EXTREME OBSERVATIONS AND DIVERSIFICATION IN LATIN AMERICAN EMERGING EQUITY MARKETS

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ABSTRACT

In this paper, we focus on the tails of the unconditional distribution of Latin American emerging markets stock returns. We explore their implications for portfolio diversification according to the safety first principle, first proposed by Roy (1952). We find that the Latin American emerging markets have significantly fatter tails than industrial markets, especially, the lower tail of the distribution. We consider the implication of the safety first principle for a U.S. investor who creates a diversified portfolio using Latin American stock markets. We find that a U.S. investor gains by adding Latin American equity markets to her purely domestic portfolio. For different parameter specifications, we find a more realistic asset allocation than the one suggested by the literature based on the traditional mean-variance framework.

JEL: G15, G12.

Keywords: Portfolio diversification, Extreme value theory, Emerging markets.

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1. INTRODUCTION

The well documented high average stock returns and their low correlations with industrial markets seem to make emerging equity markets an attractive choice for diversifying portfolios. De Santis (1993) finds that adding assets from emerging markets to a benchmark portfolio consisting of U.S. assets creates portfolios with a considerable improved reward-to-risk performance. Harvey (1995a) finds that adding equity investments in emerging markets to a portfolio of industrial equity markets significantly shifts the mean-variance efficient frontier to the left. Within the context of a traditional mean-variance context, Harvey (1994) provides a detailed analysis of conditional and unconditional asset allocation that includes emerging markets. He finds that the optimal unconstrained weights for emerging markets increase over time from 40% in 1980 to almost 90% in 1992. The above results seem to contrast with the also well documented "home bias," see French and Poterba (1991) and Tesar and Werner (1995a, 1995b). In particular, Tesar and Werner (1995b) study U.S. equity flows to emerging stock markets and find that the U.S. portfolio remains strongly biased toward domestic equities.

In this paper, we follow the Jansen, Koedijk and de Vries (1996) to explore the implications of the *safety first* criterion in an international asset allocation context. Roy (1952) introduced the safety first criterion, which was further developed by Arzac and Bawa (1977). Under the safety first criterion, an investor minimizes the chance of a very large negative return, a return that, if realized, would reduce the investor's portfolio value below some threshold level. A safety first investor might be worried about a one-time large event that might drive her or her firm out of business. The safety first rule might be more appropriate for investors investing in emerging markets than in well established markets because emerging markets equity distributions are greatly influenced by extreme returns.[1] As shown in this paper, one of the differences between emerging and industrial markets is the behavior of extreme returns. These observed

[1] Harvey (1995a, 1995b) and Claessens et al. (1995) document that emerging markets returns significantly depart from normality. This departure from normality is greatly influenced by the behavior of extreme returns.

extreme returns produce a fatter tail empirical distribution for emerging markets stock returns than for the industrial markets.

Fat tails for stock returns in industrial markets have been extensively studied. Mandelbrot (1963) and Fama (1965) point out that the distribution of stock returns has fat tails relative to the normal distribution. Mandelbrot (1963) proposes a non-normal stable distribution for stock returns, in which case the variance of the distribution does not exist. Blattberg and Gonedes (1974) and, later, Bollerslev (1987), in an ARCH context, propose the Student-t distribution for stock returns, which has the appeal of a finite variance with fat tails. Jansen and de Vries (1991) and Loretan and Phillips (1994) use extreme value theory to analyze stock return in the U.S. Their results indicate the existence of second moments and possibly third and fourth moments, but not much more than the fourth moment. Jansen et al. (1996), JKV thereafter, and De Haan et al. (1994) use extreme value theory to operationalize the safety first rule in portfolio selection. They show that using extreme value theory allows calculations of the probability of extreme events, even for an event for which there is no in-sample observation. This approach is very useful for decision makers that worry about the possible occurrence of an extreme event.

