. In particular, they clearly indicate the economic significance of both interdependence and contagion.

Starting with interdependence, the probability response curves show that changes in all types of financial variables lead to sizable changes in the crash probabilities. The effects seem larger for the bond market and equity volatility variables than for the currency and interest related variables. The results can be interpreted as follows: suppose for instance that the emerging bond markets have an influence on the stock markets we consider. When relatively large shocks to these bond markets occur, then the influence on the stock markets is also larger than normal, resulting in a large dependence between the stock markets, although the dependence structure has not changed. This is exactly what we observe in the graphs. For the bond market, except for the US, lower bond returns lead to higher probabilities of regional and global crashes. For the lowest return on the Latin American bond market this even result in a 25 percent probability of a global crash. The interest rate variables seem to have less influence on stock markets, although the effects are not negligible. The volatilities show a little stronger effect than the interest rate variables.

Interest rate levels as well as stock market volatilities are persistent and tend to move together across the different regions (see also the correlations within groups in table 1). That is, we would expect the US and European equity volatility to move together, for instance. Because the coefficient estimates for these variables also have the same sign, it may be more realistic to assess their effect on the crash probabilities by taking these cross-correlations into account. We therefore additionally show ”joint” probability response curves for these variables in Figure 1. The joint volatility response curve is computed by varying the volatilities of the four regions between the respective minimums and maximums. For the joint interest response curve we do the same. Here the economic relevance of the interest and volatilities becomes clear. When all volatilities are high the probability of observing no crash is equal to 23 percent, while there is a probability of 44 percent probability that a regional or global crash occurs. The joint interest rate curve also shows substantial probabilities of crashes when the interest rates are simultaneously at a high level, as opposed to the marginal effects of individual interest rates.

Knowing to which extent financial variables contribute to severe crashes is important for policy makers as well as investors, as they both want to be able to anticipate on these crashes before they occur. Although this is not directly related to contagion in the sense of crashes spreading from local to regional and even global, our results strongly suggest that stability of exchange rates and bond markets as well as low levels of interest rates and stock market volatility play an important role to avoid more severe crashes.

The probability response curves for the previous day crash dummies provide evidence for the presence of financial contagion. Given that no crash occurred on the previous day, the probabilities of the different crashes are equal to 70 percent for no crash, 20 percent for a local crash, 7 percent for a regional crash and 3 percent for a global crash. The percentages increase substantially conditional on a crash on the previous day. If a local crash occurred on the previous day these probabilities become 61, 25, 10 and 4 percent. All crashes become more likely. Thus, when one single emerging market crashes, the investment risk for a well diversified global investor already increases. This is even more pronounced when a regional crash occurred. In this case the regional and global crash probabilities almost double to 12 and 5 percent, respectively. The most striking result is obtained when a global crash occurred on the previous day, following which the probability of again observing a global crash triples to 9 percent. Regional and local crash probabilities also increase substantially to 18 and 32 percent respectively.

Finally, the extreme currency and bond market graphs indicate that contagion from other markets to the stock market exists. For the extreme currency depreciations this effect is stronger than for the bond market. The probability of a global crash increases from 3 to 8 percent as the number of extreme depreciation increase from 0 to 6, indicating the influence of emerging currencies on global stock markets.

4.3 Conditional effects

Our base model discussed above provides evidence for both interdependence and contagion, in the sense that the linkages with other financial variables exist in all states of the stock market but cannot completely capture the crash dynamics. In this section we explore whether these contagion effects may be due to differences in the effects of the financial variables on the crash probabilities conditional on the occurrence of a particular type of crash the previous day. If, for example, the relations between the financial variables and the crash probabilities are found to be stronger in times of turmoil, this can be interpreted as excessive dependence in the financial markets. This may be then be considered as an intermediate form of contagion and interdependence.

To test for the presence of this mixed type of interdependence and contagion we proceed as follows: we interact one of the financial variables x_{ti} in the model with the dummy variables indicating that no crash or a local, regional or global crash has occurred on the previous day. Thus we obtain four state dependent variables $x_{ti}D_{tj} \equiv x_{ti|j}$, where D_{tj} is the dummy variable taking the value one if crash type j occurs at time t and zero otherwise. We then estimate a ordered logit model including these four new conditional variables and the other variables in their original form. We repeat this procedure for each of the financial variables included in the model, resulting in sixteen separate ordered logit regressions. The reason for not estimating a model which has coefficients varying with the crash type for all financial variables simultaneously is the large number $(16 \cdot 4+3+3+1 = 71)$ of coefficients in such a model.

If this intermediate form of interdependence and contagion were relevant, we would expect to find clear patterns in the estimates of the state-dependent coefficients. For instance, for the average currency change variables we expect to find the coefficients becoming more negative conditional on more severe crashes, as this implies that the higher the turmoil the stronger the relation between stock market crashes and currency changes.

To formally examine whether these extensions of the model lead to better classifications and predictions of the observed crashes, we perform a likelihood ratio test for the null hypothesis that the coefficients $\beta_{i|j}$, $j = 0, 1, 2, 3$, of the state-dependent variables are equal. This test statistic is χ^2 distributed with three degrees of freedom corresponding to three parameter restrictions, $\beta_{i|0} = \beta_{i|1} = \beta_{i|2} = \beta_{i|3}$.

[Insert Table 5 around here]

Table 5 reports the regression results and the p-value of the test for equal state-dependent parameters for the sixteen estimated regression models. To save space we do not report the estimates of the other coefficients in these models[9]. In general we do not observe clear patterns in the estimates of the state-dependent coefficients. In particular, for almost all variables the conditional estimates fluctuate around the unconditional estimates of the base model in a seemingly random fashion. In addition, except for the bond returns and stock market volatility in Asia, the likelihood ratio tests do not reject the null of equality of the conditional coefficients, confirming that the relation between crashes and the financial variables are not dependent on past crashes. Thus, the effects of the financial variables on the crash probabilities are constant over time and do not depend on the degree of turmoil in the financial markets. Thus we find no evidence of this intermediate type of contagion and interdependence.

However, there are some interesting but also counterintuitive results in table 5. First, while the average currency depreciation in the base model was not significant, this relation becomes significant when a global crash has occurred on the previous day. . For the average currency depreciation in Asia we observe the same pattern, but here the coefficients are not significant. It seems that normal, contrary to extreme, currency depreciations increases the crash probabilities only if a global crash occurred on the previous day. Thus, in times of high turmoil investors also seem to take into account normal depreciations.

In the conditional regressions for the interest rates some past crash dummies become insignificant, while the conditioned interest rate variables remain insignificant. To a lesser extent this also occurs in the volatility regressions. These are more statistical than economical results: As the interest rates and volatilities are strictly positive, the dummy variables and their respective conditional variables attain the value zero or a value larger than zero simultaneously. This results in very high correlations, around 0.95, between the past crash dummies and the conditioned variables. Because in these cases the likelihood of the regressions does not improve significantly compared to the base model, we do not go into this problem further. To summarize, the effects of the explanatory variables do not significantly

[9]The estimates of the other coefficients hardly change compared to the base model.

differ conditional on the occurrence of crashes on the previous day.

4.4 Sensitivity tests

In this section we perform several sensitivity tests to assess the robustness of the results of the base model. First, as discussed before, given that we define the occurrence of a crash for an individual market using the raw daily returns, our results may be influenced by the effects of time-varying volatility. We examine the relevance of these effects by estimating the ordered logit regression with the dependent variable constructed from crashes defined using standardized returns instead.

[Insert Table 6 around here]

From the estimation outcomes in table 6 we see that, except for the volatility coefficients, the results do not change substantially. Hence we conclude that the results are not driven by volatility effects. Our second sensitivity test also relates to the definition of crashes in individual markets. We now use the 2.5th lower percentile instead of the 5th percentile, leading to less crashes for each individual market and, consequently, also less local, regional and global crashes.

