THE NORMAL, THE FAT-TAILED, AND THE CONTAGIOUS: MODELING CHANGES IN EMERGING MARKET BOND SPREADS*

By
Paul R. Masson
Shubha Chakravarty
Tim Gulden

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Brookings Institution
1775 Massachusetts Avenue
Washington, DC 20036

Abstract

We examine the statistical properties of daily changes in emerging market bond spreads over US treasuries, and simulate an agent-based model to attempt to replicate those properties. The actual data indicate that changes in spreads: 1) are definitely not normally distributed, exhibiting much fatter tails; 2) are serially correlated, suggesting deviation from market efficiency; and 3) exhibit excessive co-movement, suggesting contagion. A simple model of interacting traders produces alternating booms and crashes, as in reality, but is not capable of producing fat-tailed distributions or contagion. We focus on an extended model with market makers whose bid/asked spreads widen with increased volatility and the size of their inventory. This model highlights the role of liquidity (or lack of it) in explaining large rate movements and contagion.

* This paper is a progress report of work on modeling financial markets using heterogeneous agent models. Though it has benefited from comments received at a conference on "International Financial Contagion" in Cambridge, UK (May 30-31, 2003) and a seminar at Brookings, the paper is still preliminary and results should not be taken as definitive. We are grateful to Heather Milkiewicz for research assistance, to Adrian de la Garza for providing the emerging market spread data, and to Rob Axtell, Martin Evans, and Carol Graham for comments and encouragement. We would also like to acknowledge our debt to Elizabeth Littlefield and Michael Mauboussin for sharing their knowledge of how the market works. Jon Parker provided help with ASCAPE programming.

I. Introduction

Despite extensive study of capital flows to developing countries, it is safe to assert that there remain a number of issues where there is not yet a clear consensus among economists. Three important issues stand out. First, though there are many models of balance of payments crises, there is little agreement in particular cases on the dominant cause. In particular, are crises the results of poor economic fundamentals or of a self-fulfilling crisis triggered by a rush for the exits by investors?[1] Second, are crises "contagious", that is, does a crisis in one country trigger one in another? Or using an alternative definition of contagion, do asset prices show more co-movement in periods when there is a crisis than in tranquil times? And third, if there is contagion, what are its causes: macroeconomic fundamentals, or instead financial contagion operating through shifts in investor attitudes or holdings across a range of countries triggered by a crisis in one country? While there are many models that embody channels by which financial contagion might operate, there has been little systematic testing among alternatives.

While we do not pretend to resolve these outstanding questions in this paper, we approach them in ways that have not received much attention to date in the literature. We first study the distribution of changes in interest rates on emerging market debt (or rather, spreads relative to US treasury securities), in order to identify stylized facts that successful models should be able to replicate. The **first** stylized fact is that the distribution is very much not normally distributed, but rather exhibits fat tails indicating that extreme events are much more likely than for the normal. This is a stylized fact that is significant, because it may allow one to distinguish among models of financial crises and contagion. A fat-tailed distribution may also imply quite different optimal portfolio behavior on the part of risk-averse investors, since its variance may be infinite, making the standard mean-variance portfolio model inappropriate.

A **second** stylized fact is that changes in spreads are serially correlated, indicating a departure from market efficiency. This applies to almost all emerging market bonds, and typically the first-order serial correlation coefficient is positive, and significant.

We also examine co-movements of spreads across countries, comparing them to the co-movements of economic fundamentals. This leads to a **third** stylized fact, namely that there is clear evidence of contagion, defined as excessive co-movement: changes in spreads (and hence asset returns) are considerably more correlated across countries than are macro-economic fundamentals.

We then proceed to formulate a model of investment in emerging markets with the goal of replicating these stylized facts. This model is an extension of the single-country model in Arifovic and Masson (2000). It combines a simple balance of payments crisis model with hypotheses concerning the formation of expectations by investors. In particular, we assume that investors form and update their expectations on the basis of the success (or otherwise) of their investment strategies. If the latter are successful (in the sense of giving a better return than some

[1] See for instance, the debate between Obstfeld on the one hand and Krugman and Garber, on the other, about the causes of the Mexican crisis of 1994-95 (see Krugman, 1996). Krugman, however, changed his position following the Asian crisis, now admitting that there were self-fulfilling elements.

randomly chosen comparator), then the investor retains the expectation and strategy; otherwise, the investor adopts the comparator's strategy. In addition, investors at times experiment by randomly choosing a new rule. Thus, the investors in the model do not have very good information about economic fundamentals (the evolution of the trade balance and foreign exchange reserves), but adapt their strategies on the basis of past results. This has the potential of producing bandwagon effects, that is, serial correlation of changes of asset holdings and spreads. In addition, to a greater or lesser extent imitation effects exist, which may result in herding behavior. Finally, both economic fundamentals and investor behavior contribute to triggering crises, which occur when a country's reserves go to zero, forcing it to default: this can occur as a result of a bad shock to the trade balance or because a sufficient number of investors withdraw their capital (a "sudden stop" in Calvo's words). The model, when implemented for a single emerging market bond, has some success in producing an alternation of booms and crashes in emerging markets, similar to actual data (see Arifovic and Masson, 2000).

The model also succeeds in producing serial correlation of changes in spreads, as is present in the actual data. It is clear that the "bounded rationality" of investors means that past success in investing reinforces strategies in a way that produces serially-correlated changes in returns. To the extent that imitation occurs also, there will be herding, i.e. reinforcement of strategies **across** investors.

However, after we explored more deeply the simulation properties of the model, it became clear that it has difficulty in reproducing two of the stylized facts described above, namely fat-tailed distributions and excessive co-movement in interest rate spreads for pairs of emerging market countries. We present simulations of various parameterizations; while the first two moments of the distribution can easily be reproduced, the fourth moment is much smaller than in the data, indicating that the simulated distribution has much thinner tails than the actual one. Indeed, simulated changes are even more thin-tailed than the normal. Furthermore, correlations in spreads are small, even when the fundamentals are assumed to be highly correlated. Instead, the model would predict small negative correlations, as portfolio shifts out of one asset, would, other things equal, produce inflows into the others. It is clear that herding behavior, which is consistent with positive serial correlation in returns on individual country bonds, need not produce contagion, which requires some cross-country linkage based on economic fundamentals, correlated expectations, shifts in attitudes to risk, or portfolio rebalancing affecting the whole asset class.

We proceed to discuss other mechanisms that could plausibly operate to replicate the fat tails and contagion. In particular, we focus on one of them, the changing degree of liquidity in the market, as a possible explanation of extreme movements. Market practitioners point to the fact that at times of crisis, the market "dries up", as everyone attempts to get out at the same time. This suggests that it would be useful to attempt to model the role of market makers, who typically deal in a number of different securities, and who may need to react to losses in one market by increasing their bid-asked spreads for the other bonds with which they deal. Moreover, their attitude to risk may be affected by a crisis in one country which causes increased volatility. The microstructure of trading in emerging market bonds seems to be a promising area for future research, and one that has so far received little attention, unlike the foreign exchange market (see, e.g., Evans and Lyons, 2002).

II. Empirical Regularities in Emerging Market Bond Spreads

The time series properties of prices and returns have been studied for a number of financial assets, including equities, government bonds, and foreign exchange (see Bouchaud and Potters, 2000, for a survey). This does not seem to have been done in any great detail for the international bonds (in particular, for Brady bonds, collateralized by US treasury securities that were issued in the 1980s to securitize bank debt incurred by developing countries, and Eurobonds, which have been issued more recently by some of the larger emerging market countries). However, studying the distribution of returns on emerging market debt, or more specifically of spreads between the interest rate on their debt and that on US treasuries, is an important way to understand the riskiness of investing in these securities.[2] For instance, normally distributed returns have a relatively small likelihood of major changes, and exhibit finite variance. In contrast, financial crises (and bouts of euphoria) may produce very large changes and hence an investor would be subject to large risks; indeed, for some distributions that are relevant for financial markets, the variance may be infinite (and variance would not therefore be an appropriate measure of risk). Also relevant are the autocorrelation properties of spreads, because they may indicate unexploited arbitrage opportunities, and the correlation of spreads across different emerging economies. The latter may be an indication of contagion, which is often considered to characterize these markets (for a recent assessment and discussion of its causes, see papers in Claessens and Forbes, 2001).

The study of empirical regularities described here uses a set of spreads on emerging market debt compiled by JP Morgan using daily data from 31 December 1993 to 19 July 2002. This data base comprises virtually the universe of all developing countries issuing Brady bonds and Eurobonds. The list of countries is the following (those included in JP Morgan's so-called EMBI+ index, see JP Morgan, 1995): Argentina, Brazil, Bulgaria, Colombia, Ecuador, Korea, Mexico, Morocco, Panama, Peru, Philippines, Poland, Qatar, Russia, South Africa, Turkey, Ukraine, and Venezuela. However, not all countries had bonds outstanding during the whole period 1993-2002; what observations existed were pooled to study the distribution of spreads (see Appendix Table 1 for data availability).

The Distribution of Changes in Spreads

Of particular interest in studying the distribution of changes in spreads (or of returns) are the stable Pareto-Levy distributions, of which the normal is one, because they may result from the application of a central-limit theorem. In particular, if changes in the log of prices or in spreads over a short interval are drawn from an arbitrary distribution but are independent, then changes in prices or spreads over longer intervals are simply the sum of independent random variables, and their distribution will be governed by a central limit theorem as the length of the interval goes to infinity. If the variance of short-run changes is finite, the resulting distribution will be the normal distribution. If not finite, other distributions in the Pareto-Levy class will result. Moreover, distributions of this class are self similar, in that if the short-run changes are given by a particular Pareto-Levy distribution, then so will be their sums over any finite interval

[2] We describe the distribution of spreads, rather than returns, because this is the way the data are usually reported.

(with no need to appeal to a central limit theorem). However, it is possible that for the finite intervals of interest, changes in spreads may not be well described by distributions of this class. In other financial data, typically the tails are fatter than for the normal, and yet variances are finite (Bouchaud and Potters, 2000). Of interest therefore is the shape of those tails, and the speed with which they converge to zero.

Figure 1 plots the distribution resulting from pooling the available observations on the daily first differences in spreads, in basis points, for the countries mentioned above, over at most December 31, 1993-July 19, 2002. This gives 27,842 data points, exhibiting extreme daily changes of -10.70 and + 11.54 percent--both of which relate to Russian bonds, occurring on November 20th and August 27th of 1998, respectively. The observations were grouped into bins of width 100 basis points, and plotted against their corresponding frequencies shown in the figure. It can be seen that the distribution of the spreads is roughly symmetrical. Sample statistics are reported in Table 1. The mean of the distribution is less than a basis point, and its standard deviation is 48.3 basis points.

The corresponding normal distribution with the same mean and variance plotted in Figure 1 has a log-log scale and thus takes the shape of a parabola. It can be seen that the sample is very non-normal, with much fatter tails. A Jarque-Bera test for normality[3] (a X^2 with 2 degrees of freedom) massively rejects the null hypothesis.

Given the interest in the behavior of the tails, we also plot the cumulative distribution based on the left and right tails. Here, the left tail is reversed in sign to make it parallel the right one. The way recommended by Bouchaud and Potters (pp. 58-59) to estimate the cumulative distribution is not to use bins but rather to keep each of the points, noting that the probability of getting a value greater than X where k is the rank of X from largest to smallest (out of N) is

$$P(x>X)=k/(N+1)$$

Using this method, we can generate a cumulative distribution using all 27,842 points, and we plot it in log-log space in Figure 2 (excluding the zero observations). Focusing just on the tails with $|X|>250$ gives the plot in Figure 3.

A log-log regression gives a characterization of the exponential decay of the tails of the distribution. The slope coefficient gives the rate of decay. In particular, we regress

$$Log\ Y = a + b \log X$$

where Y is the probability of observations greater than X (or less than X, if X is negative).

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[3] The test statistic is $\frac{N}{6}[(\kappa-3)^2/4+s^2]$, where N is the number of observations, κ is kurtosis, and s is skewness.

The points in Figure 3 are closely clustered around a straight line, which is described by the following least-squares regression (standard errors in parentheses):

$$\log Y = 3.795 - 2.619 \log X$$
$$(0.088) \quad (0.034) \qquad \text{No. of obs}=167, \qquad \overline{R^2} = 0.97$$

The slope coefficient falls outside the usual range of –3 to –5, found for other asset markets (Bouchaud and Potters, p. 62), its smaller magnitude implying slower decay in the tails and greater kurtosis than in the typical financial market. Given its small standard error, the slope is significantly less than 3 in magnitude. This suggests that emerging market debt involves considerable risk from large movements in spreads, more so than developed country equities, foreign exchange, or bonds.

Comparing Different Countries' Distributions

To date, we have assumed that the different countries' changes in spreads were drawn from the same distribution. This can be tested. Figure 4 plots the distributions, for Argentina, Brazil, Bulgaria, Mexico, Morocco, Nigeria, Poland, and Venezuela, over a common sample period (November 1, 1994-July 19, 2002), a total of 1929 observations for each country.[4] Table 2 provides summary statistics for each of the distributions.

Some differences across countries are readily apparent from the figure and table. The variability, as measured by the standard deviation or the spread of the distribution, is largest for Argentina and Nigeria, and smallest for Poland; the remaining ones are roughly comparable, in a middle range. For all countries, kurtosis is very large, and all reject the hypothesis of normality, at a p-value less than .001.

Table 3 compares pairs of distributions, reporting the Kolmogorov-Smirnov test of the hypothesis that the distributions are the same (it is based on the maximum difference between the two cumulative distribution functions). In almost all cases, equality of distributions can be rejected at the 5 percent level. Exceptions are Argentina and Venezuela, Brazil and Bulgaria, Bulgaria and Morocco, Bulgaria and Venezuela, and Brazil and Morocco.