In this paper, we focus on Latin American emerging markets. These markets are of particular interest to U.S. investors. Among emerging markets, they have been the largest recipients of U.S. net purchases of foreign equity from 1978 till 1991, see Tesar and Werner (1995b). De Santis (1993) finds that the Latin American markets are associated with the largest gain in portfolio performance to a U.S. investor who wants to diversify a purely domestic portfolio. In addition, these markets have undergone substantial changes in financial regulations and macroeconomic policies. We find that emerging markets have fatter tails than industrial markets. The tail estimates suggest that the distribution of Latin American emerging markets might not have second moments. Using JKV's methodology, we also find that a U.S. investor gains by adding Latin American equity markets to her purely domestic portfolio. For different parameter specifications, however, we find a Latin American portfolio weight of 15%, which is a more realistic asset allocation than the one suggested in the literature based on the traditional mean-variance framework.

This paper is organized as follows. Section 2 briefly introduces the safety first principle and the JKV approach to operationalize it. Section 3 describes the data and performs a preliminary analysis of the series. Section 4 summarizes the results. Section 5 concludes the paper.

2. SAFETY FIRST AND EXTREME VALUE THEORY

2.1 Safety First[2]

Suppose an investor's initial wealth and initial value of asset j are W_o and $V_{o,j}$, respectively. This investor can invest in the risky assets with weights ω_j's or borrow and lend an amount b at the free-risk rate r (b>0 represents borrowing). A safety first investor specifies a disaster level of wealth, s, and the maximal acceptable probability of this disaster, δ. Let $W_{1,j}$ be the random final value of asset j and let μ be the expected return of the portfolio, i.e., μ=E(R). Arzac and Bawa (1977) study the implications of a lexicographic form of the safety first principle.

$$\max_{w_j,b}(p,m) \quad s.t. \sum_j w_j V_{o,j} - b = W_o, \qquad (1)$$

where

$\pi = 1$, if $P = \text{Prob}(\Sigma_j \ \omega_j V_{1,j} - br \leq s) \leq \delta$,

$\pi = 1-P$, otherwise.

The safety first condition can be written as

$$\text{Prob}(R \leq q_\delta(R)) \leq \delta, \qquad (2)$$

where R is the return of the investor's portfolio, and $q_\delta = r + (s-W_o r)/(W_o+b)$. The return of the portfolio can only be less than the quantile q_δ with probability δ. The safety first principle is violated whenever

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[2]This section is based on Arzac and Bawa (1977).

$$q_d(R) < r + \frac{s - W_o r}{W_o + b}. \tag{3}$$

Arzac and Bawa (1977) show that a risk averse safety first investor can solve the optimization problem in two stages. First, the investor maximizes the ratio of the risk premium to the return opportunity loss that she can incur with probability δ,

$$\max_{w_j} \frac{E(R) - r}{r - q_d(R)} \tag{4}$$

and determine the optimal weights, the ω_j's. In the second stage, the investor determines the amount to be borrowed from the budget constraint and the scale of the risky part of his/her portfolio from

$$W + b = \frac{s - W_o r}{q_d(R) - r}. \tag{5}$$

In order to derive testable implications for the safety first theory, it is necessary to specify the δ-fractile of the portfolio in terms of estimable characteristics of the risky assets. Roy (1952) and Arzac and Bawa (1977) proposed using the Tchebychev inequality to approximate the tail of the risky portfolio distribution from above. As shown by JKV, the Tchebychev bound may be a poor approximation to the exact bound. They improve the bound by using extreme value theory.

2.2 Extreme value theory[3]

Consider a stationary sequence of X_1, X_2,..X_n of i.i.d random variables with distribution function F(.). We want to find the probability that M_n , the maximum of the first n random variables, is below a certain value x (M_n could be multiplied by -1 if one is interested in the minimum). We denote this probability by

[3] This section is based on JKV, Section III.

$P(M_n<x) = F^n(x)$.The distribution function $F^n(x)$, when suitably normalized and for large n, converges to a limiting distribution G(x), where G(x) is one of three asymptotic distributions, see Leadbetter, Lindgren and Rootzen (1983). Since returns on financial assets are fat tailed, Koedijk et al. (1990) and JKV consider the limiting distribution of G(x) which is characterized by a lack of some higher moments:

$$G(x) = 0, \qquad \text{if } x \leq 0. \tag{6}$$

$$= \exp(-x)^{-1/\gamma} = \exp(-x)^{-\alpha}, \qquad \text{if } x>0,$$

where $\gamma=1/\alpha>0$ and α is the tail index. Leadbetter, Lindgren and Rootzen (1983) show that when the dependence among the X_i's is not too strong, this limiting distribution is valid. The Student-t with finite degrees of freedom, the stable distribution, and the stationary distribution of the ARCH process are in the domain of attraction of the limit law G(x). The tail index α can be estimated and indicates the number of moments that exist.