[Insert Table 7 around here]

Table 7 shows that also in this case the results are quite insensitive to this alternative crash definition. Our final two sensitivity test are based on variations on the crash classification as explained in Section 2.2, to examine whether the results are robust to changes in the definitions of local, regional and global crashes. In the first alternative classification we do not identify a global crash in case a regional crash occurs in Asia on day t + 1 following a regional crash in the US or Europe on day t. Furthermore, we also abandon the occurrence of regional emerging market crashes when 3 or more individual emerging market in a particular region crash. In the second alternative classification a global crash occurs when three or four regions crash instead of two (from which one has to be developed).

[Insert Table 8 around here]

[Insert Table 9 around here]

The estimation results using these alternative classifications hardly differ from the original one, see tables 8 and 9. In sum, the sensitivity tests demonstrate that our results are not driven by arbitrary choices for the crash definitions and crash classifications, and are not due to the effects of time-varying volatility.

5 Comparison with binomial model for global crashes

In this section we asses the economic relevance of our classification of crashes into local, regional and global crashes. We investigate whether taking into account local and regional crashes adds value in the prediction of global crashes, compared to a model for global crashes only.

5.1 In-sample comparison

For that purpose, we compare our ordered logit regression model with a binomial logit model for global crashes. That is, using the definition that a crash occurs in a given market if the return falls below the 5th percentile of the empirical return distribution, we classify each day as either "no global crash" or "global crash" using the classification rules described in Section 2.2. The resulting binomial series is linked to the same financial variables as used in the ordered logit model plus a dummy variable indicating whether a global crash occurred on the previous day. We then analyse the ability of the ordered logit model and the binary logit model to predict global crashes. The difference between these two models obviously provides direct evidence on the importance of taking into account local and regional crashes for the purpose of forecasting global crashes.

[Insert Table 10 around here]

The estimation results for the binomial model are shown in table 10. Theoretically we could have a bias here if global crashes have different relations with the explanatory variables, than local or regional crashes do. However, in section 4.3 we found that this was not the case. Comparing these results with the estimates for the ordered logit model in table 4 reveals several advantages of using an ordered instead of a binomial approach. First, the coefficients from the ordered logit model are estimated with more precision than those of the binomial model. The standard errors of the estimates for the ordered logit model are on average two times smaller than those of the binomial model. For instance, the standard errors of the two extreme event coefficient estimates are 0.05 and 0.03 for the ordered model against 0.10 and 0.06 for the binomial model. Second, the ordered model shows more consistency concerning the signs of the estimates across different regions. For the interest rate and the equity volatility variables, we find that the estimated coefficients have the same sign for all four regions in the ordered model, while in the binomial model different signs occur within these groups of variables.

Jointly modelling local and regional crashes thus increases the precision and the interpretability of the estimates for the explanatory variables. The ordered logit model also uses the local and regional crashes in the parameter estimation, which increases the total amount of observed crashes. In this way we avoid one of the weaknesses of binomial crash models, namely that crashes occur too infrequent to estimate relations with high precision. On the other hand, from the results in section 4 our model is still capable of distinguishing global crashes as different from less severe crashes.

[Insert Figure 2 around here]

Figure 2 shows the estimated probabilities of observing a global crash obtained from the binomial model and the ordered logit model, as well as the observed global crashes. We see that a model that simultaneously considers local, regional and global crashes performs better in detecting global crashes than a model for global crashes only. Particularly periods in which more global crashes occur are better detected by our ordered logit model. The effects of the 1997 Asian crisis, the 1998 Russian debt crisis are much clearer indicated by the ordered model than by the binomial model. Further, at the time the internet bubble burst (around March, 2000) the ordered model clearly shows increased global crash probabilities, while the binomial model hardly indicates the presence of any turmoil in financial markets. During the turbulent period between 2001 and 2003 the binomial model produces somewhat higher global crash probabilities than the ordered model. However, in those periods the ordered model's crash probabilities are also relatively high. After 2003 less global crashes occurred, but for the crashes that did occur, the ordered model is more successful in detecting these crashes than the binomial model. This holds in particular for the period between December 2003 and December 2005.

5.2 Out-of-sample

Next we examine the out of sample potential of the ordered model, compared to the binomial model, in forecasting global crashes for the period January 2002 till July 2007. Both models are estimated over the period July 1996 till December 2001. Based on the conventional wisdom that too many insignificant parameters often lead to bad forecasting performance, we firstly use a variable selection criterion to reduce the number of variables included and obtain more parsimonious forecasting models. For both the ordered and binomial models we start with the full model and then remove the least significant variable from the regression. Then the model is reestimated without the eliminated variable and from the new regression again the least significant variable is removed. This process is continued until the coefficients for all remaining variables are significant at the 10% level[10].

[Insert Table 11 around here]

Table 11 reports the results from this general-to-specific model selection procedure for both the ordered and binomial models. The results show that for both models the number of regressors is drastically reduced. The obtained ordered model contains more variables than the binomial model. Except for the previous crash dummies, which are all significant in both models, the ordered model contains six financial variables, while in the binomial model only four variables are included. This could be expected as the ordered model's estimates are more precise, as we concluded in the previous section.

To asses the forecast performance of both models in detecting global crashes, we compute forecasts of the probability of observing a global crash from both models for the period January 2002 - July 2007, showed in figure 3. The ordered model is clearly more successful than the binomial model in forecasting global crashes. The period May 2002 till June 2003 includes many global crashes. At the beginning of this period our ordered model already correctly warns for the occurrence of global crashes, while the binomial model's crash probabilities hardly increase. Then, during the period between July and October 2002, for both models the global crash probabilities strongly increase, with maxima above 0.4. In this period both models are able to identify the global crashes that occurred. After October 2002 the turmoil in the global markets continues,as indicated by the number of global crashes that occur. In this aftermath, the ordered model again forecasts the global crashes much better than the binomial model. Finally, after 2003 some small turmoil periods occurred and in all

[10]Stricter significance levels would result in models with too few variables to make a fair comparison between the ordered and binary models.

these cases our ordered model, contrary to the binomial model, indicates this correctly.

[Insert Figure 3 around here]

6 Conclusions

In this paper we have investigated what the determinants of different types of stock market crashes are, and whether these crashes propagate from local to regional or global crashes. We start by identifying crashes as local, regional or global and looked at the transmission mechanism of these crashes. We find that more severe crashes are mostly preceded by less severe crashes. Our approach differs from other studies by explicitly defining different types of crashes, and modeling their occurrence as a domino effect.

In explaining the occurrence and evolution of crashes we find evidence on interdependence between the stock markets and other asset markets. More precisely, information from the currency, stock and bond market are determinants of the probabilities to end up in a local, regional or global crash. For investors or policy makers our findings indicate that careful attention should be paid to the stability of these fundamentals.

Additionally, we infer the presence of contagion effects. We showed that the probabilities of different types of crashes are individually as well as jointly significantly related to crashes on the previous day. We also find evidence for contagion from the currency market to the stock market, while not between the bond and stock markets.

We conclude that the occurrence and evolution of crashes is determined by interdependence as well as contagion. Finally we conclude that our ordered model detects and forecasts turmoil better than a standard binomial model for global crashes.

We show that modelling crashes as evolving like a domino effect is important for regulators as well as investors. By using our approach causes of crashes are better understood and crashes can be predicted more accurate. This implies, for instance, that investors can make a better allocation of their investments when global crashes are more likely. We also show, with our ordered model, that using local and regional crashes adds to the precision of estimation compared to a binomial model for global crashes. This approach is not limited to global stock markets only, but can also be applied on different markets within a country or on different sectors within a specific market.