Autocorrelation

One reason that central limit theorems may not apply (and that distributions of returns over long time periods do not converge to stable Pareto-Levy distributions) is that returns on short intervals may be autocorrelated. Table 4 reports for each of the countries the first order autocorrelation coefficient and also the Llung-Box Q-statistic to test the cumulative correlogram for lags 1 to 5 against the null of no serial correlation (those significant at the 5 percent level or below are starred).

[4] Other countries had data available for shorter periods. See Appendix Table 1 for data availability.

It is interesting that most of the countries have a positive first order autocorrelation coefficient, which is generally significant, while only two countries, Nigeria and South Africa, have significantly negative first order autocorrelation. The typical positive first autorrelation coefficient is followed by both positive and negative ones (not reported). For most countries, the correlogram for lags 1 to 5 is significantly different from zero. The same is true for the composite index, given as the last row of the table. For whatever reason, then, the changes in spreads do not seem to be independent from day to day. This could be due to market inefficiencies that allow arbitrage opportunities to exist, or could reflect lack of trading so that spreads quoted do not correspond to actual transactions.

Comovement of Countries' Spreads

Another important question is the extent that countries' spreads move together. Co-movement was particularly notable at the time of the Mexican tequila crisis in 1994-95, and the crisis in East Asia in 1997-98 that was triggered by the thai baht devaluation. Spreads around the time this occurred are plotted in Figures 5 and 6, respectively. Major exchange rate crises also occurred in Russia in August 1998 and in Brazil in February 1999, leading to large devaluations of those countries currencies and increases in their sovereign spreads. These events are plotted in Figures 7 and 8, along with those of similar countries. The Figures suggest that by the time the Brazilian crisis occurred, the degree of co-movement was considerably less. This can be compared with the even more recent 2001 crisis in Argentina, displayed in Figure 9, which also does not show obvious evidence of co-movement among spreads.

Co-movement could be due to a number of factors, some reflecting macroeconomic fundamentals, and some not (Masson, 1999a, 1999b). Among the former are trade linkages and exposure to the same environment for interest rates coming from the industrial countries or the state of the world economy. Among the latter would be psychological factors leading to a common re-evaluation of the prospects for all (or a subset) of emerging markets (despite no objective similarities), or self-fulfilling jumps between equilibria. Correlations of spreads in excess of those dictated by fundamentals might suggest the existence of self-fulfilling shifts in investors' sentiment with respect to emerging markets. Thus, the lower co-movements at the time of the Brazil and Argentine crises in 1999 and 2001, respectively, may be evidence that contagion effects due purely to correlated shifts in expectations have become less important, as investors differentiate between the situations that countries face.

Using data for daily changes in spreads over a period of 6 months centered on the time of the crisis, for the 5 episodes cited above one sees that correlations were highest for the East Asian and Brazilian crises. There is a tendency, as pointed out by Glick and Rose (1999) for co-movement to be strongest within a region in the earlier crises (Mexico and East Asia), but there is little evidence for regional contagion in the Brazil and Argentine crises. Whether the positive correlations are due to economic fundamentals or pure contagion is impossible to judge without further examination of the economic linkages among countries. In the model we describe below, the economic fundamental is the country's trade balance, but the correlations among the trade balances of the countries for which we have spreads data are not consistently positive (for instance, among Latin American countries), there are also a number of negative ones (not surprisingly, given that trade balances need to add up to zero across the world). Thus, the hypothesis that they are completely justified by movements in macroeconomic fundamentals is not supported—at least for the fundamentals implied by this particular model.

A useful summary measure of the degree of co-movement is the percent of the total variation accounted for by the first principal component. This measure is presented in Table 5 for the changes in interest rate spreads in each of the 5 episodes, for the 8 countries for which correlations were available in time periods. This table indicates that this measure of crisis co-movement was highest in the East Asian crisis of 1997-98. The more recent Brazilian crisis of 1998-99 and the Argentine crisis of 2001 produced a lower explained variance for the first principal component, suggesting a decline in contagion.

The use of correlations may be problematic, however, for two reasons. **First**, distributions with fat tails may also have infinite variance, which would make the correlations undefined (this is true, for instance, of Pareto-Levy distributions with characteristic exponent in excess of two). Other measures of co-movement are possible in this case, based on *copulas* (see Bouyé et al., 2000). However, the calculation of copulas also involves distribution assumptions. **Second**, comparing correlations across time periods for which the **variances** are different may suggest that correlations have changed when this is not the case. This problem for instance arises when testing for contagion defined as an increase in correlation during crisis (i.e. high variance) periods (Forbes and Rigobon, 2002). Above, we have compared **crisis** comovement in different episodes, so we are not subject to that criticism, but it could be nevertheless that variances also differ across crisis periods.

As an alternative to correlations, therefore, we present non-parametric measures of "co-exceedances", that is, the simultaneous occurrence of extreme events (see, e.g., Longin and Solnik, 2001; Malevergne and Sornette, 2002). In particular, for a pair of countries, we count the number of days for which the change in spreads were simultaneously in the left tail or right tail (i.e. x% tail or 1-x% tail, respectively) of each country's cumulative distribution. Since the supports of the distributions are different, obviously the thresholds for the tails are also different. We are interested in two issues. **First**, we would like to see whether co-exceedances are significantly greater than would be the case if the distributions were independent. **Second**, we want to compare the two tails to see whether co-exceedances are more likely in the right tail (increases in spreads, which are usually associated with crises and contagion) than in the left tail (declines in spreads).

Suppose that we calculate the proportions in the left and right tails as follows:

$$L_{ij}^{\alpha} / N_j^{\alpha} = \Pr(x_j < G^{-1}(\alpha) \mid x_i < F^{-1}(\alpha))$$
$$R_{ij}^{\alpha} / N_j^{\alpha} = \Pr(x_j > G^{-1}(1-\alpha) \mid x_i > F^{-1}(1-\alpha))$$

where *L* and *R* are the co-exceedances in both countries' tails and *N* the number of observations in each tail, and F and G are the cumulative distribution functions of x_i and x_j. It can first be noted that if the distributions are independent, then the expected value of $L_{ij}^{\alpha} / N_j^{\alpha}$ or $R_{ij}^{\alpha} / N_j^{\alpha}$ is precisely *α*.

So we propose the statistic

$$k_{ij}^{\alpha} = (L_{ij}^{\alpha} / N_j^{\alpha} - \alpha)$$

for the left tail and

$$k_{ij}^{\alpha} = (R_{ij}^{\alpha} / N_j^{\alpha} - \alpha)$$

for the right tail. Given the sample size, it is a simple matter to calculate the likelihood of this value occurring under the null hypothesis. This provides the appropriate significance level for a test that the two distributions are independent.

Our measure is related to the "tail dependence coefficient" λ, which is equal to the limiting value of our statistic as α goes to zero:

$$\lambda = \lim_{\alpha \to 0} k_{ij}^{\alpha}$$

However, as Malevergne and Sornette (2002) point out, tail dependence is very difficult to estimate without knowledge of the underlying distributions, since numbers of observations go to zero as one goes further out in the tails. Moreover, tail dependence coefficients have the unfortunate property that they may be zero even when the underlying variables are not truly independent. For our purposes, it is sufficient to describe the finite sample by tabulating the co-exceedances for small, but non-zero values of α, while not attempting to calculate asymptotic tail behavior.

Table 7 gives the number of co-exceedances in both tails, for values of $\alpha = .05, .025,$ and .01. Several interesting things emerge from the results. First, co-exceedances in both tails are each significantly greater than under the null hypothesis of independence. Given 1929 observations, there are respectively 96, 48, and 19 observations in each tail, for the three values of α chosen. Looking at right 2.5 percent tail for Argentina and Brazil, for instance, gives

$$k_{Arg,Bra}^{.025} = (\frac{14}{48} - .025) = .2666$$

The likelihood of getting 14 of the 48 observations in the tail is considerably less than 1 percent. The following are the 5 percent and 1 percent critical values, for the tails defined in the above three ways.

	$k^{.05}$ (96 obs)	$k^{.025}$ (49 obs)	$k^{.01}$ (19 obs)
5 percent	.0433 (9 obs)	.0579 (4 obs)	.0937 (2 obs)
1 percent	.0640 (10 obs)	.0787 (5 obs)	.1455 (3 obs)

Thus, in Table 6, all the coexceedances are significantly greater at the one percent level than would be expected if the two distributions were independent. It is also striking that co-exceedances seem to occur as often in the left tail (declines in spreads) as in the right tail. Thus, the interpretation of contagion as more important in crisis periods is not borne out by these data.

What could explain this result, which seems to go against received wisdom?[5] First, we are using higher frequency data than many other studies, so that what are normally considered "crisis periods" include in our sample large **declines** in spreads, as well as increases (this is confirmed when dates of these tail events are scrutinized; see Appendix Table 2 for the observations in the one-percent tails). Second, some of the downward movements (as well as upward ones) may not be the result of "contagion" at all (i.e. the effect of one emerging market on another) but rather due to some common, global event (termed "monsoonal effects" in Masson (1999b). They could, for instance, reflect an easing of U.S. monetary policy or new information concerning G-7 policies with respect to bailing out third world debtors. Finally, it is interesting that the largest co-exceedances in the 2.5 percent tails, for instance, are between Mexico and Venezuela (26 in right tail), Bulgaria and Poland (22 in right tail), Mexico and Poland (22 in right tail), and Morocco and Venezuela (22 in left tail)—not particularly regionally based, in opposition to the consensus reflected in Glick and Rose (1999). Nevertheless, a wider set of countries (including especially those in Asia) would be necessary to analyze this issue properly.

III. A Model of Emerging Market Crises

We proceed to describe a canonical balance of payments crisis model, and in the next section examine to what extent it can replicate the actual data. The model links the ability of a country to service its debts to the existence of non-negative reserves: once reserves hit zero, a default is triggered, leading to losses by investors. The evolution of the balance of payments, i.e. the sum of the trade balance, interest payments, and net capital flows, is the key to the ability of a country to repay its borrowings, and the interest on them.

Investors choose from a very simple menu of investments: in the one emerging market case (to be generalized to several below), they form expectations of the probability of a default, and choose to invest either in the safe (US treasury) security, paying a known return r^*, or the emerging market bond, paying r_t. The amount that they invest this period in the emerging market bond, summed across all investors, is denoted D_t.

A default occurs at t if reserves would otherwise go negative. The basic balance of payments equation in the model is:

$$R_t = R_{t-1} + D_t - (1 + r_{t-1})D_{t-1} + T_t \qquad (1)$$

where R_t are reserves, and T_t is the trade balance[6]. The trade balance is a stochastic process which in this model constitutes the economic fundamental.

Investors form expectations of the probability of default. Let investor i's estimated probability be π_t^i and expected size of the default be δ_t^i. We assume that the market interest

[5] Though Forbes and Rigobon (2002) conclude that there is "interdependence, not contagion": no significant increase in correlations during crisis periods, once correction is made for the variance effect.

[6] Reserves could also be assumed to earn interest, but since the US rate is assumed constant this complication adds little to the model.

rate is set to equal to the US rate plus the average of all *n* investors' expectations, plus a risk premium. More exactly, the market rate plus unity is a geometric average over unity plus the expected probability times the size of devaluation, times unity plus the US rate, times one plus the risk premium ρ:

$$1 + r_t = (1 + r^*)(1 + \rho)\left(\prod_{i=1}^{n}(1 + \pi_t^i \delta_t^i)\right)^{1/n} \quad (2)$$

This formulation allows us to determine both the interest rate, which reflects average expectations, and the quantity of capital flowing to emerging markets, which reflects the skewness of the expectations of default. To illustrate this assume that risk aversion is zero, so that an investor puts all her money in either the safe asset or the emerging market bond, whichever pays the higher expected return. If an investor then has a more optimistic assessment of the probability (and size) of default than the average embodied in r_t, she will put all her money in emerging market bonds (negative holdings of either asset are ruled out). If less optimistic, then she will put her wealth into the safe asset. In these circumstances, the skewness of the distribution of expectations across investors will determine the amount that is invested in emerging markets: positive skewness of the distribution of devaluation expectations will indicate that more than half of investors are to the left of the average (hence more optimistic) so that investment in emerging markets will be higher than in the case of negative skewness (see Arifovic and Masson (2000)).

Investors are not assumed to observe the economic fundamental (the trade balance) or reserves. Starting from some distribution of initial priors, expectations are updated on the basis of past investment returns, with an element of imitation and experimentation. In particular, if investor i puts a proportion x_t^i into the emerging market bond (and the rest into the safe asset), by analogy with evolutionary biology one can define "fitness" (which is in effect the rate of return) as

$$\mu_t^i \equiv (1 - x_t^i)(1 + r^*) + x_t^i (1 + r_t)/(1 + \delta_t) - 1$$

where δ_t is the **actual** default size (or zero, if no default) in period t. Then investor i, in updating her expected probability and size of default (π_t^i, δ_t^i), will compare the fitness of her expectations with those of a randomly chosen comparator (where the probability of being picked depends on relative fitness—i.e., more successful rules are more likely to be imitated[7]); if the latter's fitness is greater, she will adopt the comparator's expectations; if less than or equal, keep her own. In addition, with some probability p_{ex} she would simply discard her expected probability of default π_t^i and pick a new one randomly (drawn from a uniform distribution) on the interval $[0, \pi^{\max}]$, and similarly for the size of default, if it is endogenous. However, in the simulations below we assume for simplicity that the size of default is fixed and known, because, for instance, a default triggers fixed costs that are independent of the amount of the shortfall of reserves. So, in this case, both expected and actual default size (if one occurs) are known and equal to $\overline{\delta}$. We will henceforth assume this to be the case.

[7] As in Arifovic and Masson (2000), if returns are negative, the underlying expectations are not imitated.