To estimate α we use Hill's (1975) moment estimator. We first obtain the order statistics $X_{(n)}$, $X_{(n-1)}$,..., $X_{(1)}$ from our sample, where $X_{(n)}>X_{(n-1)}>...> X_{(1)}$, etc. Then, the Hill estimator is given by:

$$\hat{g} = \frac{1}{m}\sum_{i=1}^{i=m} \ln(X_{n+1-i}) - \ln(X_{n-m}), \tag{7}$$

where m is the number of upper order statistics included. The Hill estimator can be applied to either tail of a distribution by calculating order statistics from the opposite tail and multiplying the data by -1. We can also combine the tail observations (by taking absolute values) to estimate a common α. Goldie and Smith (1987) show that $(1/\hat{a} - 1/\alpha)m^{1/2}$ is asymptotically normal $N(0,\gamma^2)$ if m increases suitable as n tends to infinity.

One critical aspect of the Hill estimator is the choice of m. We use a bootstrap procedure proposed by Hall (1990), which is also used by JKV. After calculating α we estimate the quantiles q_p using the following formula:

$$q_p = X_{(n-m)}\left(\frac{m}{pn}\right)^{\hat{\gamma}}. \tag{8}$$

This formula estimates the quantiles q_p that will only be exceeded with probability p.

Tail estimates using extreme value theory have been estimated for exchange rates by Hols and de Vries (1991) and Koedijk et al. (1990), and for stock returns by Jansen and de Vries (1991) and JKV.

3. DATA

Data of weekly returns of stock indexes from six industrial and four emerging Latin American markets are obtained from Morgan Stanley Capital International (MSCI). The sample covers the period from the last week of August 1989 to the third week of April 1996. We take 1989 as our starting date because prior to 1989 equity markets in Latin America were almost inaccessible for direct investments by foreign investors. They were accessible primarily through country funds. The return on each market is computed based on a value-weighted portfolio of securities that trade in that market. Since Latin American countries have experienced high inflation and high inflation volatility, we use returns expressed in U.S. dollars. All indexes are constructed so as not to double count those stocks multiple-listed on foreign stock exchanges. Stocks are selected for inclusion on the basis of liquidity and market value.

Table 1, Panel A shows univariate statistics for the data. We note the usual high return-high standard deviation characteristic of emerging markets. We test for normality using the Jarque-Bera (1980) test, JB, which follows a chi-squared distribution with two degrees of freedom. Although for both series normality is rejected by the JB, in emerging markets the rejection is stronger.[4] This stronger rejection arises mainly from higher kurtosis. Panel A also shows the first autocorrelation coefficient, RHO, and Ljung-Box (1978), LB(q), autocorrelation tests. The LB is used as a quick check of the autocorrelation structure of the series.[5] The first order autocorrelation coefficients and the LB tests, for mean returns, for both Latin American emerging markets and industrial markets are quite similar, and, with the exception of Argentina and Mexico, there is no evidence for autocorrelation. For the squared returns, however, the LB test rejects the no autocorrelation null hypothesis in all the markets with the exception of the U.K., Australia, and Canada. Latin American emerging markets tend to show even higher squared autocorrelations. In Table 1, Panel B, we analyze the impact of large positive and negative observations in our sample by leaving out of the analysis the five largest and five smallest observations. All the industrial markets, with the exception of Japan and Australia, pass the JB normality test, while among the Latin American emerging markets, only Chile passes the JB normality test. The source of non-normalities in Argentina, Brazil, and Mexico does not seem to be driven solely by a few extreme observations.