Further research on this topic should include implementing this model on other markets. One could try to explain contagion of returns in the bond markets. Using this model on currency returns would also be interesting, although one has to find a solution for the problem that currency returns are bilateral. A last suggestion for further research would be to test the forecasting properties of our ordered logit model more extensively. Especially interesting is the performance of the model during the 1997 Asian flu, the 1998 Russian virus, the 2001 burst of the internet bubble, and the very recent sub-prime crisis

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Table 1: Descriptive statistics of daily log returns

	ARG	BRA	CHI	COL	MEX	VEN	IND	KOR	MAL	PHI	TWN	THA	LAT	ASI	USA	EUR
Mean	0.07	0.14	0.08	0.10	0.16	0.01	0.12	0.08	−0.02	−0.04	0.00	−0.07	0.14	0.03	0.07	0.09
Volatility	0.35	0.35	0.17	0.23	0.26	0.40	0.25	0.42	0.30	0.26	0.28	0.37	0.23	0.18	0.18	0.17
Min	−0.34	−0.15	−0.06	−0.14	−0.15	−0.46	−0.12	−0.22	−0.24	−0.10	−0.11	−0.17	−0.12	−0.07	−0.07	−0.06
Max	0.15	0.14	0.07	0.16	0.14	0.21	0.09	0.27	0.23	0.20	0.08	0.17	0.12	0.07	0.06	0.05
Skewness	−1.90	−0.35	−0.27	−0.22	−0.16	−2.25	−0.39	0.24	0.75	0.91	0.01	0.36	−0.61	−0.23	−0.11	−0.25
Kurtosis	33.61	8.45	6.46	19.08	9.82	56.19	7.17	14.29	34.84	19.47	5.51	10.23	10.22	5.75	6.43	5.39
5% quantile	−0.032	−0.035	−0.016	−0.021	−0.025	−0.035	−0.025	−0.038	−0.025	−0.025	−0.028	−0.034	−0.023	−0.018	−0.018	−0.018
Argentina	1	0.37	0.27	0.17	0.38	0.14	0.10	0.12	0.09	0.09	0.12	0.11	0.44	0.14	0.23	0.22
Brasil	0.51	1	0.38	0.21	0.46	0.22	0.13	0.17	0.13	0.13	0.15	0.12	0.76	0.21	0.25	0.28
Chile	0.37	0.51	1	0.21	0.37	0.20	0.13	0.15	0.15	0.13	0.16	0.16	0.46	0.23	0.22	0.24
Colombia	0.16	0.19	0.23	1	0.22	0.18	0.12	0.10	0.14	0.12	0.10	0.10	0.24	0.15	0.05	0.13
Mexico	0.45	0.59	0.48	0.19	1	0.19	0.15	0.16	0.15	0.14	0.13	0.16	0.66	0.18	0.35	0.29
Venezuela	0.12	0.17	0.14	0.07	0.18	1	0.09	0.08	0.11	0.15	0.08	0.10	0.24	0.13	0.11	0.14
India	0.08	0.14	0.14	0.10	0.15	0.04	1	0.17	0.14	0.17	0.15	0.20	0.16	0.29	0.10	0.15
Korea	0.10	0.18	0.18	0.08	0.20	0.06	0.22	1	0.20	0.19	0.28	0.29	0.19	0.50	0.13	0.15
Malaysia	0.08	0.08	0.14	0.06	0.14	0.07	0.14	0.24	1	0.33	0.16	0.33	0.15	0.33	0.06	0.13
Philippines	0.08	0.12	0.16	0.11	0.13	0.07	0.16	0.23	0.29	1	0.12	0.32	0.15	0.28	0.08	0.16
Taiwan	0.07	0.12	0.18	0.08	0.11	0.04	0.19	0.30	0.20	0.19	1	0.18	0.17	0.47	0.11	0.14
Thailand	0.11	0.15	0.22	0.09	0.16	0.09	0.18	0.31	0.37	0.35	0.24	1	0.18	0.33	0.06	0.11
Latin America	0.59	0.91	0.63	0.26	0.84	0.22	0.17	0.22	0.13	0.15	0.15	0.19	1	0.24	0.33	0.33
Asia	0.13	0.22	0.28	0.15	0.23	0.09	0.44	0.67	0.50	0.40	0.75	0.50	0.27	1	0.11	0.23
US	0.36	0.43	0.36	0.10	0.55	0.07	0.06	0.09	0.01	0.05	0.06	0.05	0.55	0.09	1	0.32
Europe	0.30	0.39	0.42	0.18	0.47	0.12	0.18	0.20	0.14	0.14	0.16	0.19	0.49	0.27	0.43	1

The upper part of the table shows summary statistics including the annualized mean, annualized volatility, minimum, maximum, skewness, kurtosis and 5% lower quantile of the log returns on the stock indices. The lower part of the table reports a correlation matrix contains two types of correlations; the linear correlation between the stock index returns in the lower triange, and the conditional probabilities of observing a crash in a given (row) country conditional on the occurrence of a crash in another (column) country in the upper triange. The sample is from July 1996 to July 2007. We compute statistics for the countries indices as well for the regional indices. Country indices are denoted by their country code, whereas the continent indices are denoted by LAT, ASI, USA and EUR respectively.

Table 2: Crash probabilities transition matrices

A: Normal returns

	0	1	2	3
0	0.72	0.19	0.07	0.03
1	0.57	0.27	0.10	0.06
2	0.45	0.27	0.17	0.11
3	0.27	0.23	0.29	0.20

B: Standardized returns

	0	1	2	3
0	0.71	0.19	0.08	0.02
1	0.56	0.29	0.10	0.05
2	0.51	0.24	0.16	0.09
3	0.23	0.24	0.30	0.22

C: Bootstrap returns

	0	1	2	3
0	0.68	0.20	0.08	0.04
1	0.61	0.24	0.10	0.05
2	0.55	0.25	0.13	0.07
3	0.44	0.22	0.21	0.13

D: Bootstrap standardized returns

	0	1	2	3
0	0.68	0.20	0.09	0.03
1	0.60	0.25	0.10	0.05
2	0.58	0.23	0.13	0.06
3	0.41	0.23	0.23	0.13

The daily transition probabilities for the crash regimes. The numbers 0, 1, 2 and 3 correspond to no crashes, local, regional and global crashes respectively. Panel A is based on identified crashes of the sample returns. Panel B shows the same results for the standardized returns. Most right columns in both panels report the total number of the different crashes observed. Panel C and D shows the transition matrices computed from 10000 return series generated by the stationary bootstrap, for respectively the sample and the standardized returns. For the bootstrap the continue probability of 0.5 is used. Crashes are defined as the 5% lower quantile of the return distribution. The sample is from July 1996 to July 2007.

Table 3: Correlation matrix of explanatory variables

FX change LA	1															
FX change Asia	0.07	1														
Bond LA	−0.24	−0.11	1													
Bond Asia	−0.13	−0.18	0.52	1												
Bond US	0.00	0.05	0.07	0.39	1											
Bond Europe	0.00	−0.07	0.00	0.15	0.31	1										
Interest LA	0.08	0.03	−0.01	0.02	0.01	0.01	1									
Interest Asia	0.01	0.09	0.00	−0.02	0.02	0.00	0.27	1								
Interest US	0.02	0.05	−0.02	0.01	0.04	0.00	0.20	0.36	1							
Interest Europe	−0.02	0.05	0.00	−0.01	0.01	−0.04	0.02	0.61	0.60	1						
Volatility LA	0.01	0.05	0.04	0.07	0.01	−0.01	0.12	0.13	0.19	0.20	1					
Volatility Asia	0.02	0.05	0.00	0.00	0.02	0.02	0.23	0.26	0.33	0.09	0.61	1				
Volatility US	0.03	0.03	0.02	0.04	0.02	0.01	0.23	0.08	0.38	−0.03	0.53	0.54	1			
Volatility Europe	0.01	0.02	0.00	0.04	0.02	0.01	0.17	−0.07	0.28	−0.16	0.58	0.58	0.82	1		
Extreme FX	0.04	0.07	−0.02	−0.06	0.02	0.02	0.09	0.27	0.05	0.02	0.29	0.31	0.11	0.14	1	
Extreme bond	0.04	0.00	−0.04	−0.08	0.00	0.00	0.14	−0.03	0.01	−0.16	0.27	0.23	0.34	0.33	0.20	1

This table reports the correlations of the explanatory variables. Correlations are computed over the sample July 1996 - July 2007.