Investors' wealth is endogenous and evolves over time, depending on investor strategy and the rate of return:

$$W_t^i = (1+\mu_{t-1}^i)W_{t-1}^i - \bar{r}W_{t-1}^i \qquad (3)$$

where the last term is consumption out of wealth (at a constant, exogenous rate $\bar{r}$. The model is completed by a stochastic process for the trade balance. This specifies the trade balance as an AR(1) model:

$$T_t = \alpha + \beta T_{t-1} + u_t \qquad (4)$$

where $u_t \sim N(0,\sigma^2)$. Estimates based on annual data for various countries are found in Masson (1999a). An isomorphic model would replace the balance of payments equation by the government's budget constraint, impose an upper bound on debt (provoking default if reached), and replace the trade equation with a stochastic process on the primary (non-interest) government deficit. Such a model would give qualitatively similar results.

The simplest version of the model is as described above. However, there are two further complications that need to be explained: 1) portfolio selection when investors are risk averse, and 2) conversion of the model from an annual frequency to the monthly or daily frequency that matches our empirical data for emerging market spreads. These complications are briefly discussed here; details are given in appendices.

To account for risk aversion, we assume that investors maximize expected utility. Substituting into the first order conditions a second-order Taylor's expansion of the utility function, we obtain the familiar mean variance model of choice between a riskless asset and one or several risky assets. For the case of just one emerging market bond the resulting expression for the proportion of the portfolio held in the emerging market bond will be given by

$$x_t^i = \frac{b^i\left(r - \dfrac{1+r}{1+\bar{\delta}}\pi_t^i\bar{\delta} - r^*\right)}{\pi_t^i(1-\pi_t^i)\bar{\delta}^2} \qquad (5)$$

The expression in the denominator is the variance of the return on the risky asset, while the numerator (multiplied by a parameter b^i that is inversely proportional to a measure of risk aversion) is the expected yield differential in favor of the risky asset, if positive.

If $0 < x_t^i < 1$, then the proportion accounted for by the emerging market bond in *i's* portfolio given by (5): if not, then $x_t^i = 0$ or $x_t^i = 1$. In the limiting case of zero risk aversion ($b^i \to \infty$), investors merely select the asset yielding the highest expected return (given the constraints $0 \le x_t^i \le 1$). The general case is discussed in Appendix I.

For the model to be useful it needs to integrate high frequency financial markets with lower frequency economic fundamentals. Appendix II discusses the approach taken, namely to convert equation (4) to a monthly or daily autoregression on the assumption that the true stochastic process in fact operates at the higher frequency. In addition, adjustments have to be made to make stocks and flows consistent. Interest rates have to be scaled appropriately, as does the probability of default. At a daily frequency, it makes little sense to update expectations on the basis of one-period returns; thus, we specify a memory horizon $h \geq 1$ over which past returns are averaged when comparing fitness with a comparator[8]. Finally, we take account of the possibility that not all investors are active at a daily frequency; we specify a probability p_{inv} that an investor will update expectations and alter her portfolio in any given period.

III. Results of a Simple Model with One Emerging Market Bond and a Safe Asset

The model is essentially that of Arifovic and Masson (2000), calibrated to the reserves and external debt of Argentina in 1996, and using a stochastic equation for the trade balance that is estimated with historical data[9]. As in Arifovic and Masson, the model produces a succession of booms and crashes. However, as we will see it does not produce a distribution for the changes in spreads that has fat tails.

The model was first converted to a daily frequency, using the method described in Appendix II. This produced the following equation for the trade balance (as a percent of GDP, as are the other variables):

$$T_t = 0.23282 + 0.99867 T_{t-1} + \varepsilon_t \qquad (6)$$

where $\sigma_\varepsilon = 0.73198$ is the standard deviation of shocks to the trade balance. A crisis is triggered if the country's reserves would otherwise go below a certain threshold, here assumed to be zero. A crisis is best interpreted as a (possibly partial) default[10] on contracted debt in a proportion $0 \leq \overline{\delta} \leq 1$ that prevents reserves from going negative. It is assumed that $\overline{\delta} = 1$, so that a default reduces the value of debt by half.

The distribution of simulated daily changes in emerging market spreads over the US treasury bill rate is summarized in Table 7, for simulation runs of length 28000 (of which the first 100 were dropped to minimize the effects of initial conditions). It can be seen that unlike the actual data for changes in spreads, the simulations do not produce fat tails. In fact, the distribution has thin tails, not fat tails, since the kurtosis is less than the value of 3 that characterizes the normal. As a result, normality is rejected at a very small p-value, using the Jarque-Bera test. It is also the case that the simulations tend to produce serial correlation in changes in spreads (not reported); since this stylized fact is easy to replicate, we do not dwell on it further.

Table 7 explores whether the absence of fat tails is robust to tweaking the model's parameters. The table presents statistics for simulations with alternative values for risk aversion,

[8] Sections IV and V report on simulations at a monthly frequency, however.
[9] See Masson (1999a).
[10] However, it can also be interpreted as a devaluation that lowers the foreign currency value of debt contracted in domestic currency. See Masson (1999a).

the probability of experimentation, the probability of investing in a given period, the maximum value for the probability of default, the standard deviation of shocks to the trade balance, and the endogeneity of wealth. Increasing the value of π^{max} from 0.1 to 0.5 causes dramatic increases in the dispersion of changes in spreads, while introducing risk aversion also has that effect, but more moderately. In contrast, decreasing the probability of experimentation, not surprisingly, lowers volatility. Other changes reported in the table have relatively modest impacts. In particular, a striking result is that multiplying by 10 the standard deviation of shocks to the trade balance (row 6) scarcely affects the distribution of the change in spreads. Thus, the fluctuations in the model—capital flows into and out of emerging markets that provoke occasional crashes and spikes in spreads—result from shifting expectations rather than economic fundamentals (see also Arifovic and Masson, 2000).

None of the above changes has a great effect on skewness or kurtosis, and the Jarque-Bera test strongly rejects normality, as before. Thus, though these changes affect the range and variance of the distribution of changes in spreads, in all cases the distribution exhibits thin tails, not fat ones. The model as it stands does not seem able to replicate this stylized fact, one that is strongly present in the actual data. Our results contrast with the view expressed by Cont and Bouchaud (2000) to the effect that herd behavior (which we have present in our model in the form of imitation) is sufficient to produce fat tails in returns.

IV. Simulating a Model with Several Emerging Market Bonds

We then proceed to simulate a model in which there is more than one emerging market bond, in order to consider contagion phenomena. As detailed in Appendix I, in this case, investors need to formulate estimates of the covariance of defaults among emerging market countries when allocating their portfolios. We take the correlation between them (or correlation matrix, in the case of more than 2 risky assets), but not the variances, as given; that is, investors do not update their priors concerning the extent that returns move together. One would expect that the perceived correlation would be a key parameter for explaining the existence of contagion.

The simulations were performed with a model with only two emerging market countries, each of which with parameters identical to the one emerging market case above, with uncorrelated shocks to the trade balance. Because the added complexity of the model slowed execution time and in order to approximate more closely the typical time horizons of investors, we simulated at a monthly, not daily frequency. The actual distribution of monthly changes in spreads is given in Table 8 and plotted in Figure 10. It can be seen that there is still clear evidence of excess kurtosis when compared to the normal, but given the smaller sample size (1297 observations) the distribution is less smooth.

An interesting issue is whether it is *investors' beliefs* that emerging market bonds are similar that induces contemporaneous crises. A variant of this argument has been used to explain the East Asian crisis, namely the "wake up call hypothesis" (Goldstein, 1998): a crisis in one country (Thailand) made investors realize that there were fundamental problems in neighboring countries with similar institutions—or investors may have been misled into thinking there were, even though this was not the case. If the latter, true economic fundamentals might be uncorrelated, though investors treated them as being correlated. Investors might either over-estimate the degree of correlation, or think that other investors' portfolio shifts would produce correlation where none existed. Such behavior might conceivably produce a self-fulfilling, rational expectations equilibrium, in which there was contagion across emerging market bonds.

Table 9 gives the effect of varying the perceived correlation in the defaults by the two banks[11]. This determines the expected degree of covariance of their returns; all investors assume the same (unchanging) correlation, though investors continue to formulate different expectations of the probability of default. The table reports on simulations where that covariance is fixed at a value that goes from –1.0 to 1.0. To repeat, the covariance of the two countries' macro-economic fundamentals, in these simulations, is actually zero: innovations to the two emerging markets' trade accounts in their balance of payments are in fact uncorrelated.

The striking result is that for most of the values of the perceived correlation coefficient–even when it is positive—the correlation of returns is negative. Thus, there seems to be no self-fulfilling element to expectations here: even if investors believe that crises will occur simultaneously in the two emerging markets, this does not provoke co-movement of their spreads relative to US treasuries. Thus, this conjectured co-movement is not sufficient to explain any contagion phenomenon, quite to the contrary.

The explanation for the negative co-movement in spreads is simple: since the two assets are substitutes in an investor's portfolio, there is a tendency to increase holdings of one when the other asset is viewed as having a greater chance to default. This portfolio substitution effect dominates any effect resulting from treating the two assets as somehow members of the same risk class. Indeed, the effect of conjecturing a negative correlation among their returns makes investors want to hold both assets, since doing so reduces overall portfolio risk. The reason for this can be seen in equation (A4) of Appendix I. A more negative correlation, other things equal, increases demands for the two securities. Paradoxically, this may thus produce positive correlation in their defaults, not the negative one that was conjectured, since by varying holdings in tandem investors will provoke contemporaneous booms and crises. The converse applies when investors conjecture positive correlations. However, these effects again are very small on the joint distribution of emerging market spreads, producing only very slight differences in their correlations. Moreover, differences in the latter are not systematically related to the perceived correlations of default.[12]

In sum, the simple model with two emerging markets does not do a better job in mimicking the stylized facts than one with one market, since in addition to producing thin tails (kurtosis is less than for the normal for each of the simulations in Table 9), it does not provide an explanation for contagion. Thus, the model either needs to be replaced or extended in order to provide an adequate depiction of regularities in emerging market debt. In the next section, we consider an extension that models the varying liquidity of the market through the introduction of

[11] We simulated 1000 months (corresponding roughly to the pooled sample of actual data), but dropped the first 100 observations.

[12] An alternative, which we have not tried, is to make investors' expectations of the probabilities of default in the two emerging markets move in tandem. This would, by construction, force their interest rates to move together.

a market maker who varies his bid/ask spread as a function of the market's volatility and his inventory position.

V. Liquidity: Introducing a Secondary Market and a Market Maker

Conversations with market professionals suggest that emerging market bonds suffer from periods of pervasive illiquidity, and that this applies across a range of countries rather than being localized in just a single country facing difficulties in its balance of payments. We therefore expand the model by introducing a secondary market in emerging market debt, bonds now assumed to have two periods to maturity (except the US asset, which takes the form of cash). Investors purchase debt from emerging market governments when they are issued (the primary market), with rates of interest determined as described above. However, if investors want to sell before maturity, or buy a bond with only one period remaining until maturity, they need to deal in the secondary market with a market maker who quotes a buy and a sell price, which differ by the bid/ask spread, and whose average price reflects the market maker's inventory of the security.

Liquidity is often defined as the narrowness of the bid-ask spread. Unfortunately, such data are not publicly available on a consistent basis for emerging market bonds. In future work, we hope to obtain proprietary data from market participants.

There is an extensive literature modeling the behavior of market makers.[13] Market makers are usually assumed to avoid taking speculative positions, making their income by trading, not investing. Therefore, the size of their inventory of securities has an important role in influencing the size of their spread (O'Hara and Oldfield, 1986). Shen and Starr (2000) develop a model of optimal market maker behavior in which the spread depends positively on the security price's volatility, the volatility of order flow, and the market maker's net inventory position. We follow them in making liquidity (which is inversely related to the size of bid/ask spreads) depend on the market maker's costs, which rise with increasing volatility. We extend their model by including more than one security. We also assume (as do Shen and Starr) that threat of entry leads to zero profits in the long run. Thus, the model mimics competitive behavior (though for simplicity we include only a single market maker in the model). However, the Shen-Starr model takes the evolution of prices over time as exogenous. This is not useful for our purposes, since market makers deal sequentially with many investors and could acquire unbounded inventory positions unless they adjust the price. Instead, market makers in our model make decisions both on the price level and on the spread; we assume that these decisions are separable.

We proceed to describe the investor's decision tree and the role of the market maker.
Investor. Instead of 3 assets—the riskless US bond and 2 emerging market bonds—we now have 5, since investors hold emerging market bonds with remaining terms to maturity of 1 and 2 periods. However, each country's bonds are viewed as perfect substitutes, since the probability

[13] LeBaron (2001) discusses alternative market structures for agent-based financial models, including models with market makers, while Farmer and Joshi (2002) study the interaction of investors with different trading strategies in a model with market makers.

of default is the same in both periods and the investor does not face stochastic consumption shocks so is indifferent to the term to maturity. Thus, at the beginning of each period, each investor calculates optimal holdings (x_0, x_1, x_2) of US, emerging market 1 and emerging market 2 bonds, respectively, as described in Appendix I. After having redeemed maturing bonds, she has holdings (ω_1, ω_2) of emerging market bonds which she compares with her desired holdings. Let $\Delta_i = x_i - \omega_i$.

If Δ_i>0, she buys Δ_i one-period bonds from the market maker or new two-period bonds directly from the emerging market country, depending whether or not

$$\frac{(1+r_{i,-1})^2}{p_i^b} > 1 + r_i$$

That is, the investor chooses the bond with the highest return (since bonds pay 2 periods' interest at maturity, the market maker's selling price on a one-period bond p_i^b has to reflect accrued interest).

If Δ_i<0, then the investor sells – Δ_i to the market maker, unless

$$\frac{(1+r_{i,-1})^2}{p_i^s} < 1 + r^*$$

That is, the investor liquidates her excess holdings unless the market maker's price is so low that the return to holding on to them is greater than the return from investing in the safe asset.