Table 2 focuses on the extreme observations in our sample. Four our purposes, extreme observations are defined as observations, which are outside of two standard deviations. Under normality, the expected total number should be around 17. Table 2 shows that the Latin American emerging markets tend to have a lower total number of extreme observations than the industrial markets, although they are not statistically different. Table 2 also shows the number of single extreme observations, where a single extreme observation is defined as an extreme observation not followed or preceded by another extreme observation in four weeks. Again, with the exception of Germany, this number is smaller for the emerging markets

[4]Harvey (1995b) and Claessens et al. (1995) test for normality using different tests. They reject normality for many emerging markets.

[5] The LB test should be carefully interpreted. The LB test can be misleading if the innovations follow heavy tailed distributions. The statistic might not converge in probability to the usual chi-squared distribution.

than for the industrial markets. This result shows that the Latin American emerging markets tend to have the extreme observations more clustered than the industrial markets. For example, in Argentina out of eighteen extreme observations only three are single extreme observations. In contrast, in the U.K., eleven extreme observations out of eighteen are single extreme observations. The last eight columns of Table 2 show the two largest returns, the 95% percentile, the 90% percentile, the two smallest returns, the 5% percentile, and the 10% percentile from each series. We find that, in absolute value, the two smallest returns tend to be larger than the two largest returns. This behavior of the extreme observations seems to reverse faster in emerging markets than in industrial markets, as the percentile in Table 2 show. We also find that the two largest returns tend to be closer than the two smallest returns. Of particular relevance to investors is the behavior of large negative returns. In the Latin American emerging markets, we find that the second smallest return is at least 40% larger than the minimum return. In industrial markets, however, the second smallest return is on average 14% larger than the minimum return. We conclude that one of the main differences between Latin American emerging markets and industrial markets is given by the behavior of the returns on the tails of the distribution, especially on the lower tail. In the rest of the paper, to save space in the tables, we will keep Japan, U.K. and U.S. as representatives of industrial markets.

Table 3 shows the correlation matrix for returns and squared returns.[6] Panel A shows the typical low correlation of stock returns in emerging markets and industrial markets. The regional correlations are on average larger than the correlations with developed markets. These low correlations are usually interpreted as an indication of potential benefit for international portfolio diversification. With few exceptions, Panel B shows consistently lower correlations for squared returns. Engle and Susmel (1993) show that higher correlations for the squared returns than correlations for the level returns might be indicating the existence of common time-varying components in the variance. From that perspective, the results in Panel B show no evidence of common time-varying volatility in Latin American emerging

[6] Note that the covariance of squared returns maybe a misleading measure if the returns have as

markets or in the industrial markets.

4. TAIL ESTIMATES AND THEIR IMPLICATIONS TO INVESTORS

4.1 Tail estimates

Table 4 reports our estimates of the tail index of the returns' distribution. The upper tail, α_+, the lower tail, α_-, and the common tail, α, are reported in the first, second and third columns, respectively. Below each point estimate, we report standard errors and the number of order statistics used to estimate the tail index, m.

The lower tail tends to be fatter (smaller) than the upper tail. This is especially true for all Latin American emerging markets. With the exception of Mexico, the equality of both tails, however, cannot be rejected. More important, both tails tend to be fatter for the Latin American emerging markets than for the industrial markets. More important, this result is true for the lower tail and common tail. We also test for the existence of second moments. If α is significantly lower than two, the equity returns do not have second moments. The test is a one-sided test and follows a standard normal distribution under the null hypothesis. The null hypothesis is clearly rejected for industrial markets and for Brazil and Chile. It cannot be rejected for Mexico and Argentina.

We calculate exceedence levels for different probabilities. The exceedence levels are calculated using equation (7). Recall that exceedence levels are returns that can only be achieved with a given probability. We use as probabilities for the exceedence levels multiples of the inverse of the sample size, n=346. In the last three columns of Table 4 we report these calculations. For example, focusing on Chile, the fifth column indicates that with probability 0.29% (1/346) we can observe a negative return of -18.9%. That is, in the Chilean case, there is a 1 in 346 chance that an investor will observe a weekly return of -18.9% or less. Note, that the exceedence level is substantially higher than the minimum observation for Chile in the

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heavy tails as is shown, later, in Table 4.