Table 4: Regression results general model

A: Regression estimates

	Coefficient	St. error	t-statistic	p-value
Currency change LA	-4.08	8.07	-0.51	0.61
Currency change Asia	6.55	7.68	0.85	0.39
Bond returns LA	-24.48	6.40	-3.82	0.00
Bond returns Asia	-13.81	15.44	-0.89	0.37
Bond returns US	35.40	15.92	2.22	0.03
Bond Returns Europe	-10.33	6.80	-1.52	0.13
Interest level Latin America	0.00	0.00	0.44	0.66
Interest level Asia	0.04	0.02	2.40	0.02
Interest level US	0.05	0.08	0.61	0.54
Interest level Europe	0.04	0.04	0.89	0.37
Volatility LA	0.52	0.72	0.72	0.47
Volatility Asia	1.88	0.85	2.20	0.03
Volatility US	1.42	1.07	1.33	0.18
Volatility Europe	2.44	1.24	1.97	0.05
Extreme FX	0.15	0.05	2.90	0.00
Extreme Bond	0.03	0.03	0.85	0.39
Local	0.40	0.10	4.06	0.00
Regional	0.62	0.14	4.30	0.00
Global	1.21	0.21	5.83	0.00
$\alpha_{(0\to1)}$	2.53	0.19		
$\alpha_{(1\to2)}$	3.90	0.19		
$\alpha_{(2\to3)}$	5.19	0.20		
Log likelihood	-2613.26			
R^2	0.07			

B: Jointly significance tests on groups of variables

	Log likelihood	D.F.	p-value
Currencies	-2613.61	2	0.70
Bonds	-2628.64	4	0.00
Interest	-2623.23	4	0.00
Volatilities	-2640.72	4	0.00
Extreme events	-2618.41	2	0.01
Past crashes	-2637.23	3	0.00

Ordered logistic regression results with as dependent variables the crash categories and independent variables as shown in the table. The variables local crash, regional crash and global are dummy variables attaining the value one if these types of crashes occurred on the previous day. The sample is from July 1996 to July 2007. Likelihood ratio tests on the joint significance of different groups of variables are also reported in the table.