Market maker. The market maker is assumed to be a middle man who covers costs but takes no speculative position; he aims to minimize his exposure, long or short. Assuming that there are the same quadratic costs to deviating from zero holdings in either bond (as in Shen and Starr), his spread could depend on the volatilities in the two markets. (In the simulations reported below, we assume equal weights on the two volatilities, but we discovered that allowing **no** volatility spillovers produces similar simulation results). We calculate volatilities as exponentially-weighted averages of the absolute value of the change in the rate in the primary market. We also make spreads decline as net worth increases, to enforce the zero long-run profit constraint. The spread is set at the beginning of each period. Within each period, the market maker deals sequentially with investors who want to transact, quoting a buy or a sell price. The market maker (since he does not initially hold an inventory of bonds) is not prevented from going short, but adjusts his price as he transacts in order not to accumulate too large a long or short position.

Thus,

$$spread_t = [A + B \bullet (vol_{1t} + vol_{2t})]e^{-C \bullet NW_t}$$

$$vol_{it} = (1-\gamma)\sum_{j=1}^{\infty} \gamma^{j-1} \mid \Delta r_{it-j} \mid$$

$$price_{it} = (1 + r_{it-1})e^{-\theta X_{ti}}$$

where *A,B*, *C*, *γ,* and *θ* are positive parameters, vol_{it} is the volatility of rate i*,* Δr_{it} is the one-period change in the primary market interest rate set on bond i, *NW* is the net worth of the market maker, and X_{it} is the market maker's net holdings of security *i*. In the limit $\gamma \to 0$ volatility depends only on the absolute value of the change in the rate in the most recent period; $\gamma = 1$ weights all past periods the same.

The spread is fixed at the beginning of the period, while the market maker's price varies within the period, depending at each point on the inventory position that has resulted in his transactions with investors. Thus he buys at p_{it}^{b} and sells at p_{it}^{s}, where the prices are given by

$$p_{it}^{b} = price_{it} * (1 - spread_t)$$

$$p_{it}^{s} = price_{it} * (1 + spread_t)$$

The market maker's holdings evolve as he transacts with each investor. After dealing with investor *j*,

$$X_{it}^{(j)} = X_{it}^{(j-1)} - \Delta_{it}^{(j)} \bullet price_{it}^{(j)} \bullet (1 + sign(\Delta_{it}^{(j)}) \bullet spread_t)$$

The latter term depends on whether the transaction is a buy or a sell, that is, on the sign of the investor's excess demand. In fact, the simulations randomize the order investors transact with the market maker so that investors *j-1, j, j+1,…* vary from period to period. At the end of each period of buying and selling with all the investors who want to transact, the market maker either covers his short position by buying one-period bonds from the emerging market country, or holds his long position until it matures in the following period.

Table 10 gives the results of simulations at a monthly frequency with the inclusion of the market maker as described above, where the effects of changing key parameters that characterize the market maker's behavior (*B, θ,* and *γ)* are explored.[14] In each case, the simulation was run over 1800 periods. Across cases, the same seed was used, so that the results are comparable and are not due to the random numbers chosen. The first 500 simulated periods were ignored in each case—a longer period than before because this model seemed more sensitive to initial conditions. Several differences are notable with respect to the earlier simulations where liquidity did not play a role. **First,** there is now excess kurtosis compared to the normal—i.e. fat tails, not thin ones as before. This is illustrated in Figure 11. Interestingly, excess kurtosis applies to **both** the primary and secondary markets, though the determination of interest rates in the primary market has formally not been changed. Instead, it seems that transactions in the secondary market, by affecting the amounts held of primary securities, increase the likelihood of

[14] Other parameter values used were the following: $P_{ex}=.1; P_{inv}=1.0; \pi^{max}=0.1; b^{max}=5; \sigma_\varepsilon=0; A=0; C=0.002$. The number of comparators used by each investor (discussed below) is 2

large changes in primary interest rates. **Second,** despite lack of correlation in economic fundamentals, the changes in **secondary** market returns in the two emerging markets are very highly correlated. Somewhat surprisingly, the same is now true in almost all cases for the **primary** market as well. What could explain this? It seems as though lack of liquidity causes investors to sustain losses, either by paying high spreads or holding on to securities that default. This leads to low overall fitness, and investors then tend to revise their expectations of default on both securities upward. **Third,** though there is excess kurtosis and the Jarque-Bera test comfortably rejects normality, kurtosis is lower than in the actual data, where it is of the order of 80, not 15 as in Table 10. Moreover, that degree of kurtosis seems remarkably insensitive to the explorations of parameter values reported here (and other plausible ones that are not reported). Indeed, it is hard to trace a systematic effect of the changes in parameter values, except perhaps on the standard deviation of changes in rates. Clearly further investigation is needed. **Finally**, though perhaps of little significance, all of the simulations exhibit positive skewness, while the actual data (Table 8) exhibit negative skewness.

In addition, we revisited the issue of how investors' expectations formation might influence the results. To summarize, in the basic version of the model each investor either compares her beliefs to those of a randomly-chosen comparator, where the the latter is more likely to be chosen the higher is his fitness, or (with probability p_{ex}) experiments by choosing a new strategy chosen randomly. In Table 11, we see if comparing to more than one other randomly-chosen investor (in particular, having 1, 2, or 3 comparators), affects the distribution's properties, and whether the results are sensitive to p_{ex}. The other parameters in each case are set to their values in RUN 3, where the number of comparators is 2 and $p_{ex}=0.1$ (see Table 10). It turns out that both matter. Having more comparators (at least in this range) increases kurtosis substantially. It seems that having more comparators increases the possibility of large and sudden shifts of opinion, producing occasional, larger interest rate movements. In contrast, increasing the probability of experimentation substantially **reduces** kurtosis. In this case, there is not enough imitation causing herd behavior that is the source of financial crises (and large changes in interest rates). Also interesting is that more experimentation **reverses** the positive correlation that emerged in the market maker model.

Of course, other information structures are also possible and relevant (see, e.g., Watts 1999). For instance, there could be a group of trend setters (e.g. Goldman Sachs, Tiger Fund, or other large investment banks or hedge funds) whose strategies are widely watched and imitated. Or it could be that imitation is regional, with traders in New York, London, and Tokyo constituting separate groups. Exploring these possible networks among traders may be a subject of our future research, which we would hope to make precise by interviews with actual market participants. There may also be different access to information; market makers (and big investment banks generally, whether or not they make a market in a particular security) are widely believed to benefit from superior knowledge relative to other investors (in part because of their contacts with emerging market countries and their role as underwriters). Agent-based models are particularly useful for studying such interactions (see, for instance, Epstein and Axtell, 1996).

In order to examine sensitivity to random draws we present in Table 12 a summary of the results for a particular set of parameters (RUN 3), simulated with 10 different realizations of the random variables. The table shows that there is considerable variation across runs, but that the discussion above based on single runs is not unrepresentative.

Clearly, the introduction of a market maker and changing liquidity makes a significant step toward reproducing the stylized facts contained in the actual data. It could be objected that the model is very special and unrealistic. However, there are two crucial linkages here that help to reproduce some of the features of the actual data on emerging market spreads, and these features would also remain in more realistic and detailed models. The **first** linkage results from the assumption that the market maker's increases with volatility. It does not appear, however, that having the market maker respond to volatility in one market by raising bid-ask spreads in the other market as well is a necessary feature to produce the co-movements we see in the simulations. **Second**, investors choose to retain their holdings in emerging market debt when liquidity is too low, that is, the prices at which they can sell are too unattractive (relative to holding on to their bonds). In any model of optimal portfolio selection, there will be prices at which investors will refuse to transact in the secondary market, and hence their initial holdings will matter. When expectations shift suddenly in the same direction, low liquidity will mean that prices need to adjust a lot in order to make it possible for investors to trade and get closer to their desired portfolio positions. Being locked into their holdings may cause them to incur large losses if there is a subsequent default, and this will then change the dynamic of their expectations formation and their desired bond holdings next period. The endogeneity of spreads is also important in causing serial correlated effects. Iori (2002) finds that if thresholds defining a no-trading range are constant over time (or zero), then volatility clustering does not occur in her model.

VI. Concluding Comments

We have identified various important features of the data for interest rates on emerging market debt, and formulated a model, which, after being extended to include endogenous liquidity, is able to replicate some of those features--in particular, fat tails in the distribution of the changes in spreads (against US treasury securities) and positive correlation between changes in emerging market interest rates (even though the economic fundamentals are assumed uncorrelated in the simulation model). The analysis is necessarily exploratory and suggestive, rather than definitive. Nothing proves that some other model, even a reasonably parsimonious one like that presented here, may not replicate the stylized facts as well as, or better than, this one. And despite its simplicity, there needs to be more exploration of the effects of changing parameters or structure in order to understand the essential factors at work. We have identified the networks involved in imitation as a promising avenue to explore. Our model, like other models of heterogeneous agents, has interesting interactions between cross sectional variability and time series volatility. Moreover, frictions that inhibit continuous rearranging of portfolios produce non-convexities with interesting distributional implications.[15] We hope to understand better in future work the key aspects of heterogeneity that produced the observed time series properties.

[15] There is an analogy here with the literature on income inequality and growth (see Galor and Zeira, 1993).

Other financial models have also produced returns with fat tails, for instance through assuming that there are two types of traders, noise traders and fundamentalists, whose numbers vary in some fashion (see for instance, Lux 1998 and Lux and Marchesi 1999). Most of the analysis to date has been applied to equity, foreign exchange, or developed country bond markets, all of which are deep, liquid markets. Studying the emerging debt markets is valuable in itself, not least because sharp movements in rates are associated with fears of (and the occurrence of) large defaults and currency devaluations. But, in addition, periods of illiquidity in these markets are much more of an issue than for advanced country financial markets, and contagion across markets has generated more concern also. Indeed, Rigobon (2002) find that the upgrade of Mexico, by increasing the universe of potential investors, significantly decreased c-movements with other emerging markets. He therefore ascribes an important role to liquidity factors in explaining contagion. We hope to obtain data from market participants that confirms the link between volatility and illiquidity. In any case, the results of our paper suggest that endogenous liquidity can, in and of itself, produce some of these features, and hence warrants further research in the context of emerging market fluctuations.

Appendix I. Investor Portfolio Selection with Risk Aversion

We consider here the case with one riskless asset and two risky assets; it generalizes easily to the case of several risky assets. Portfolio return R is given by

$$R = x_0 r^* + x_1(\frac{1+r_1}{1+\delta_1} - 1) + x_2(\frac{1+r_2}{1+\delta_2} - 1) \qquad \text{(A1)}$$

where r^*, r_1, and r_2 are the interest rates on the riskless (US) asset, and on emerging market bonds 1 and 2, respectively. Realized default proportions are denoted δ_i. Portfolio proportions sum to 1, so we can also write the portfolio return as

$$R = r^* + x_1(\frac{1+r_1}{1+\delta_1} - 1 - r^*) + x_2(\frac{1+r_2}{1+\delta_2} - 1 - r^*) \qquad \text{(A2)}$$

By assumption, the investor maximizes a utility function $U(R)$ with respect to x_1 and x_2. The first order conditions are:

$$E\left[U'(R)\left(\frac{1+r_1}{1+\delta_1} - 1 - r^*\right)\right] = 0$$

$$E\left[U'(R)\left(\frac{1+r_2}{1+\delta_2} - 1 - r^*\right)\right] = 0$$

We expand U in a second-order Taylor's expansion around the expected return

$$\overline{R} \equiv E(R) = r^* + x_1(\mu_1 - r^*) + x_2(\mu_2 - r^*)$$

where $\mu_i \equiv E(\frac{1+r_i}{1+\delta_i} - 1)$:

$$\begin{aligned} U'(\overline{R})(\mu_1 - r^*) + U''(\overline{R})(x_1 \operatorname{var}_1 + x_2 \operatorname{cov}_{12}) = 0 \\ U'(\overline{R})(\mu_2 - r^*) + U''(\overline{R})(x_1 \operatorname{cov}_{12} + x_2 \operatorname{var}_2) = 0 \end{aligned} \qquad \text{(A3)}$$

where

$$\operatorname{var}_i \equiv E(\frac{1+r_i}{1+\delta_i} - \mu_i)^2$$

$$\operatorname{cov}_{12} \equiv E[(\frac{1+r_1}{1+\delta_1} - \mu_1)(\frac{1+r_2}{1+\delta_2} - \mu_2)]$$

Writing

$V \equiv \begin{bmatrix} \operatorname{var}_1 & \operatorname{cov}_{12} \\ \operatorname{cov}_{12} & \operatorname{var}_2 \end{bmatrix}, x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}$ and letting $b \equiv -\frac{U'(\overline{R})}{U''(\overline{R})}$ the first order conditions can be solved to yield

$$x = bV^{-1}(\mu - r^*) \qquad \text{(A4).}$$

As is well known from portfolio theory, the composition of the risky asset portfolio will not depend on the degree of risk aversion (the inverse of b)—that is, the portfolio proportions captured by ratio x_1 / x_2 will be independent of *b*. However, the proportion of the total portfolio held in the safe asset will depend inversely on *b*. In the limit as $b \to 0, x \to 0$ and all assets are held in the safe asset. In the simulations, *b* varies across investors, and is initialized by drawing from a uniform distribution in a pre-specified range.

The expected return on each bond depends on the expected default. Default size is assumed known and exogenous (and $\overline{\delta} = 1$, which implies that default reduces the value of the bond by half), so the key variable is each investor's estimate of the probability of default on bond bond i*,* π_i, which varies from investor to investor (we omit the superscript identifying the investor). So the expected return for a given investor can be written:

$$\mu_i = \pi_i \left(\frac{1+r_i}{1+\overline{\delta}} - 1 \right) + (1-\pi_i) r_i = r_i - \frac{1+r_i}{1+\overline{\delta}} \pi_i \overline{\delta},$$

its variance

$$\mathrm{var}_i = E\left(\frac{1+r_i}{1+\delta_1} - 1 - \mu_i \right)^2 = \pi_i \left(\frac{1+r_i}{1+\overline{\delta}} - 1 - \mu_i \right)^2 + (1-\pi_i)(r_i - \mu_i)^2,$$

and the covariance between bonds *1* and *2*

$$\mathrm{cov}_{12} = E\left[\left(\frac{1+r_1}{1+\delta_1} - 1 - \mu_1 \right) \left(\frac{1+r_2}{1+\delta_2} - 1 - \mu_2 \right) \right] = \rho_{12} \sqrt{\mathrm{var}_1 \, \mathrm{var}_2}\ ,$$

where ρ_{12} is the investor's estimate of the correlation between the two asset's returns. In the simulations this correlation is a fixed parameter which is assumed to describe the expectations of all investors.