sample, -33.40% (see Table 2). The Chilean exceedence level has an associated 95% confidence interval of (-12.0%, -49.4%). Similarly, for Chile, the sixth column indicates that there is an almost .0015 (1/692) chance that an investor would experience a weekly return of -26.7% or less. The associated 95% confidence interval for this exceedence level is (-15.5%, -84.9%). Now, focusing on the U.S., the fifth column shows that there is a 1/346 probability of observing a negative return of -6.2%. Again, the estimated exceedence level for the U.S. is above the minimum U.S. observation in the sample, -7.82%. The U.S. exceedence level, however, has a 95% confidence interval of (-4.6%, -11.8%). From the last three columns in Table 4, we observe that the exceedence levels are quite disperse for Latin American emerging markets. However, 95% confidence intervals on the Latin American exceedence levels are large and, therefore, the differences among Latin American exceedence levels do not seem statistically different. For the industrial markets, the exceedence levels are quite concentrated. Again, confidence bands are such that the differences among industrial markets exceedence levels do not seem to be statistically different.

We want to test the structural stability of the tail estimates for Latin American equity markets. These markets have experienced substantial deregulation and liberalization during the past six years. We test for Argentina and Brazil, the two markets that we have enough observations to do a sensible estimation, if the tail index has changed. For Argentina, the tail index is 2.63 before liberalization and 2.99 after liberalization. For Brazil, the tail index is 2.60 before liberalization and 2.80 after liberalization. Even though there is a mild decrease in the fatness of the tail, a formal test cannot reject the equality of the indexes before and after economic reform. These results complement previous results, using monthly data, that do not observe any significant change in volatility, see De Santis and Imrohoroglu (1997) and Bekaert and Harvey (1995, 1997). However, they seem to contradict Hargis (1994), who also uses weekly stock returns for the same Latin American markets. Hargis (1994) reports a decrease in volatility after liberalization.

4.2 *Safety first portfolio diversification*

In this section, we study the diversification possibilities which the Latin American emerging markets afford a U.S. safety first investor. For simplicity, assume that the U.S. investor is considering investing in an equally weighted Latin American Index. In the U.S., the investor can lend or borrow at the risk-free rate, r, which we take as the weekly 90-day LIBOR. We construct 21 portfolios, increasing the percentage of the investment in the Latin American Index from 0% to 100% by increments of 5% (for brevity we do not report all the portfolios). As pointed out by JKV, the tail index, α, is unaffected by forming these portfolios, since the fattest tail dominates the portfolio. In Table 5, however, we estimate all the tail indexes for all portfolios. As it can be seen, for portfolios composed of 25% or more of the Latin American Index, the lower tail estimates are dominated by the Latin American markets, i.e., the tail index is close to two. For portfolios composed of 20% or less of the Latin American Index, the contribution of the Latin American markets is too small to dominate the U.S. Index, and therefore, the tail of the portfolio is very similar to the U.S. tail.

In order to study the implications of the safety first principle for the U.S. investor, we need to specify the parameter values of δ and s. First, we assume that δ is equal to .0029 (once every 6.7 years, or a 1 in 346 chance).[7] Second, we use two conservative values of s: .9W and .95W. For both levels of δ, the optimal investment in the Latin American Index is 15%.[8] This allocation can be compared with a standard mean-variance allocation of 32% for the Latin American Index. The return on the optimal safety first risky portfolio is .002239% a week. The exceedence levels for the safety first optimal risky portfolio is -.057 for δ=.0029. Finally, we have to determine b, which depends on s. For example, for δ=.0029 and s=.95,

[7] We use different values for δ. The results do not change substantially.

[8] This percentage is consistent with the caps used in several global investment funds and with the cap used in Harvey (1994).

b=(.95W-.943W)/(.001-.057)=-.128W, that is, the U.S. investor will be lending, at the risk free rate, 12.8% of her initial wealth. The return on the total portfolio is (.872 x 1.002239) + (.128 x 1.001) = 1.00209. If the worst happens, the U.S. investor's final wealth is (.872 x .943)W + (.128 x 1.001)W = .9504W, or 95 percent of the initial wealth as expected.