Figure 1: Probability response curves

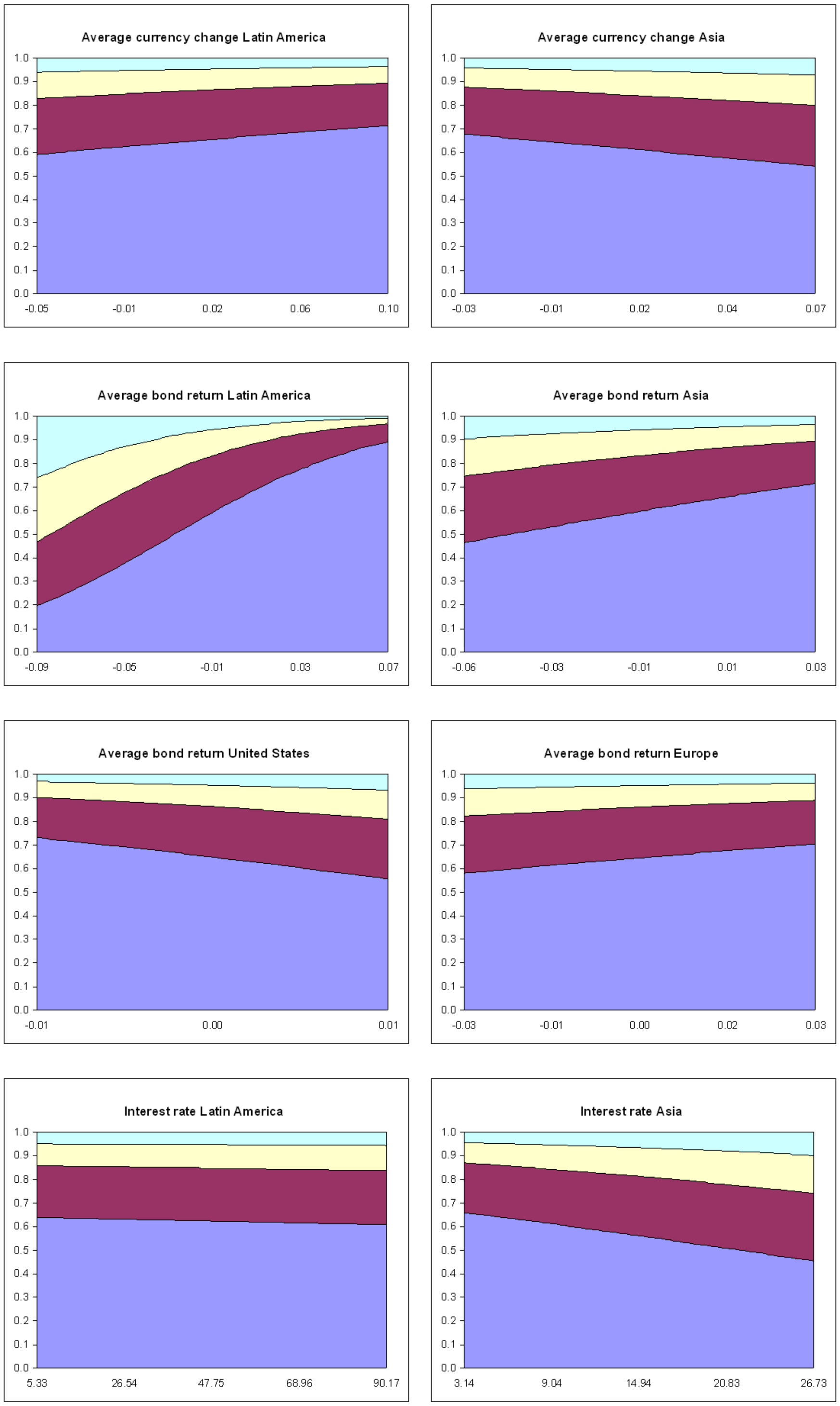


Figure 1 continued

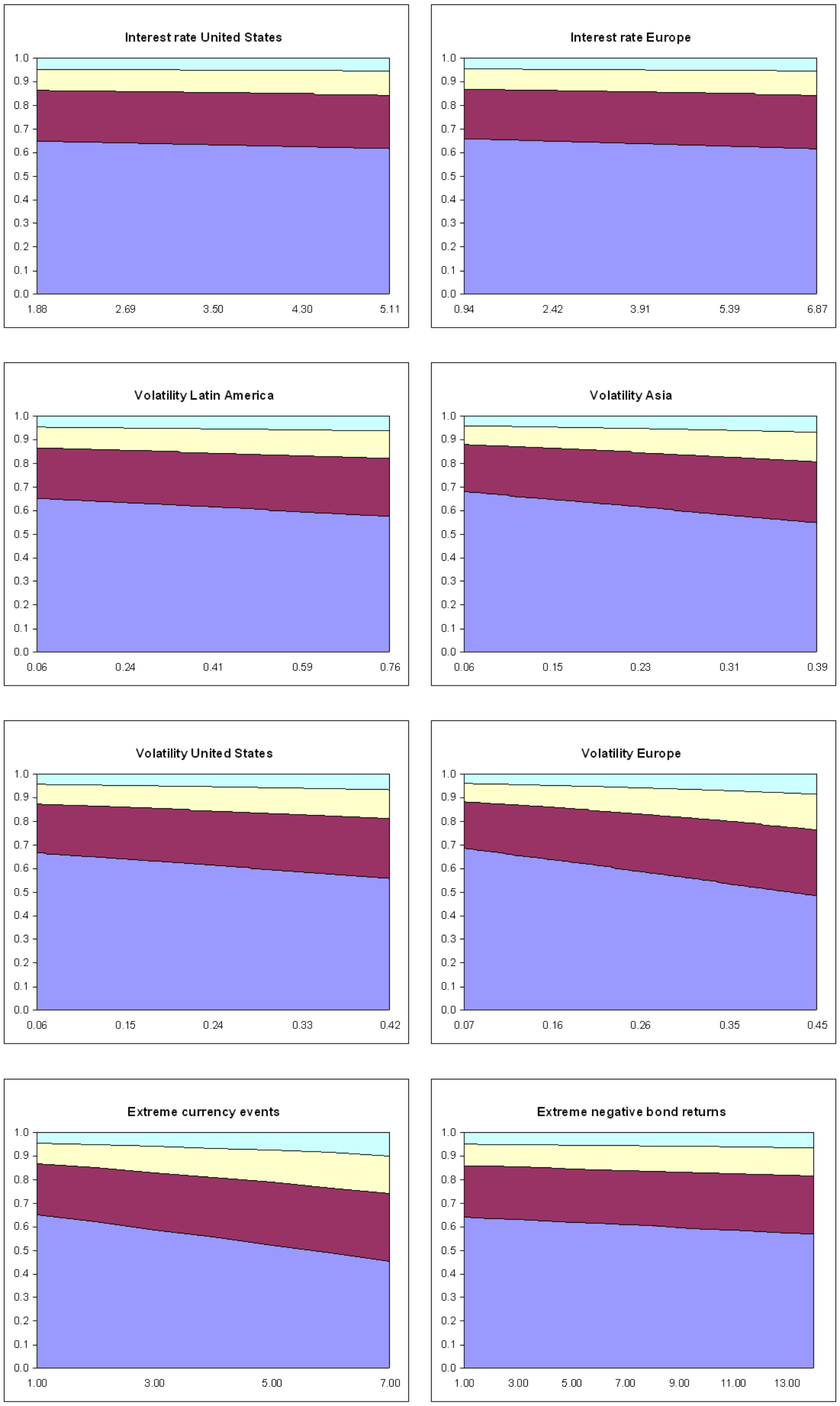
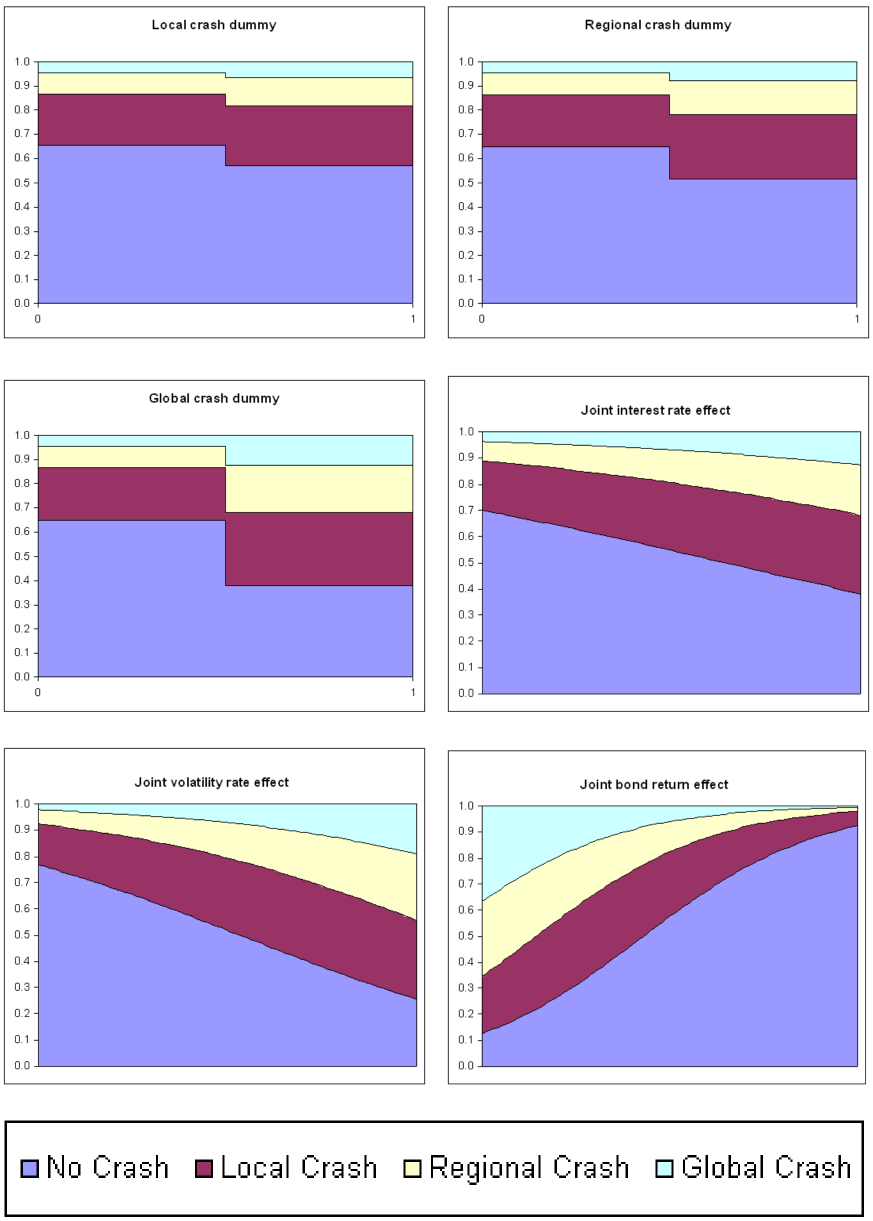


Figure 1 continued



The figures show the probability response curves. The areas are the probabilities of observing a specific type of crash. The probabilities are computed by varying one specific variable x from its minimum to maximum. Then for each point j on the probability response curve, we compute the probabilities of observing a type of crash for all t observations of the explanatory variables Z. Thus, the probabilities in the figures are the averages of $t = 2871$ probabilities. The joint response graphs for interest and volatility are computed by varying all four variables between their respective minimum and maximum.

Table 5: Regression results with crash dependent effects

Regression estimates	Coefficient	St. error	t-statistic	p-value
Currency change LA (0)	0.08	14.78	0.01	1.00
Currency change LA (1)	5.06	11.70	0.43	0.67
Currency change LA (2)	−6.48	28.25	−0.23	0.82
Currency change LA (3)	−62.20	27.00	−2.30	0.02
Local	0.38	0.10	3.72	0.00
Regional	0.60	0.15	4.05	0.00
Global	1.37	0.20	6.77	0.00
Log likelihood	−2610.48			
$\chi(3)$	0.13			
Currency change Asia (0)	8.21	14.14	0.58	0.56
Currency change Asia (1)	26.37	20.22	1.30	0.19
Currency change Asia (2)	−5.93	19.13	−0.31	0.76
Currency change Asia (3)	−44.27	46.35	−0.96	0.34
Local	0.38	0.10	3.74	0.00
Regional	0.64	0.14	4.46	0.00
Global	1.28	0.20	6.44	0.00
Log likelihood	−2611.92			
$\chi(3)$	0.44			
Bond returns LA (0)	−38.56	10.11	−3.81	0.00
Bond returns LA (1)	−34.50	11.06	−3.12	0.00
Bond returns LA (2)	−20.37	11.74	−1.73	0.08
Bond returns LA (3)	1.79	10.61	0.17	0.87
Local	0.37	0.10	3.66	0.00
Regional	0.58	0.14	4.10	0.00
Global	1.37	0.20	6.90	0.00
Log likelihood	−2608.59			
R^2	0.07			
Bond returns Asia (0)	−54.95	23.96	−2.29	0.02
Bond returns Asia (1)	−26.92	21.50	−1.25	0.21
Bond returns Asia (2)	−7.49	29.42	−0.25	0.80
Bond returns Asia (3)	41.90	23.49	1.78	0.07
Local	0.37	0.10	3.61	0.00
Regional	0.57	0.14	4.03	0.00
Global	1.23	0.19	6.48	0.00
Log likelihood	−2608.41			
$\chi(3)$	0.02			
Bond returns US (0)	28.90	19.93	1.45	0.15
Bond returns US (1)	53.31	29.58	1.80	0.07
Bond returns US (2)	32.28	38.47	0.84	0.40
Bond returns US (3)	33.10	57.41	0.58	0.56
Local	0.40	0.10	4.04	0.00
Regional	0.62	0.14	4.43	0.00
Global	1.22	0.21	5.91	0.00
Log likelihood	−2613.00			
$\chi(3)$	0.91			
Bond returns Europe (0)	−20.64	9.43	−2.19	0.03
Bond returns Europe (1)	16.12	13.06	1.23	0.22
Bond returns Europe (2)	−30.28	16.38	−1.85	0.06
Bond returns Europe (3)	4.00	19.12	0.21	0.83
Local	0.40	0.10	3.98	0.00
Regional	0.63	0.14	4.55	0.00
Global	1.19	0.19	6.23	0.00
Log likelihood	−2609.50			
$\chi(3)$	0.06			