Appendix II. Currency Crash Models at Different Frequencies

Instead of (1) the flows T_t need to be divided by n, where n is either 12 (monthly) or 365 (daily):

$$R_t = R_{t-1} + D_t - (1+r_{t-1})D_{t-1} + T_t / n \qquad (1')$$

All interest rates need to be converted from annual to a monthly or daily frequency:

$$(1+r_t^{(n)}) = (1+r_t)^{1/n}$$

where r_t on the RHS stands for the annual data, $r_t^{(n)}$ on the LHS stands for the monthly or daily data. As for the probability of a default, let π_t^i be the probability over the coming year, and ${}^{(n)}\pi_t^i$ for a fraction *1/n* of the year. Assuming that the probability of a default in each of the months or days is independent of the other, then

$$1 + {}^{(n)}\pi_t^i = (1+\pi_t^i)^{1/n}$$

Another problem is the trade balance equation, however, because the lagged endogenous variable now refers to the previous month's value, not the previous years. Persistence should be greater at higher frequency, and so should be the coefficient on the lagged endogenous variable. Suppose that the true adjustment takes place at the higher frequency, as in the following equation

$$T_t = a + bT_{t-1} + \varepsilon_t \qquad (4')$$

If we go to a lower frequency, e.g. the time period is twice as long,

$$\begin{aligned} T_t &= a + b(a + bT_{t-2} + \varepsilon_{t-1}) + \varepsilon_t \\ &= a(1+b) + b^2 T_{t-2} + b\varepsilon_{t-1} + \varepsilon_t \end{aligned}$$

More generally, if the time period is n times as long as the initial (high frequency) data, then

$$\begin{aligned} T_t &= a(1+b+\ldots+b^{n-1}) + b^n T_{t-n} + \varepsilon_t + b\varepsilon_{t-1} + \ldots + b^{n-1}\varepsilon_{t-n+1} \\ &= a\frac{1-b^n}{1-b} + b^n T_{t-n} + \varepsilon_t + b\varepsilon_{t-1} + \ldots + b^{n-1}\varepsilon_{t-n+1} \end{aligned}$$

It is this equation that is assumed to have resulted in the coefficient estimates from annual data. If we infer back from the lower frequency data, say equation (4) above on annual data, we can calculate what the coefficients in (4') should be from:

$$a\frac{1-b^n}{1-b} = \alpha \qquad\qquad b^n = \beta$$

Similarly, the variance of the shocks to the trade balance needs to be adjusted downward using

$$\sigma_\varepsilon^2 = \frac{1-b}{1-b^n}\sigma_u^2$$

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Table 1. Summary Statistics for the Distribution of Daily Changes in Spreads, All Countries
(in basis points)

Mean	0.214
Standard Deviation	48.32
Skewness	-0.305
Kurtosis	86.06
Largest	1154
Smallest	-1070
Jarque-Bera test for normality	8,004,456
Number of Observations	27,842

Table 2. Summary Statistics for Distribution of Daily Changes in Spreads, Nov. 1, 1994 - July 19, 2002
(in basis points)

	Argentina	Brazil	Bulgaria	Mexico	Morocco	Nigeria	Poland	Venezuela
Mean	3.09	0.37	-0.59	-0.06	-0.12	0.17	-0.17	-0.22
Standard Deviation	64.77	32.68	34.60	32.76	29.83	80.31	12.40	44.94
Kurtosis	43.69	21.65	22.59	59.99	30.09	11.94	73.43	46.78
Skewness	2.56	0.63	1.60	0.52	0.87	0.32	1.07	3.04
Largest	927	285	394	442	341	620	212	637
Smallest	-595	-347	-242	-506	-289	-611	-168	-266
Jarque-Bera	135,161	28,081	31,677	261,101	59,230	6,461	399,046	157,043

Table 3. Two Sample Kolmogorov-Smirnov Test for Equality of Distribution Functions of Daily Changes in Spreads *

	Brazil	Bulgaria	Mexico	Morocco	Nigeria	Poland	Venezuela
Argentina	0.059 (0.002)	0.055 (0.006)	0.109 (0.00)	0.070 (0.00)	0.127 (0.00)	0.212 (0.00)	0.039 (0.108)
Brazil		0.036 (0.158)	0.057 (0.003)	0.041 (0.073)	0.172 (0.00)	0.165 (0.00)	0.050 (0.017)
Bulgaria			0.090 (0.00)	0.043 (0.056)	0.150 (0.00)	0.193 (0.00)	0.033 (0.255)
Mexico				0.049 (0.019)	0.219 (0.00)	0.123 (0.00)	0.100 (0.00)
Morocco					0.182 (0.00)	0.166 (0.00)	0.056 (0.005)
Nigeria						0.304 (0.00)	0.134 (0.00)
Poland							0.211 (0.00)

* P-value in parentheses

Table 4: Autocorrelations of Daily Changes in Emerging Market Spreads

Country	1st order autocorrelation coefficient	Q-stat (lags 1-5)
Argentina	**0.079***	**47.2***
Brazil	**0.121***	**60.4***
Bulgaria	**0.106***	**47.7***
Colombia	**0.143***	**17.6***
Ecuador	**0.033 (p=0.157)**	**12.2***
Korea	**0.053 (p=0.085)**	**65.2***
Mexico	**0.089***	**119.9***
Morocco	**0.033 (p=0.126)**	**61.4***
Nigeria	**-0.074***	**15.7***
Panama	**0.072***	**66.6***
Peru	**0.029 (p=0.297)**	**20.7***
Philippines	**-0.018 (p=0.428)**	**10.8 (p=0.055)**
Poland	**0.091***	**68.6***
Qatar	**-0.050 (p=0.314)**	**4.0 (p=0.544)**
Russia	**-0.025 (p=0.378)**	**45.6***
South Africa	**-0.291***	**54.8***
Turkey	**0.061 (p=0.095)**	**7.3 (p=0.198)**
Ukraine	**-0.013 (p=0.844)**	**2.4 (p=0.789)**
Venezuela	**0.040 (p=0.061)**	**89.7***
EMBI+	**0.134***	**39.8***

***Significant at the 5 percent level**

Table 5. Proportion of Variance in the Daily Changes in Spreads explained by the First Principal Component in Various Crises

Mexican Crisis, December 1994 - May 1995	0.73
East Asian Crisis, September 1997 - February 1998	0.77
Russian Crisis, July 1998 - December 1998	0.72
Brazilian Crisis, November 1998 - April 1999	0.65
Argentine Crisis, January 2001 – June 2001	0.46

Table 6. Co-exceedances in Tails at 5, 2.5 and 1 Percent, Daily Changes in Spreads

5 Percent (96 Observations)

	Brazil		Bulgaria		Mexico		Morocco		Nigeria		Poland		Venezuela	
	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right
Argentina	**36**	**36**	**24**	**62**	**30**	**27**	**19**	**28**	**21**	**21**	**23**	**23**	**30**	**24**
Brazil			**31**	**38**	**48**	**50**	**35**	**48**	**22**	**29**	**28**	**35**	**36**	**45**
Bulgaria					**32**	**39**	**36**	**41**	**20**	**29**	**32**	**44**	**23**	**40**
Mexico							**33**	**39**	**27**	**31**	**39**	**44**	**37**	**48**
Morocco									**21**	**28**	**30**	**34**	**37**	**33**
Nigeria											**27**	**36**	**30**	**21**
Poland													**26**	**37**

2.5 Percent (48 Observations)

	Brazil		Bulgaria		Mexico		Morocco		Nigeria		Poland		Venezuela	
	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right
Argentina	**10**	**14**	**9**	**10**	**11**	**12**	**10**	**10**	**7**	**8**	**7**	**12**	**12**	**10**
Brazil			**15**	**20**	**18**	**23**	**14**	**21**	**10**	**13**	**14**	**18**	**19**	**19**
Bulgaria					**15**	**17**	**19**	**18**	**10**	**16**	**21**	**22**	**16**	**21**
Mexico							**18**	**18**	**14**	**15**	**19**	**22**	**17**	**26**
Morocco									**11**	**13**	**20**	**14**	**22**	**16**
Nigeria											**13**	**17**	**12**	**12**
Poland													**18**	**20**

1 Percent (19 Observations)

	Brazil		Bulgaria		Mexico		Morocco		Nigeria		Poland		Venezuela	
	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right
Argentina	**6**	**6**	**4**	**6**	**5**	**6**	**6**	**5**	**3**	**5**	**5**	**4**	**5**	**5**
Brazil			**6**	**8**	**7**	**10**	**7**	**10**	**4**	**6**	**5**	**6**	**9**	**10**
Bulgaria					**5**	**11**	**8**	**10**	**3**	**7**	**9**	**11**	**5**	**11**
Mexico							**7**	**7**	**7**	**8**	**7**	**10**	**8**	**9**
Morocco									**6**	**5**	**6**	**5**	**7**	**10**
Nigeria											**4**	**9**	**6**	**7**
Poland													**5**	**6**

Table 7. One Emerging Monthly Model: Effects of Daily Changes in Parameters on the Distribution of Changes in Emerging Market Spreads
(27, 900 Observations)

Simulation	Parameter Values							Distribution Statistics					
	Mem. Length	Pex	Pinv	π^{max}	b^{max}	σ_ε	wealth endogenous	Range	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
(1)	1	0.333	0.9	0.1	∞	0.73	N	(-126, 159)	.0004	36.4	0.049	-0.119	11,316
(2)	1	0.333	0.9	0.1	∞	0.73	N	(-125, 152)	.0006	36.6	0.045	-0.117	11,300
(3)	5	0.333	0.9	0.1	∞	0.73	N	(-125, 145)	.0005	34.8	0.016	-0.053	10,834
(4)	5	0.333	0.9	0.5	∞	0.73	N	(-786, 668)	-.0020	173.1	0.018	-0.031	10,683
(5)	5	0.333	0.9	0.5	5	0.73	N	(-632, 662)	.0060	153.9	0.052	0.032	10,252
(6)	5	0.333	0.9	0.5	5	7.32	Y	(-637, 718	-.0015	153.7	0.070	0.033	10,253
(7)	5	0.167	0.9	0.5	5	0.73	Y	(-596, 542	-.0005	132.8	0.005	0.042	10,170
(8)	5	0.167	0.5	0.1	5	0.73	Y	(-710, 642)	.0081	152.0	0.067	0.176	9,294
(9)	5	0.167	0.5	0.1	1	0.73	Y	(-807, 767)	.0119	172.3	0.029	0.081	9,909
(10)	5	0.167	0.5	0.1	100	0.73	Y	(-624, 697)	.0048	142.6	0.145	0.179	9,348

Table 8. Summary Statistics for the Distribution of the Monthly Change in Spreads, All Countries
(in basis points)

Mean	-2.19
Standard Deviation	55.85
Skewness	-5.70
Kurtosis	82.34
Largest	409
Smallest	-846
Jarque-Bera test for normality	347,207
Number of Observations	1,297

Table 9. Two Emerging Markets: Simulated Distribution of Monthly Changes in Spreads (900 Observations)

Assumed correlation of defaults	-1.0	-0.5	0.0	0.5	1.0
Emerging Market 1					
Mean	-0.0004	-0.0003	-0.0002	-0.0002	-0.0004
Std. deviation	1.893	1.648	1.691	1.664	1.642
Skewness	-0.0000	-0.0038	0.0208	0.0119	0.0349
Kurtosis	0.2133	0.0954	0.0978	0.0851	0.1571
Emerging Market 2					
Mean	-0.0002	0.0001	-0.0000	-0.0002	-0.0000
Std. deviation	1.898	1.650	1.679	1.652	1.642
Skewness	-0.0110	0.0462	0.0366	0.0048	0.0291
Kurtosis	0.3432	0.1458	0.0856	0.0758	0.1409
Correlation of simulated changes in spreads	-0.0083	-0.0833	-0.0929	-0.1021	0.0066

Table 10. Simulation of Market Maker Model, Monthly, Various Parameters (1300 observations)

Run 1	Secondary Markets		Primary Markets	
Standard Deviation	67.01	63.08	49.28	48.62
Mean	0.17	0.14	0.22	0.17
Kurtosis	7.30	16.27	18.37	22.25
Skewness	0.68	1.56	2.01	2.32
J-B	1100	10065	13664	21228
Maximum	443	648	480	524
Minimum	-355	-268	-215	-211
Correlation	0.49		0.69	

$\beta=100$, $\theta=.0005$, $\gamma = .95$

Run 2	Secondary Markets		Primary Markets	
Standard Deviation	55.52	63.77	46.54	48.39
Mean	-0.21	-0.18	-0.16	-0.14
Kurtosis	12.98	11.06	17.59	14.44
Skewness	1.53	0.85	2.00	1.87
J-B	5897	3671	12380	7837
Maximum	507	499	487	387
Minimum	-289	-402	-219	-207
Correlation	0.47		0.55	

$\beta=25$, $\theta=.0005$, $\gamma = .95$

Run 3	Secondary Markets		Primary Markets	
Standard Deviation	48.05	49.19	48.05	48.94
Mean	-0.39	-0.39	-0.38	-0.39
Kurtosis	19.96	11.68	19.75	11.65
Skewness	2.16	1.21	2.14	1.21
J-B	16567	4392	16169	4368
Maximum	517	416	518	416
Minimum	-227	-288	-227	-290
Correlation	0.66		0.67	