Now, we assume that our investors specifies a lower δ: .0014 (a 1 in 692 chance). We use s=.95W. For this levels of δ, the optimal investment in the Latin American Index is, again, 15%. The return on the optimal safety first risky portfolio is .002239% a week. The exceedence levels for the safety first optimal risky portfolio is -.072. Note that as the exceedence level increases, in absolute terms, the amount invested in risky assets decreases. The amount to be borrowed is b=-.3098W, that is, the U.S. investor will be lending, at the risk free rate, 30.98% of her initial wealth. The expected return on the total portfolio is (.6902 x 1.002239) + (.3098 x 1.001) = 1.001855. If the worst happens, the U.S. investor's final wealth is (.6902 x .928)W + (.3098 x 1.001)W = .9506W, or 95 percent of the initial wealth as expected.

The safety first principle puts constraints on the amount invested by investors in risky assets. For example, suppose a U.S. investor decides to invest 100% of her wealth in the Latin American Index. For δ=.0029, a 100% investment in the Latin American Index has an exceedence level equal to -.322. With s=.95W and δ=.0029, our investor will determine b =(.95W-.678W)/(.001-.322)=-.847W. If the catastrophe strikes, the U.S. investor's final wealth is (.153 x .678)W + (.847 x 1.001)W = .9516W, or 95 percent of the initial wealth as expected. The expected return of this portfolio, however, is (.153 x 1.0039025) + (.847 x 1.001) = 1.001444, which is lower than the optimal safety first allocation.

We also estimate the optimal safety first allocation for two additional Latin American Indexes: a value weighted portfolio and a GDP weighted portfolio. Table 6 compares the allocations to the traditional mean-variance allocation. Using the value weighted Latin American Index, the safety first allocation for the Latin American Index is, again, 15%, which is almost half the allocation for the Latin American Index determined by the traditional mean-variance analysis. Using the GDP weighted portfolio, however, the safety first allocation for the Latin American Index is 5%, which is considerable smaller than the 54% mean-variance allocation.

5. CONCLUSIONS

In this paper, we analyze Latin American emerging markets from a different perspective. We focus on the tails of the unconditional distribution of stock returns. We also explore the implications for portfolio diversification of the safety first principle. First, we find that the Latin American emerging markets have significantly fatter tails than industrial markets. This result is especially true for the lower tail of the distribution. Second, we consider a simple exercise to analyze the implication of the safety first principle for a U.S. investor who wants to diversify his/her domestic portfolio using Latin American markets. For different parameter specifications, we find that the safety first principle obtains an optimal portfolio weight of 15% for all Latin American markets.

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TABLE 1. UNIVARIATE STATISTICS

A. Full Sample

MARKET	MEAN	S.D.	SK	EK	JB	RHO	LB(6)	LBS(6)
I. L.A. Emerging Markets								
ARGENTINA	.417	8.87	-0.33	9.86	5590.7*	-.05	16.54*	55.38*
BRAZIL	.287	8.98	-1.29	8.24	3901.6*	.06	7.57	53.62*
CHILE	.525	4.36	-0.13	20.92	25175.2*	-.08	8.27	87.27*
MEXICO	.332	4.77	-1.45	8.86	4635.1*	.11	20.99*	10.37
II. Industrial Markets								
AUSTRALIA	.087	2.28	0.09	0.43	11.3*	-.08	10.51	10.02
CANADA	.024	1.71	-0.11	0.99	57.0*	-.08	9.69	3.40
GERMANY	.170	2.51	-0.50	1.81	203.6*	-.01	5.51	63.02*
JAPAN	-.038	3.53	-0.34	3.25	613.8*	.06	4.86	28.30*
U.K.	.122	2.24	-0.01	1.39	111.0*	-.06	3.06	6.58
U.S.	.178	1.62	-0.46	2.15	277.0*	-.06	5.08	37.89*
WORLD	.097	1.70	-0.45	2.22	295.0*	-.02	3.84	115.64*

TABLE 1. UNIVARIATE STATISTICS (continuation)