Table 5 continued

Regression estimates	Coefficient	St. error	t-statistic	p-value
Interest level LA (0)	0.00	0.01	0.55	0.58
Interest level LA (1)	0.01	0.01	0.97	0.33
Interest level LA (2)	−0.01	0.01	−1.07	0.28
Interest level LA (3)	−0.03	0.03	−1.05	0.30
Local	0.33	0.16	2.07	0.04
Regional	0.85	0.24	3.57	0.00
Global	1.70	0.47	3.58	0.00
Log likelihood	−2611.53			
$\chi(3)$	0.32			
Interest level Asia (0)	0.03	0.02	1.23	0.22
Interest level Asia (1)	0.05	0.02	2.24	0.03
Interest level Asia (2)	0.06	0.04	1.53	0.13
Interest level Asia (3)	−0.05	0.07	−0.78	0.44
Local	0.23	0.22	1.07	0.29
Regional	0.42	0.30	1.40	0.16
Global	1.69	0.44	3.81	0.00
Log likelihood	−2611.748			
$\chi(3)$	0.39			
Interest level US (0)	0.05	0.09	0.53	0.60
Interest level US (1)	0.13	0.12	1.03	0.30
Interest level US (2)	−0.14	0.17	−0.79	0.43
Interest level US (3)	0.13	0.23	0.55	0.58
Local	0.14	0.42	0.35	0.73
Regional	1.23	0.60	2.06	0.04
Global	0.93	0.84	1.11	0.27
Log likelihood	−2612.28			
$\chi(3)$	0.58			
Interest level Europe (0)	0.03	0.04	0.77	0.44
Interest level Europe (1)	0.04	0.06	0.72	0.47
Interest level Europe (2)	0.07	0.07	0.91	0.36
Interest level Europe (3)	0.00	0.09	0.00	1.00
Local	0.37	0.27	1.39	0.16
Regional	0.47	0.34	1.38	0.17
Global	1.35	0.42	3.21	0.00
Log likelihood	−2613.04			
$\chi(3)$	0.93			
Volatility LA (0)	1.04	0.85	1.22	0.22
Volatility LA (1)	0.32	1.02	0.31	0.75
Volatility LA (2)	1.26	1.17	1.08	0.28
Volatility LA (3)	−1.62	1.45	−1.11	0.27
Local	0.55	0.26	2.16	0.03
Regional	0.53	0.34	1.55	0.12
Global	1.93	0.46	4.15	0.00
Log likelihood	−2611.58			
$\chi(3)$	0.34			
Volatility Asia (0)	2.74	1.05	2.60	0.01
Volatility Asia (1)	1.86	1.32	1.41	0.16
Volatility Asia (2)	1.26	1.82	0.69	0.49
Volatility Asia (3)	−6.99	3.10	−2.26	0.02
Local	0.54	0.28	1.94	0.05
Regional	0.88	0.42	2.11	0.04
Global	3.25	0.69	4.69	0.00
Log likelihood	−2608.58			
$\chi(3)$	0.02			

Table 5 continued

Regression estimates	Coefficient	St. error	t-statistic	p-value
Volatility US (0)	2.42	1.21	1.99	0.05
Volatility US (1)	0.84	1.54	0.55	0.58
Volatility US (2)	0.10	1.80	0.06	0.95
Volatility US (3)	−0.23	2.29	−0.10	0.92
Local	0.66	0.27	2.44	0.01
Regional	1.05	0.37	2.82	0.00
Global	1.75	0.54	3.24	0.00
Log likelihood	−2611.83			
$\chi(3)$	0.41			
Volatility Europe (0)	2.97	1.30	2.29	0.02
Volatility Europe (1)	3.38	1.70	1.99	0.05
Volatility Europe (2)	0.57	1.93	0.29	0.77
Volatility Europe (3)	0.62	2.34	0.26	0.79
Local	0.34	0.27	1.23	0.22
Regional	1.06	0.37	2.86	0.00
Global	1.71	0.54	3.15	0.00
Log likelihood	−2611.88			
$\chi(3)$	0.43			
Extreme FX (0)	0.13	0.08	1.70	0.09
Extreme FX (1)	0.19	0.09	2.21	0.03
Extreme FX (2)	0.17	0.10	1.72	0.09
Extreme FX (3)	0.09	0.14	0.67	0.50
Local	0.37	0.12	3.10	0.00
Regional	0.59	0.16	3.58	0.00
Global	1.26	0.23	5.51	0.00
Log likelihood	−2613.00			
$\chi(3)$	0.91			
Extreme bond (0)	0.08	0.04	1.81	0.07
Extreme bond (1)	0.02	0.05	0.46	0.64
Extreme bond (2)	0.00	0.07	−0.03	0.97
Extreme bond (3)	−0.15	0.09	−1.79	0.07
Local	0.44	0.12	3.71	0.00
Regional	0.69	0.17	3.94	0.00
Global	1.53	0.23	6.59	0.00
Log likelihood	−2610.18			
$\chi^2(3)$	0.10			

Results of ordered logistic regressions with as dependent variables the crash categories and independent variables the same variables as in the base model, but in each regression one original variable is conditioned on previous crashes. Thus, in each regression we multiply the variable under consideration with the past crash dummies (including a no crash dummy), which leaves 4 variables. For convenience we only report the crash dummies and the crash conditioned variables. The $\chi^2(3)$-test tests whether conditioning a variable significantly improves the model. The sample is from July 1996 to July 2007.

Table 6: Regression results with standardized returns

Regression estimates	Coefficient	St. error	t-statistic	p-value
Currency change LA	-4.70	8.51	-0.55	0.58
Currency change Asia	-3.02	10.37	-0.29	0.77
Bond returns LA	-15.22	6.10	-2.49	0.01
Bond returns Asia	-22.02	15.33	-1.44	0.15
Bond returns US	34.46	15.58	2.21	0.03
Bond Returns Europe	-8.12	6.63	-1.22	0.22
Interest level Latin America	0.00	0.00	0.26	0.80
Interest level Asia	0.06	0.02	3.25	0.00
Interest level US	0.01	0.08	0.15	0.88
Interest level Europe	0.01	0.04	0.33	0.74
Volatility LA	0.16	0.69	0.24	0.81
Volatility Asia	-0.93	0.89	-1.05	0.29
Volatility US	-0.19	1.08	-0.17	0.86
Volatility Europe	1.68	1.20	1.41	0.16
Extreme FX	0.16	0.05	3.12	0.00
Extreme Bond	0.02	0.03	0.82	0.41
Local	0.54	0.10	5.56	0.00
Regional	0.71	0.13	5.40	0.00
Global	1.77	0.19	9.16	0.00
$\alpha_{(0\to1)}$	1.50	0.18		
$\alpha_{(1\to2)}$	2.82	0.19		
$\alpha_{(2\to3)}$	4.21	0.21		
Log likelihood	-2677.351			
R^2	0.05			

Ordered logistic regression results with as dependent variables the crash categories based on standardized returns and independent variables as shown in the table. The variables local crash, regional crash and global are dummy variables attaining the value one if these types of crashes occurred on the previous day. The sample is from July 1996 to July 2007.