$\beta=25$, $\theta=.0001$, $\gamma = .95$

Run 4	Secondary Markets		Primary Markets	
Standard Deviation	42.17	45.49	42.19	45.16
Mean	0.09	0.10	0.06	0.08
Kurtosis	14.08	15.51	13.96	15.85
Skewness	1.40	1.30	1.37	1.32
J-B	7067	8841	6915	9312
Maximum	380	472	379	471
Minimum	-208	-249	-208	-248
Correlation	0.72		0.72	

$\beta=25$, $\theta=.0001$, $\gamma = .99$

Table 11. Simulation of Market Maker Model, Varying Probability of Experimentation and Number of Comparators (1300 Observations)

Run 5	Secondary Markets		Primary Markets	
Standard Deviation	69.79	75.32	66.84	73.54
Mean	0.10	0.11	0.12	0.20
Kurtosis	4.75	4.06	4.85	4.17
Skewness	1.07	0.95	1.09	1.05
J-B	414	258	444	314
Maximum	438	382	385	382
Minimum	-315	-275	-319	-265
Correlation	-0.12		-0.12	

Pex=.167

Run 6	Secondary Markets		Primary Markets	
Standard Deviation	83.98	73.48	81.17	70.56
Mean	0.08	-0.09	0.08	-0.17
Kurtosis	3.01	2.30	3.02	2.43
Skewness	1.07	0.69	1.12	0.77
J-B	248	129	273	145
Maximum	364	346	364	346
Minimum	-279	-267	-236	-213
Correlation	-0.49		-0.49	

Pex=.333

Run 7	Secondary Markets		Primary Markets	
Standard Deviation	32.06	31.63	30.43	30.68
Mean	0.03	0.00	0.00	-0.04
Kurtosis	8.13	7.59	8.45	8.28
Skewness	0.97	0.85	1.01	0.89
J-B	1629	1294	1829	1677
Maximum	264	274	255	267
Minimum	-116	-141	-117	-147
Correlation	0.67		0.74	

NUMcomp=1

Run 8	Secondary Markets		Primary Markets	
Standard Deviation	43.20	42.64	43.24	42.68
Mean	-0.12	-0.14	-0.08	-0.08
Kurtosis	15.15	15.64	14.35	18.25
Skewness	1.25	1.37	1.25	1.74
J-B	8331	9051	7306	13250
Maximum	411	458	411	476
Minimum	-249	-249	-234	-232
Correlation	0.47		0.47	

NUMcomp=3

Table 12. RUN 3: Mean and Standard Deviation of Summary Statistics across 10 Replications (1300 Observations)

Primary Markets	Country 1		Country 2		Both	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Standard Deviation	42.46	4.87	43.71	5.84	43.08	5.38
Mean	-0.01	0.19	-0.01	0.15	-0.01	0.17
Kurtosis	20.72	6.68	16.33	7.99	18.52	7.37
Skewness	2.11	0.59	1.61	0.74	1.86	0.67
J-B	20,204		13,390		16,797	
Maximum	453	60	405	78	429	69
Minimum	-196	32	-250	66	-223	52
Correlation					0.59	0.14

Secondary Markets	Country 1		Country 2		Both	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Standard Deviation	43.62	4.60	44.82	5.21	44.22	4.91
Mean	-0.03	0.19	-0.01	0.14	-0.02	0.17
Kurtosis	17.80	4.54	16.25	9.32	17.03	7.33
Skewness	1.83	0.43	1.54	0.79	1.69	0.64
J-B	13,632		14,368		14,000	
Maximum	439	66	414	81	427	74
Minimum	-210	38	-256	68	-233	55
Correlation					0.56	0.13

Appendix Table 1: Data Availability

	Time Period Available
Argentina	December 31, 1993 - July 19, 2002
Bulgaria	September 1, 1994 - July 19, 2002
Brazil	May 2, 1994- July 19, 2002
Colombia	June 1, 1999 - July 19, 2002
Ecuador	March 1, 1995 - July 19, 2002
Korea	May 1, 1998 - July 19, 2002
Morocco	December 31, 1993 - July 19, 2002
Mexico	December 31, 1993 - July 19, 2002
Nigeria	December 31, 1993 - July 19, 2002
Panama	August 1, 1996 - July 19, 2002
Peru	April 1, 1997 - July 19, 2002
Philippines	December 31, 1993 - September 29, 1998; May 3, 1999 - July 19, 2002
Poland	November 1, 1994 - July 19, 2002
Qatar	December 1, 2000 - July 19, 2002
Russia	September 2, 1997 - July 19, 2002
Turkey	August 2, 1999 - July 19, 2002
Ukraine	August 1, 2001 - July 19, 2002
Venezuela	December 31, 1993 - July 19, 2002
South Africa	January 3, 1995 - February 27, 1997; May 1, 2002 - July 19, 2002

Appendix Table 2:

A. Observations in the One Percent Left Tail of the Distribution of Daily Changes in Spreads (basis points)

Trade Date	Argentina	Brazil	Bulgaria	Mexico	Morocco	Nigeria	Poland	Venezuela
28-Dec-94				-116		-259	-33	-146
5-Jan-95				-174		-294		
11-Jan-95		-112		-182		-283		-205
12-Jan-95	-287	-208	-242	-506	-197	-434	-168	-229
13-Jan-95			-97				-73	
31-Jan-95	-220	-118	-133	-163	-92	-299	-58	-234
17-Feb-95				-139				-142
10-Mar-95	-365	-180		-123	-97	-360	-61	-139
13-Mar-95			-121	-148				
14-Mar-95		-126	-138					
27-Mar-95				-164			-30	
4-Apr-95			-99	-112			-52	
7-Apr-95			-117		-76			
1-Jun-95			-98				-91	
12-Jun-95				-96	-94	-322		
23-Jan-96			-145				-120	
25-Aug-98			-189		-226		-37	
28-Aug-98		-90	-98					-192
1-Sep-98	-175	-114	-165		-249		-54	-186
2-Sep-98					-103	-415		
15-Sep-98	-235	-226	-119	-112	-124		-37	
16-Sep-98		-139		-116	-289			-235
18-Sep-98		-102						-266
22-Sep-98			-190		-78			
23-Sep-98			-162		-114	-359		-223
15-Jan-99	-218	-347		-127	-108			-182

B. Observations in the One Percent Right Tail of the Distribution of Daily Changes in Spreads (basis points)

Trade Date	Argentina	Brazil	Bulgaria	Mexico	Morocco	Nigeria	Poland	Venezuela
2-Nov-94			105				47	
3-Nov-94						265	54	
21-Dec-94			141				43	
27-Dec-94				273	133	408	68	290
4-Jan-95			116	202		330	53	
9-Jan-95		174	169	153		256	37	213
10-Jan-95	278	200	201	442	173	620	212	298
30-Jan-95			151	174				
27-Feb-95				103			39	
6-Mar-95				179			63	
7-Mar-95	275		215	190		543		177
8-Mar-95			394				107	
17-Mar-95			169				34	
30-May-95						328	36	
9-Jun-95			162		157			172
8-Mar-96			163		112			
27-Oct-97		185	203	164	165		40	148
17-Aug-98			114		100			130
20-Aug-98		105	163	96	106			637
21-Aug-98	257	216	356	170	329	314	71	
26-Aug-98		115	126		185			195
27-Aug-98	246	285	221	130		318	53	610
3-Sep-98		122			149	586		301
10-Sep-98	293	282	198	173	113	321	45	281
17-Sep-98		187			172			270
1-Oct-98		116		130				
5-Oct-98		104		114				
13-Jan-99	240	209	168	156	142			186
21-Jan-99		198			87			
12-Jul-01	327				108			
21-Jun-02	294	193						

Figure 1

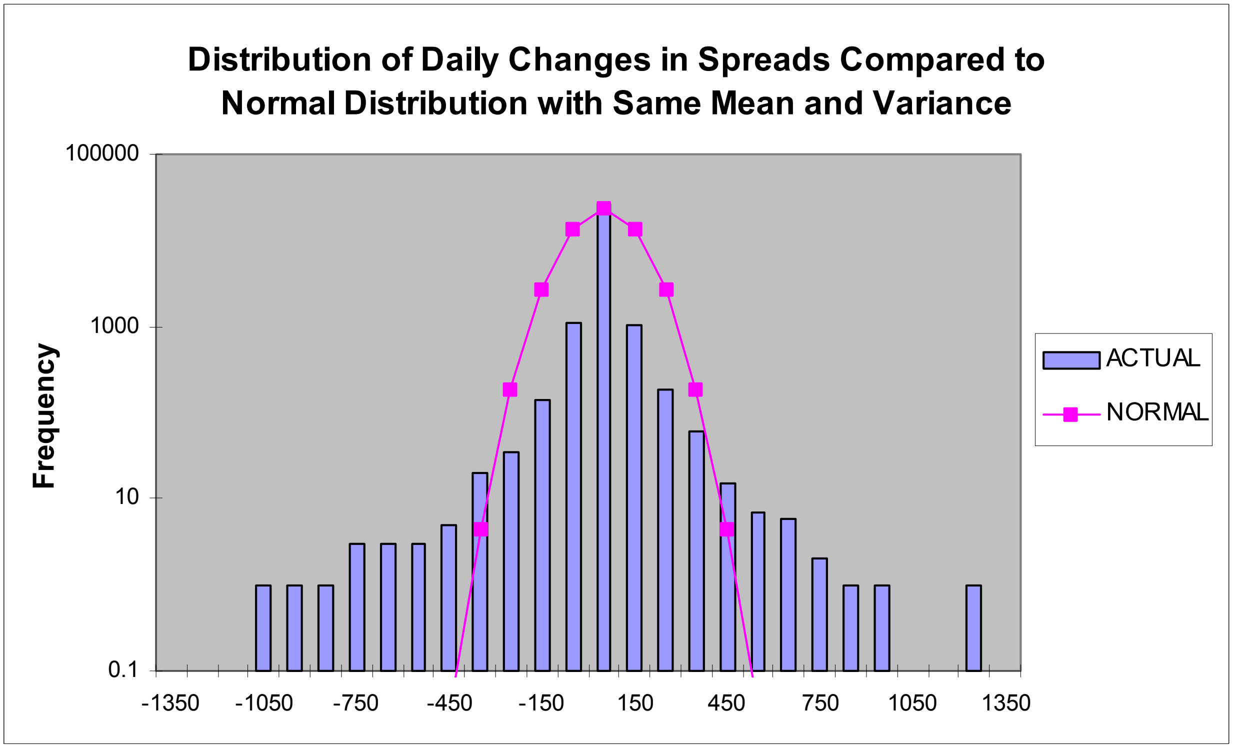


Figure 2

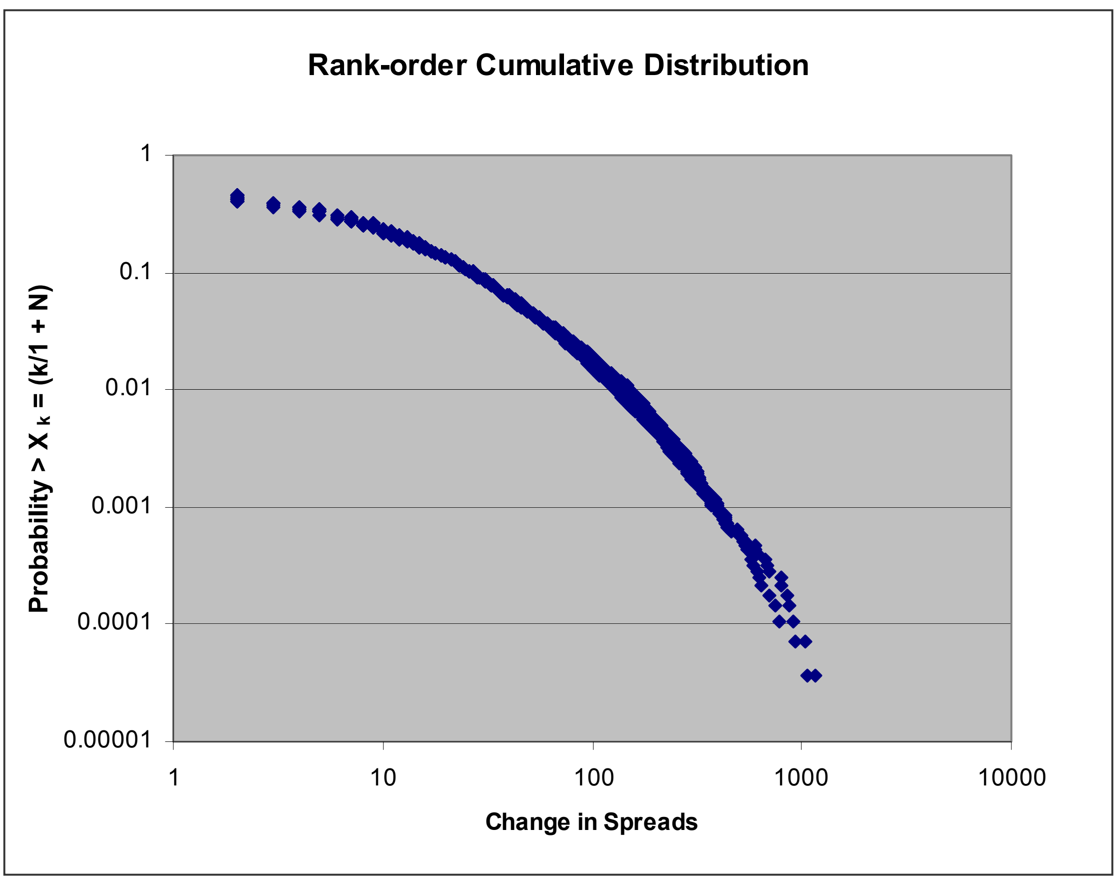
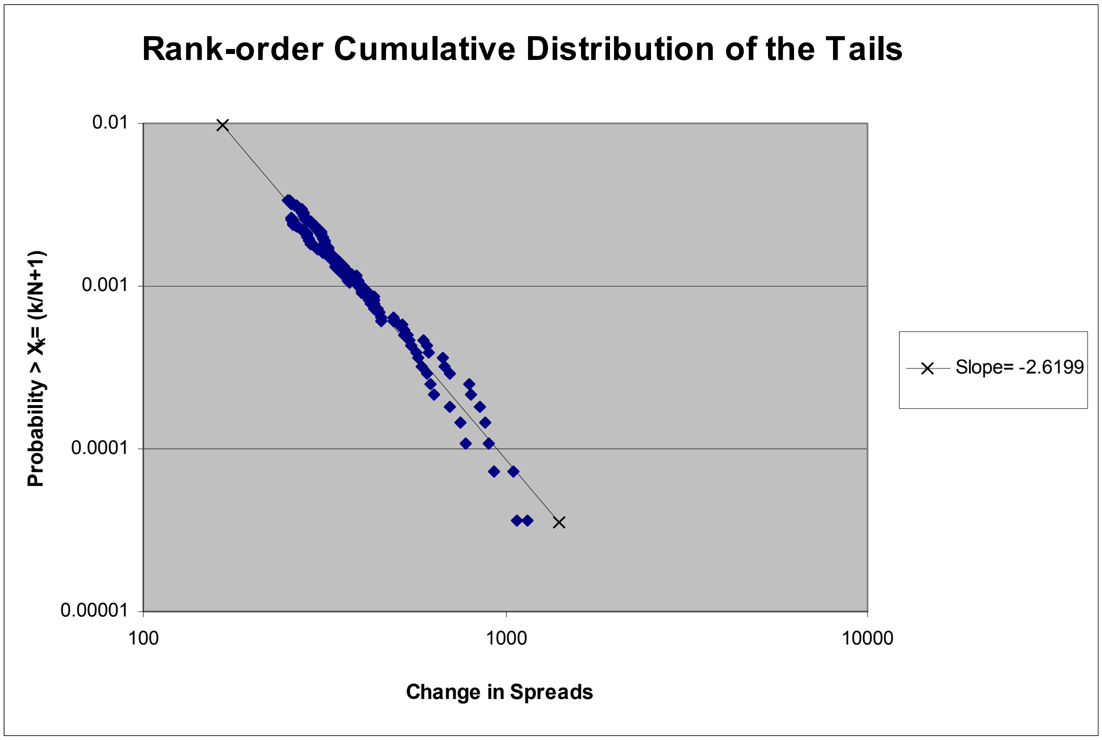