B. Truncated Sample -five largest and five smallest observations dropped-

MARKET	MEAN	S.D.	SK	EK	JB	Max	Min
I. Latin American Emerging Markets							
ARGENTINA	.468	6.67	0.25	1.11	71.7*	23.58	-19.35
BRAZIL	.480	7.15	-0.27	0.43	14.5*	17.82	-22.68
CHILE	.549	2.93	0.23	0.19	5.0	9.21	-8.20
MEXICO	.447	3.81	-0.29	0.33	11.0*	9.99	-12.14
II. Industrial Markets							
AUSTRALIA	.078	2.05	0.02	-0.33	6.0*	5.33	-4.79
CANADA	.038	1.50	0.12	0.29	5.4	3.63	-4.18
GERMANY	.196	2.18	-0.28	0.01	4.4	5.60	-6.36
JAPAN	-.022	2.95	-0.23	0.46	14.6*	7.88	-8.94
U.K.	.119	1.96	-0.10	0.11	1.2	5.01	-4.74
U.S.	.145	1.40	-0.16	0.09	1.1	3.62	-3.65
WORLD	.105	1.46	-0.30	0.10	5.6	3.80	-4.31

Notes:
* significant at the 5% level.
SK: Skewness coefficient.
EK: Excess kurtosis coefficient.
JB: Jarque-Bera (1980) normality test.
RHO: First order autocorrelation coefficient.
LB(6): Ljung-Box statistic with 6 lags for levels.
LBS(6): Ljung-Box statistic with 6 lags for squared series.

TABLE 2. EXTREME OBSERVATIONS

MARKET	Total	Single	max1	max2	max5%	max10%	min10%	min5%	min2	min1
I. Latin American Emerging Markets										
ARGENTINA	18	3	42.84	41.02	12.18	8.57	-8.08	-11.99	-32.12	-61.75
BRAZIL	15	4	31.32	27.52	13.28	10.11	-9.58	-13.47	-38.24	-66.81
CHILE	11	4	33.79	18.71	6.18	4.62	-3.33	-4.50	-18.40	-33.40
MEXICO	17	5	14.57	13.44	7.39	5.69	-4.64	-6.45	-18.74	-34.54
II. Industrial Markets										
AUSTRALIA	18	6	8.24	6.17	3.85	2.98	-2.84	-3.91	-6.21	-7.12
CANADA	16	12	5.58	4.95	2.95	2.28	-2.07	-2.54	-6.16	-6.27
GERMANY	16	4	8.10	7.49	3.87	3.02	-2.87	-4.39	-8.55	-11.74
JAPAN	20	7	14.92	10.94	5.56	3.96	-3.88	-6.32	-12.37	-18.06
U.K.	18	11	8.62	8.04	3.83	2.59	-2.71	-3.93	-6.34	-7.99
U.S.	19	9	5.70	4.31	2.91	2.18	-1.90	-2.69	-5.72	-7.82
WORLD	19	6	5.28	5.23	2.72	2.01	-2.14	-2.76	-4.88	-8.51

Notes:
Total: total number of observations larger (in absolute value) than two standard deviations.
Single: number of extreme observations not followed nor preceded by another extreme observation in four weeks.
max1: largest observation.
max2: second largest observation.
max5%: 5% fractile of the largest observations.
max10%: 10% fractile of the largest observations.
min1: smallest observation.
min2: second smallest observation.
min5%: 5% fractile of the smallest observations.
min10%: 10% fractile of the smallest observations.

TABLE 3. CORRELATION MATRIX

A.- Levels

	ARG	BRA	CHI	MEX	JAP	U.K.	U.S.	WORLD
ARG	1.000	.083	.159	.228	.042	-.076	.147	.090
BRAZIL		1.000	.132	.271	.102	.054	.171	.170
CHILE			1.000	.208	.014	.120	.113	.093
MEXICO				1.000	.097	.158	.248	.227
JAPAN					1.000	.374	.299	.799
U.K.						1.000	.351	.619
U.S.							1.000	.699
WORLD								1.000