Table 7: Regression results with crashes based on 2.5% lower quantile

Regression estimates	Coefficient	St. error	t-statistic	p-value
Currency change LA	0.28	9.88	0.03	0.98
Currency change Asia	17.48	11.68	1.50	0.13
Bond returns LA	−14.22	6.59	−2.16	0.03
Bond returns Asia	−21.44	15.99	−1.34	0.18
Bond returns US	51.37	18.19	2.82	0.00
Bond Returns Europe	−1.92	7.91	−0.24	0.81
Interest level Latin America	0.01	0.00	1.17	0.24
Interest level Asia	0.03	0.02	1.56	0.12
Interest level US	0.13	0.10	1.35	0.18
Interest level Europe	0.03	0.05	0.58	0.56
Volatility LA	0.73	0.75	0.98	0.33
Volatility Asia	1.75	1.02	1.71	0.09
Volatility US	0.65	1.24	0.53	0.60
Volatility Europe	3.75	1.33	2.82	0.00
Extreme FX	0.26	0.06	4.58	0.00
Extreme Bond	0.04	0.03	1.06	0.29
Local	0.42	0.13	3.19	0.00
Regional	0.33	0.19	1.75	0.08
Global	1.29	0.29	4.43	0.00
$\alpha_{(0\to1)}$	3.62	0.24		
$\alpha_{(1\to2)}$	4.88	0.25		
$\alpha_{(2\to3)}$	6.44	0.27		
Log likelihood	−1868.91			
R^2	0.09			

Ordered logistic regression results with as dependent variables the crash categories based on crashes defined as the 2.5% lower quantile of the empirical distribution for the indices and independent variables as shown in the table. The variables local crash, regional crash and global are dummy variables attaining the value one if these types of crashes occurred on the previous day. The sample is from July 1996 to July 2007.

Table 8: Regression results with different crash classification 1

Regression estimates	Coefficient	St. error	t-statistic	p-value
Currency change LA	-2.27	8.55	-0.27	0.79
Currency change Asia	1.85	9.65	0.19	0.85
Bond returns LA	-28.89	6.07	-4.76	0.00
Bond returns Asia	-16.62	14.69	-1.13	0.26
Bond returns US	40.97	15.55	2.64	0.01
Bond Returns Europe	-7.04	6.59	-1.07	0.29
Interest level Latin America	0.00	0.00	0.78	0.43
Interest level Asia	0.04	0.02	2.18	0.03
Interest level US	0.07	0.08	0.92	0.36
Interest level Europe	0.03	0.04	0.68	0.50
Volatility LA	0.95	0.67	1.41	0.16
Volatility Asia	1.19	0.87	1.37	0.17
Volatility US	1.48	1.05	1.41	0.16
Volatility Europe	2.54	1.16	2.20	0.03
Extreme FX	0.15	0.05	3.04	0.00
Extreme Bond	0.03	0.03	1.12	0.26
Local	0.40	0.10	4.04	0.00
Regional	0.74	0.13	5.49	0.00
Global	0.85	0.19	4.43	0.00
$\alpha_{(0\rightarrow1)}$	2.49	0.19		
$\alpha_{(1\rightarrow2)}$	3.90	0.20		
$\alpha_{(2\rightarrow3)}$	5.30	0.21		
Log likelihood	-2664.57			
R^2	0.07			

Ordered logistic regression results with as dependent variables the crash categories based on a different classification. Regional crashes on day $t+1$ in Asia do not induce a global crash anymore if on day t US or Europe encountered a crash. Further, regional emerging market crashes occurrence when 3 or more individual emerging market crashes is also abandoned. The independent variables are as shown in the table. The variables local crash, regional crash and global are dummy variables attaining the value one if these types of crashes occurred on the previous day. The sample is from July 1996 to July 2007.

Table 9: Regression results with different crash classification 2

Regression estimates	Coefficient	St. error	t-statistic	p-value
Currency change LA	-5.13	8.67	-0.59	0.55
Currency change Asia	8.38	9.83	0.85	0.39
Bond returns LA	-25.40	6.09	-4.17	0.00
Bond returns Asia	-15.81	14.94	-1.06	0.29
Bond returns US	40.87	15.61	2.62	0.01
Bond Returns Europe	-8.38	6.62	-1.27	0.21
Interest level Latin America	0.00	0.00	0.94	0.35
Interest level Asia	0.04	0.02	2.35	0.02
Interest level US	0.05	0.08	0.64	0.52
Interest level Europe	0.03	0.04	0.87	0.38
Volatility LA	0.68	0.68	1.01	0.31
Volatility Asia	1.59	0.87	1.83	0.07
Volatility US	1.50	1.05	1.43	0.15
Volatility Europe	2.39	1.16	2.06	0.04
Extreme FX	0.15	0.05	2.97	0.00
Extreme Bond	0.04	0.03	1.34	0.18
Local	0.40	0.10	4.04	0.00
Regional	0.70	0.12	5.66	0.00
Global	1.64	0.30	5.42	0.00
$\alpha_{(0\rightarrow1)}$	2.49	0.19		
$\alpha_{(1\rightarrow2)}$	3.85	0.20		
$\alpha_{(2\rightarrow3)}$	6.38	0.24		
Log likelihood	-2555.44			
R^2	0.08			

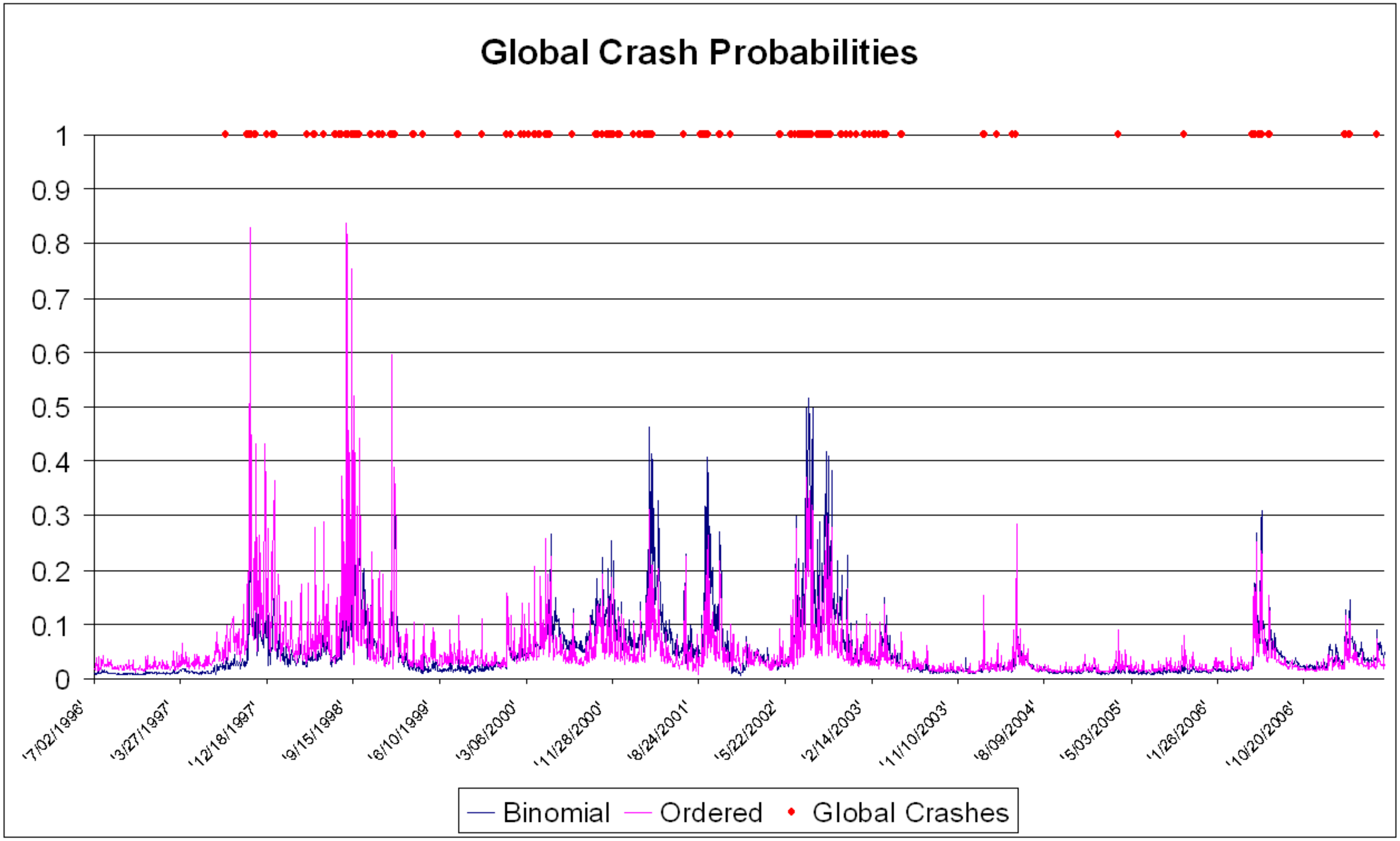
Ordered logistic regression results with as dependent variables the crash categories based on a different classification. Global crashes now only occur when 3 or more regions crash simultaneously. The independent variables are as shown in the table. The variables local crash, regional crash and global are dummy variables attaining the value one if these types of crashes occurred on the previous day. The sample is from July 1996 to July 2007.