Figure 3



Rank-order Cumulative Distribution of the Tails
0.01
0.001
0.0001
0.00001
Probability > Xk= (k/N+1)
100
1000
10000
Change in Spreads
Slope= -2.6199

Figure 4. Distribution of Daily Changes in Spreads, Nov. 1, 1994 – July 19, 2002

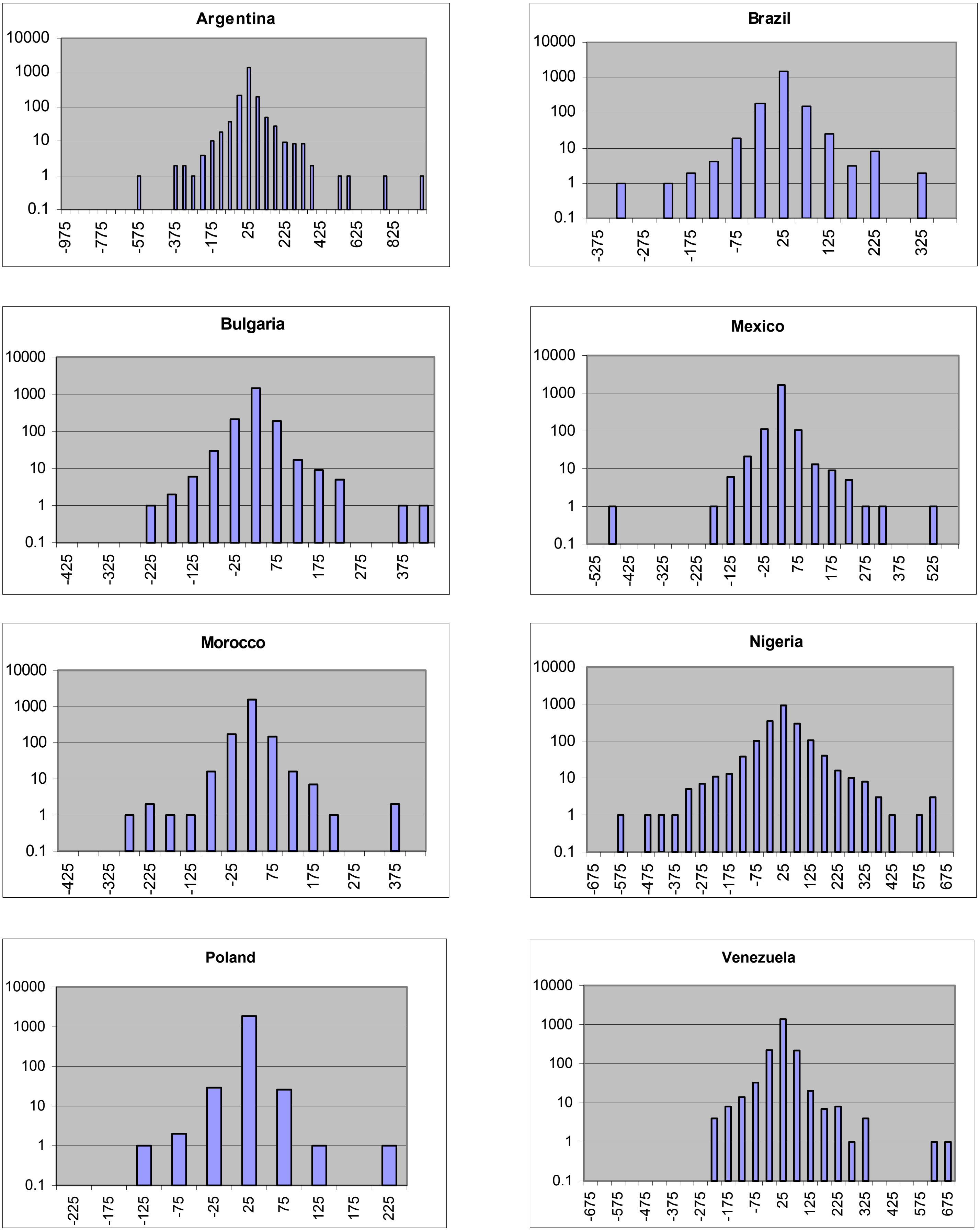


Figure 5

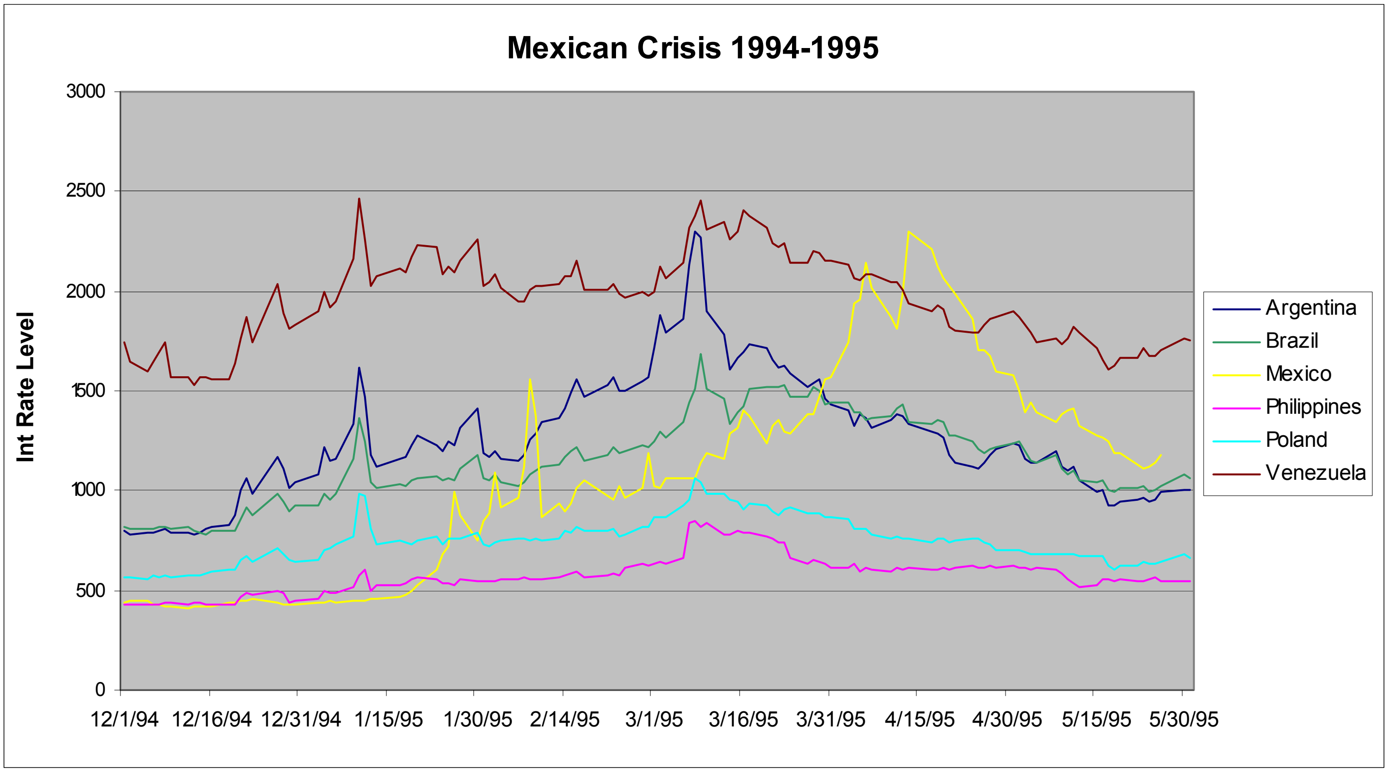


Figure 6

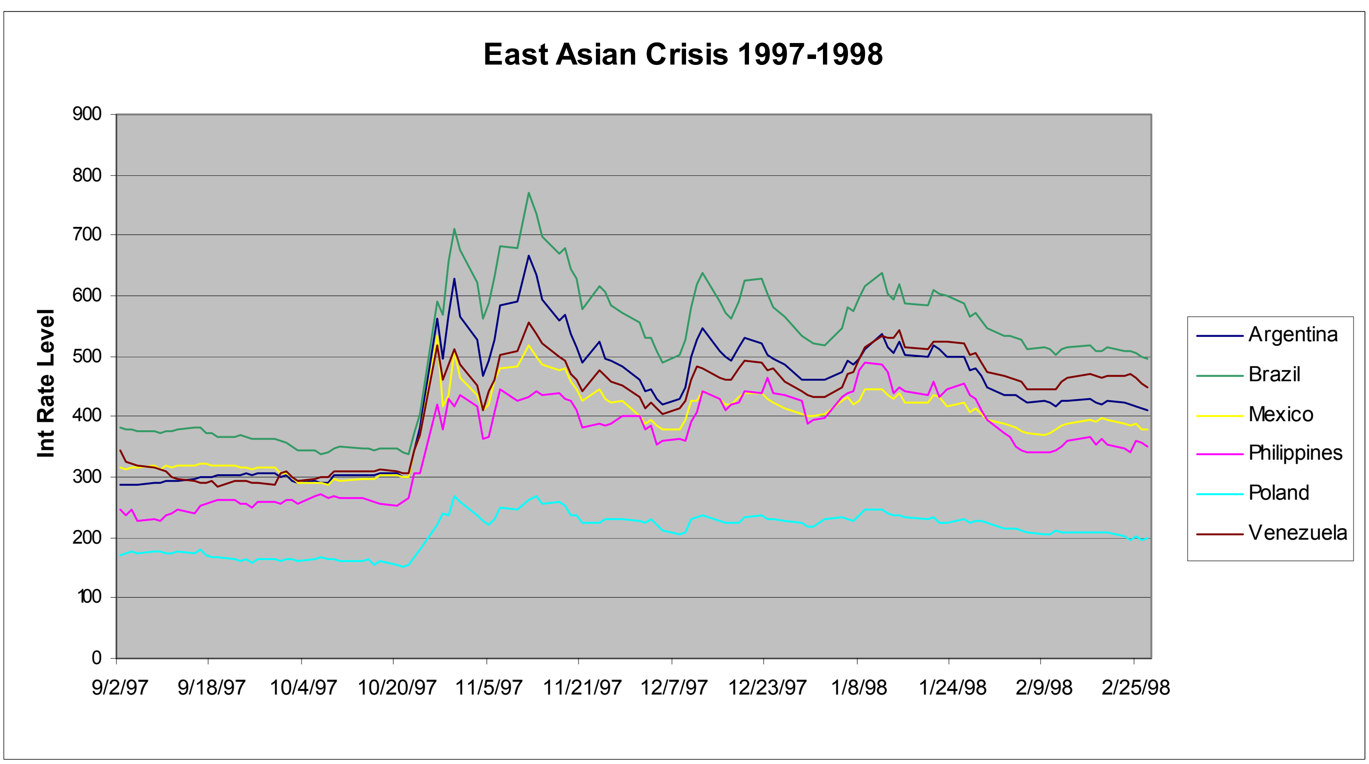


Figure 7

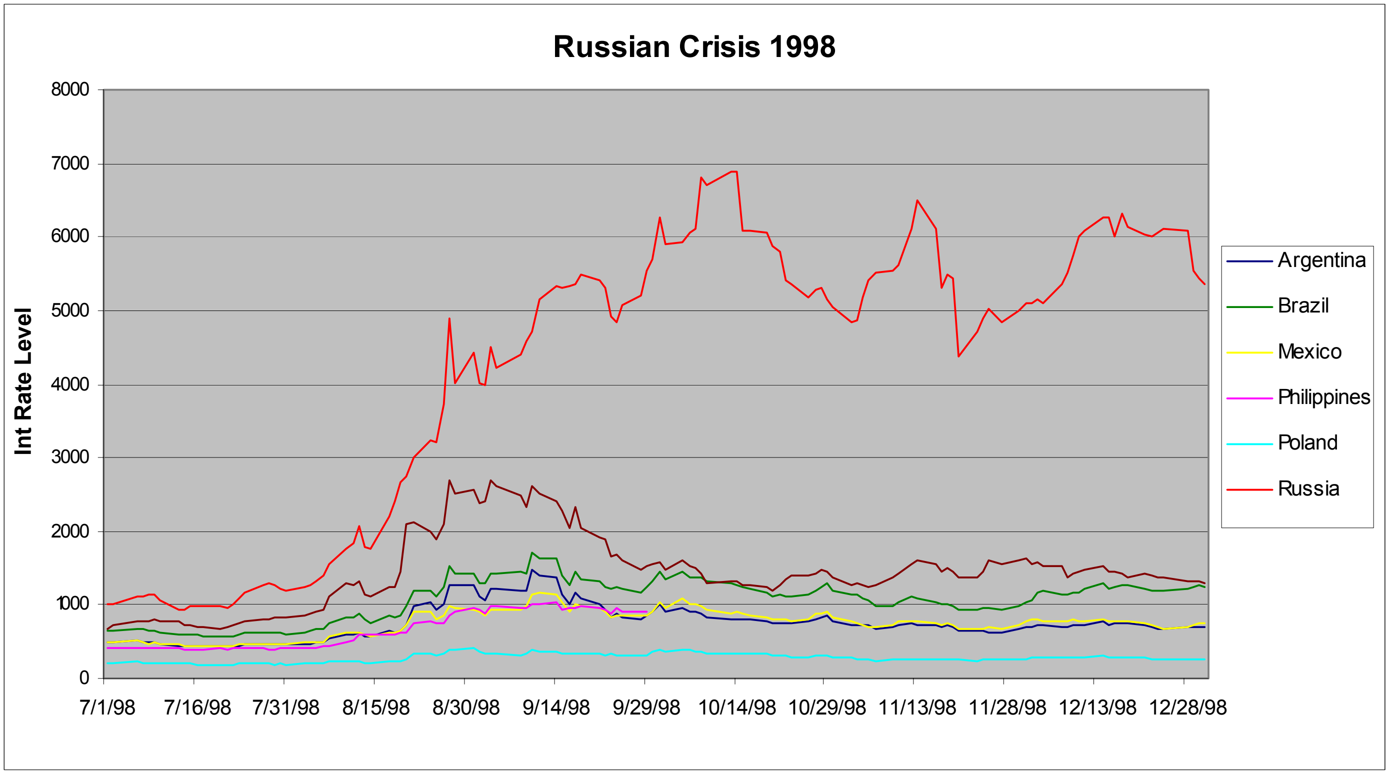


Figure 8