B.- Squared Series

	ARG	BRA	CHI	MEX	JAP	U.K.	U.S.	WORLD
ARG	1.000	.080	.071	-.001	-.020	.321	.026	.022
BRAZIL		1.000	.091	.068	.250	.071	.091	.155
CHILE			1.000	.047	-.029	.039	-.017	-.023
MEXICO				1.000	.020	.016	.093	.119
JAPAN					1.000	.138	.183	.514
U.K.						1.000	.201	.387
U.S.							1.000	.678
WORLD								1.000

TABLE 4. TAIL ESTIMATES

MARKET	α_+	α_-	α	$H_0:\alpha<2$	Lower Tail Exceedence Level (x_p)		
					p=1/n	p=1/2n	p=1/3n
ARGENTINA	2.049 (0.48) m=18	1.989 (0.35) m=32	2.522 (0.58) m=19	1.138	-.467	-.661	-.811
BRAZIL	3.203 (0.92) m=12	2.104 (0.41) m=26	2.663 (0.46) m=33	1.904	-.504	-.701	-.850
CHILE	2.373 (0.44) m=29	2.013 (0.36) m=32	2.513 (0.30) m=71	2.161	-.189	-.267	-.327
MEXICO	3.990 (1.03) m=15	1.789 (0.28) m=42	2.489(0.39) m=41	1.566	-.316	-.466	-.585
AUSTRALIA	4.88 (1.69) m=7	4.731 (1.50) m=10	5.510 (1.47) m=14	6.566	-.067	-.078	-.085
CANADA	4.149 (1.25) m=11	3.353 (0.54) m=38	3.466 (0.71) m=24	3.591	-.059	-.073	-.082
GERMANY	4.141 (1.31) m=10	3.532 (0.98) m=13	3.558 (0.80) m=20	3.484	-.081	-.096	-.106
JAPAN	3.125 (0.76) m=17	3.740 (1.13) m=11	3.111 (1.81) m=22	2.606	-.135	-.168	-.192
U.K.	3.651 (0.91) m=16	4.985 (1.50) m=11	4.404 (0.85) m=27	6.246	-.070	-.081	-.087
U.S.	4.884 (1.47) m=11	3.169 (0.62) m=26	3.984 (0.80) m=25	4.960	-.062	-.077	-.088
WORLD	2.887 (0.58) m=25	2.915 (0.58) m=25	3.307 (0.76) m=19	2.848	-.071	-.091	-.104

Notes:
Standard errors in parenthesis.
* Equality of lower tail and upper tail rejected at the 5% level.

TABLE 5. LOWER TAIL ESTIMATES FOR DIFFERENT PORTFOLIOS

ω_{LA}	SE(α_-)	Exceedence Levels (x_p) and Returns			
		$x_{1/n}$	(R-r)/(r-q)	$x_{1/2n}$	(R-r)/(r-q)
0%	0.622	-.062	.0146	-.077	.0118
5%	0.556	-.061	.0166	-.077	.0133
10%	0.676	-.059	.0188	-.074	.0149
15%	0.704	-.057	.0211+	-.072	.0169+
20%	0.721	-.063	.0201	-.080	.0166
25%	0.405	-.085	.0167	-.118	.0121
30%	0.476	-.089	.0171	-.123	.0124
40%	0.585	-.098	.0177	-.131	.0132
50%	0.464	-.135	.0144	-.192	.0101
60%	0.396	-.182	.0118	-.272	.0079
70%	0.276	-.209	.0113	-.311	.0076
75%	0.291	-.212	.0116	-.310	.0079
80%	0.385	-.257	.0100	-.394	.0065
85%	0.398	-.272	.0098	-.415	.0064
90%	0.315	-.252	.0110	-.368	.0075
95%	0.292	-.280	.0103	-.414	.0069
100%	0.269	-.322	.0093	-.486	.0061

Notes:
ω_{LA}: Proportion of the Latin American Equity Index in the portfolio.
+: preferred portfolio.

TABLE 6. ASSET ALLOCATION FOR DIFFERENT PORTFOLIOS

LA Index	ω_{LA}	
	Mean-Variance Allocation	SF Allocation
Equally Weighted	0.32	0.15
Value Weighted	0.35	0.15
GDP Weighted	0.54	0.05

Notes:
ω_{LA}: Proportion of the Latin American Equity Index in the portfolio.