Table 10: Binomial Regression

Regression estimates	Coefficient	St. error	t-statistic	p-value
Currency change LA	9.96	18.58	0.54	0.59
Currency change Asia	−20.21	23.31	−0.87	0.39
Bond returns LA	−19.35	10.52	−1.84	0.07
Bond returns Asia	12.89	26.49	0.49	0.63
Bond returns US	35.43	32.68	1.08	0.28
Bond Returns Europe	−6.56	13.92	−0.47	0.64
Interest level Latin America	−0.02	0.01	−1.15	0.25
Interest level Asia	−0.02	0.05	−0.34	0.73
Interest level US	0.60	0.18	3.29	0.00
Interest level Europe	−0.06	0.09	−0.62	0.54
Volatility LA	1.20	1.28	0.94	0.35
Volatility Asia	2.02	2.02	1.00	0.32
Volatility US	−1.30	2.22	−0.59	0.56
Volatility Europe	7.03	2.21	3.19	0.00
Extreme FX	0.21	0.10	2.15	0.03
Extreme Bond	0.03	0.06	0.44	0.66
Global	0.74	0.27	2.73	0.01
constant	−6.40	0.51	−12.42	0.00
Log likelihood	−491.83			
R^2	0.13			

Binomial logistic regression results with as dependent variables a dummy variable attaining the value one if a global crash occurred and zero otherwise. The independent variables are as shown in the table. The variable Global is the dependent variable lagged one period. The sample is from July 1996 to July 2007.

Figure 2: Probabilities of a global crash in the binomial and ordered logit model.



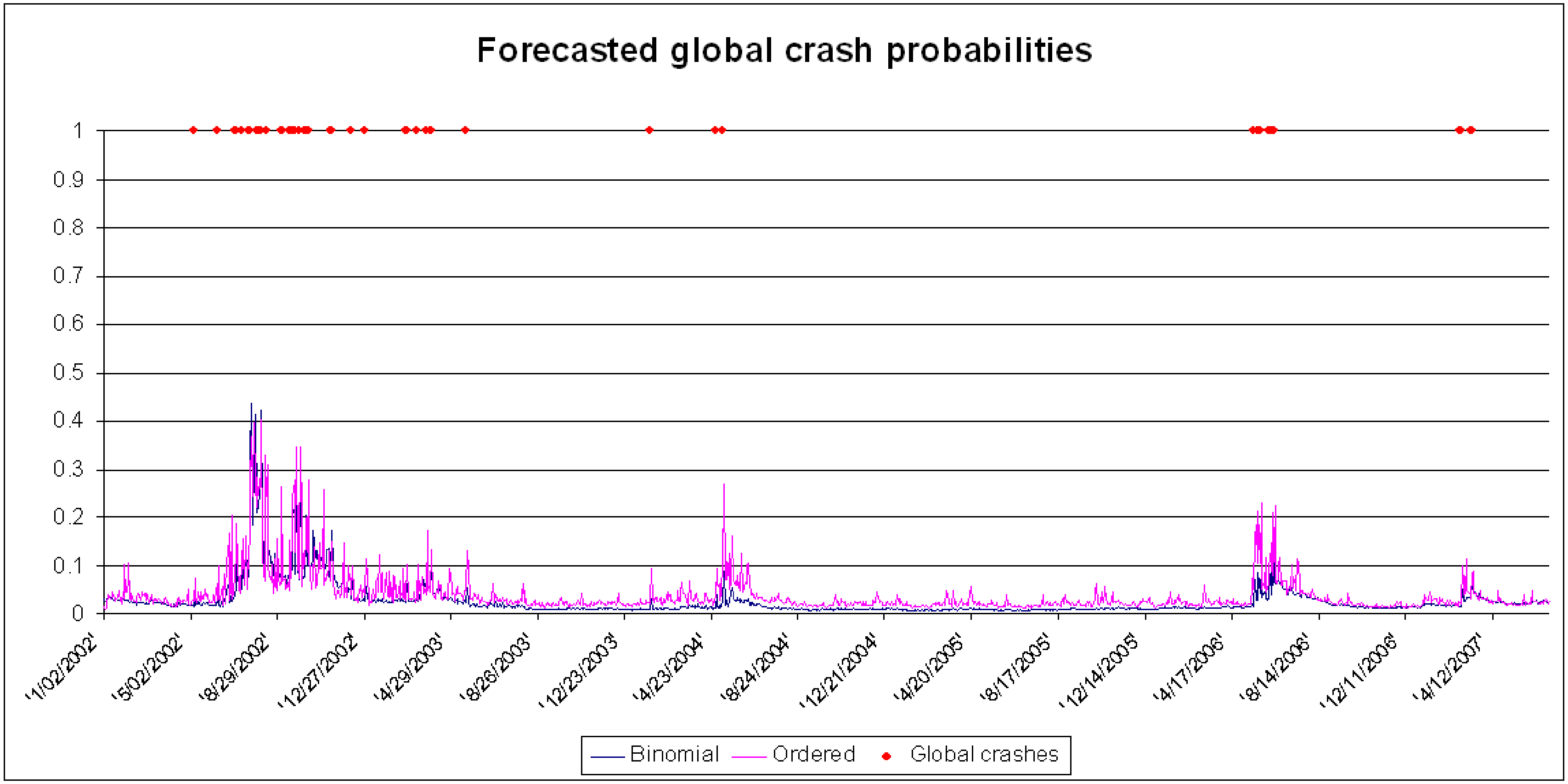
The graph shows the estimated probabilities of observing a global crash for the ordered as well as the binomial crash model. Additionally, the observed occurrences of the global crashes are also shown in the the graph. The sample covers the period July 1996 to July 2007.

Table 11: Ordered and binomial regression estimates obtained from the general-to-specific model selection.

Regression estimates ordered model				
	Coefficient	St. error	t-statistic	p-value
Bond returns LA	-23.98	5.91	-4.06	0.00
Bond returns US	43.93	19.70	2.23	0.03
Interest level Latin America	-0.01	0.01	-1.87	0.06
Volatility Asia	4.23	0.99	4.28	0.00
Volatility Europe	4.15	1.08	3.84	0.00
Extreme FX	0.16	0.06	2.55	0.01
Local	0.27	0.14	1.91	0.06
Regional	0.68	0.18	3.76	0.00
Global	0.92	0.28	3.27	0.00
$\alpha_{(0\to1)}$	2.19	0.22		
$\alpha_{(1\to2)}$	3.46	0.23		
$\alpha_{(2\to3)}$	4.92	0.26		
Regression estimates binomial model				
Bond returns LA	-25.04	9.93	-2.52	0.01
Interest level US	0.39	0.21	1.88	0.06
Volatility Asia	3.74	2.20	1.70	0.09
Volatility Europe	7.17	2.11	3.41	0.00
Global	0.72	0.43	1.67	0.09
constant	-6.76	0.92	-7.36	0.00

This table reports the regression results for the binomial and ordered logistic regressions, after the removal of insignificant parameter estimated. An iterative procedure is used where in each iteration the least significant variable is removed. Continuing this procedure until all variables are significant at the ten % level results in our two final models. The independent variables are as shown in the table. The variable Global is the dependent variable lagged one period. The sample is from July 1996 to December 2001.

Figure 3: Probabilities of a global crash in the binomial and ordered logit model.



The graph shows the forecasted out of sample probabilities of observing a global crash for the ordered as well as the binomial crash model. Additionally, the observed occurrences of the global crashes are also shown in the the graph. The sample covers the period January 2002 to July 2007.