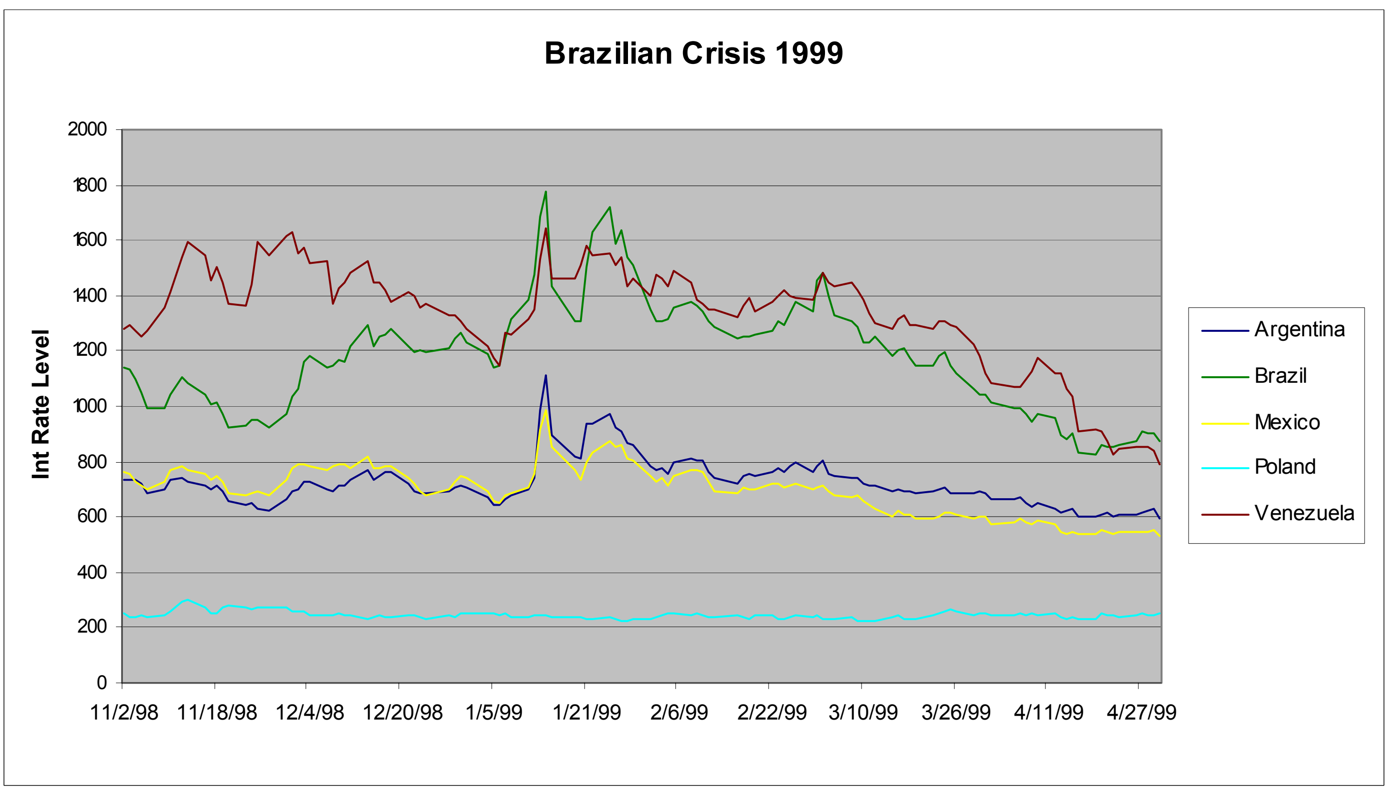
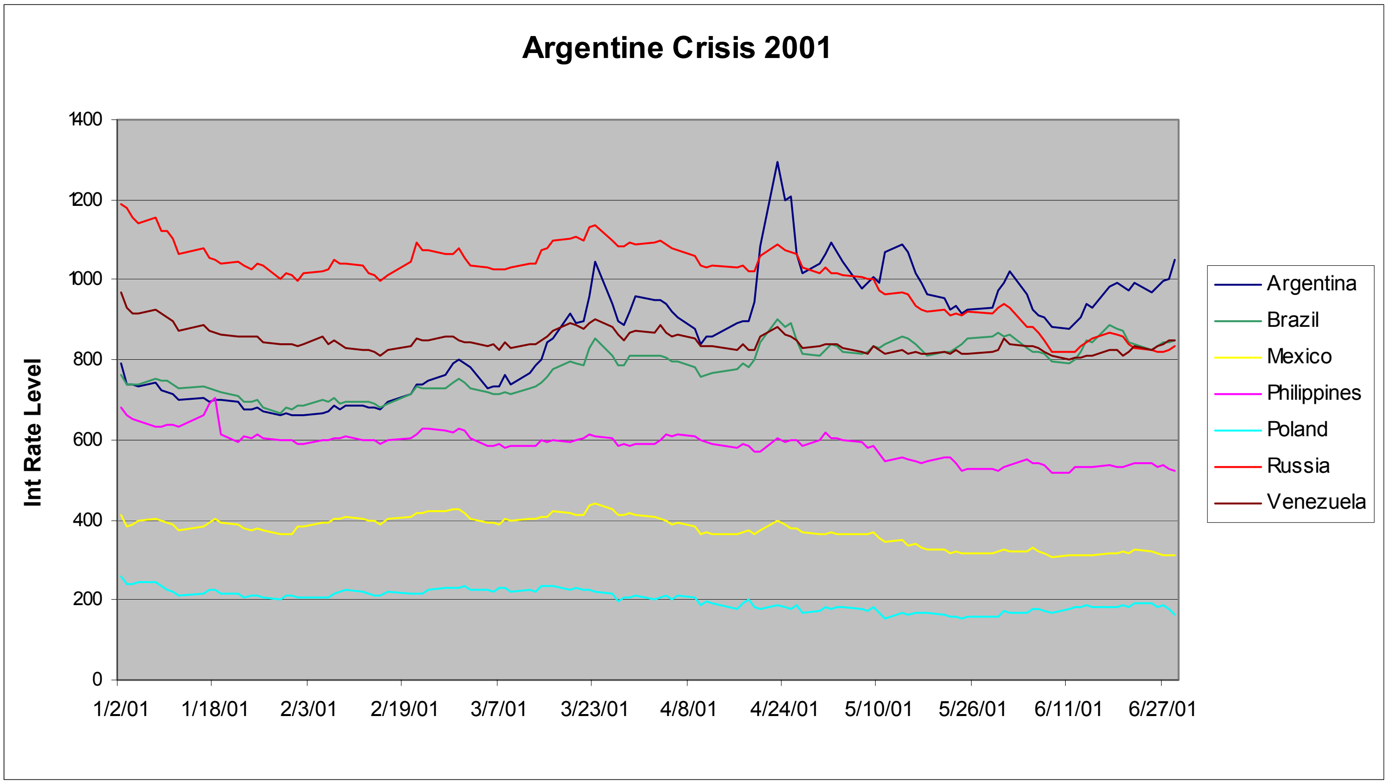


Figure 9



Argentine Crisis 2001
Int Rate Level
1400
1200
1000
800
600
400
200
0
1/2/01
1/18/01
2/3/01
2/19/01
3/7/01
3/23/01
4/8/01
4/24/01
5/10/01
5/26/01
6/11/01
6/27/01
Argentina
Brazil
Mexico
Philippines
Poland
Russia
Venezuela

Figure 10

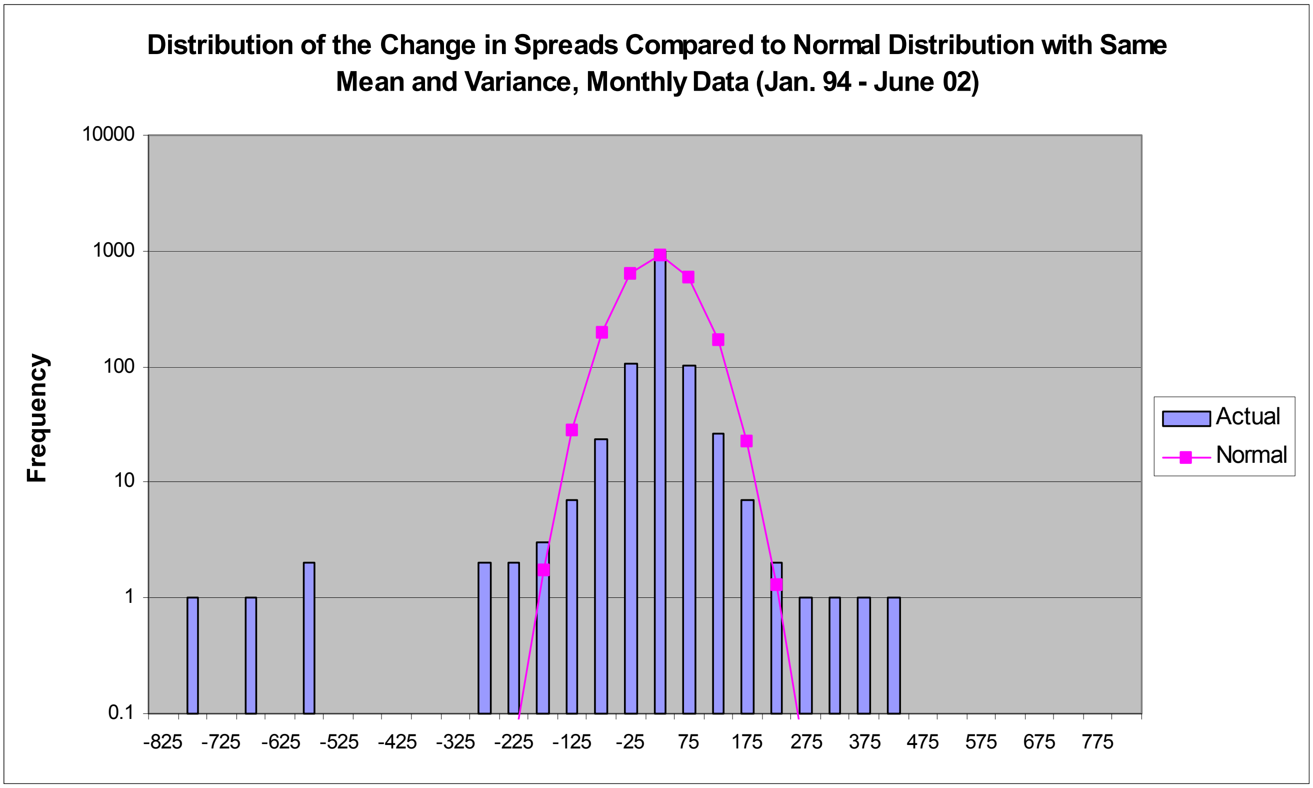


Figure 11. Distribution of Simulated Monthly Changes in Spreads, Market Maker Model (RUN 3) (1300 Observations)