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RE-EMERGING MARKETS

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ABSTRACT

Recent research shows that emerging markets are distinguished by high returns and low covariances with global market factors. These are striking results because of their immediate implications for the international investor. One key issue is whether these results may be attributed to recent emergence.

Most of today's emerging markets are actually *re-emerging markets*, i.e. markets that attracted international attention earlier in the century, and for various political, economic and institutional reasons experienced discontinuities in data sources.

To analyze the effects of conditioning on recent emergence, we simulate a simple, general model of global markets in which markets are priced according to their exposure to a world factor; returns are only observed if the price level exceeds a threshold at the end of the observation period. The simulations reveal a number of new effects. In particular, we find that the brevity of a market history is related to the bias in annual returns as well as to the world beta. These patterns are confirmed by long-term histories of global capital markets and by recent empirical evidence on emerging and submerged markets. Even though these results can also be explained by alternative theories, the common message is that basing investment decisions on the past performance of emerging markets is likely to lead to disappointing results.

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Introduction

Recent research shows that emerging markets are distinguished by, among other things, high returns and low covariance with global market factors.[1] This is a striking result, because of its immediate implications for the international investor. Emerging markets appear to be very attractive investments since they provide very large expected returns, with or without adjusting for systematic risk. One explanation is that of Bekaert and Harvey (1995), who suggest that the apparent contradiction between low factor loadings and high *ex post* market returns may be due to the pricing of local factors preceding full emergence and integration into the global market.[2] In other words, a global investor with the ability to diversify idiosyncratic risk may take advantage of higher returns demanded by local, poorly-diversified investors. Perhaps this is why private capital flows into emerging countries has reached $210 billion in 1995, a four-fold increase in just five years.

One key issue is whether the stylized empirical facts about emerging markets may be due to conditioning on recent emergence. The challenge to financial analysts is that a market cannot be observed unless it has emerged—that is, it has become large enough, and/or organized enough for the International Finance Corporation (IFC), for instance, to begin collecting data and creating an index. We rarely observe what we might call *submerged* markets, which have fallen or remained below a threshold. Further, some of the recently emerged markets are really *re-emerging* markets, since they have existed for many more years than commonly believed. Almost invariably, emerging market studies use whatever data are available from recent historical performance, without regard for markets that previously failed.

As we show in this paper, markets tend to emerge, submerge and re-emerge through time. Consider, for instance, the case of Argentina. Even though the Argentinian stock market is usually classified as "emerging," it actually dates back to 1872. Since it emerged in 1975, this market has grown at an average rate of 22.6% per annum, measured in dollars. However, collecting data before the market "submerged" reveals a less-then-stellar performance, of -23.6% per annum over 1947 to 1965. What we have found is that many emerging markets are actually re-emerging and that performance since the last emergence is invariably higher than before emergence. This disparity has serious implications for the performance evaluation of emerging markets.

The potential for bias has already been noted in the literature. In particular, Harvey (1995) notes that the high recent means may be partially due to survivorship, although this effect is not quantified. Brown, Goetzmann and Ross (1995) [BGR] provide analytical results for a simplified model where all markets start at the same time and are eliminated as they fall below a performance threshold; they show that *ex post* means are a direct consequence of survival.[3]

No previous study, however, has attempted to measure the effect of conditioning upon recent emergence, which is the purpose of this paper. We approach these issues in two ways, using simulations and analyzing historical data.

First, we provide simulations of a model of global markets that is quite general. While conditioning upon survival of an absorbing lower bound as in BGR is a useful analysis, it does not adequately characterize the processes that typify global stock markets over the twentieth century. We expect markets to start at various points in time, to display different expected returns, and to be censored at the end of the sample period. Thus, while the BGR analysis can be thought of as "down and out" conditioning, the current paper explores the effects of using "last time up" data. We model a price threshold that does not eliminate markets, but instead simply determines how far back historical time series can be constructed, which we believe is more realistic. As we show, this type of conditioning induces additional effects of interest.

We find that conditioning upon market history, where *history* is defined as the length of time since the market has "emerged" results in a number of empirical regularities. Among other things, the brevity of a market history is closely related to the bias in annual returns imparted by survivorship, as well as to the low level of covariance with the rest of the markets. These findings are potentially useful for international investors, because *merely knowing that a market has recently emerged* contains information about the future distribution, as well as about its future prospects for survival. The simulations also reveal another effect, whereby markets with low expected returns tend to emerge later. This *sorting* effect interacts with the usual survival effect to increase the bias from conditioning. These effects are such that cumulative returns after emergence should display a convex pattern.

Second, we provide historical evidence on the extent of survivor conditioning among global markets over the long term. We find that global market data from standard sources are typically characterized by interruptions, reflecting the fact that collecting return data on submerged markets is not an easy matter when investors have lost interest, and/or the market has closed. Turning to recent, high quality IFC data, we provide evidence of empirical regularities consistent with the simulations. In particular, we find that returns are greatest and betas low when markets have just emerged. Cumulative returns after emergence display the convex pattern predicted from simulations. Alternatively, these results can be explained by a number of alternative hypotheses, such as structural changes in emerging economies or price pressures due to the attention brought by official recognition of a market. The common message, however, is that historical performance may be a poor guide to future returns.

This paper is organized as follows. Section I discusses the process by which markets typically emerge and how this is modelled in our simulations. Section II presents the results from the simulation model, which are analyzed in Section III. In Section IV, we provide performance results for markets which have emerged in the last twenty years. Section V contains some concluding comments.

I Modeling Emergence

I.1 How Markets Emerge

There is a broad range of reasons for market emergence. In fact the common presumption is that markets emerge due to some fundamental economic or political shift. We do not develop an explanatory model for global market emergence, because the effects are obviously numerous and complex. Rather, we focus on one likely characteristic of emergence – capital appreciation. In our simplified model, markets emerge because the market prices of existing firms increase, or submerge following price drops.[4] Alternatively, prices may be viewed as summary statistics for changing economic and political conditions.

Suppose a number of markets started trading 100 year ago, each with about the same capitalization (without loss of generality), but with differing expected returns. Later, this assumption will be relaxed. In our simple setting, markets with lower expected returns will have lower capitalization in the future than those with higher expected returns, on average. Thus, time will sort markets according to their respective drift processes.

The key feature of our analysis is that we assume that we only observe markets whose market capitalization exceeds a barrier, or threshold, at the end of the sample period. Figure 1 illustrates the model. We define a market as an *emerged* market if it has crossed the barrier from below at least once since $t = 0$, and if the *last* crossing, as of $t = 100$ was from below.

In the BGR setup, markets all start above the barrier but are discarded as soon as they hit the barrier. In the case where the drift is known and the barrier is constant, analytical solutions are available to calculate the bias in the observed mean. In this paper, by conditioning upon "last time up," we are also implicitly conditioning upon survival since last emergence, and thus, we expect similar post-emergence biases as those found in BGR. The survival bias in BGR, however, is not the whole story.

In our model, the time of emergence contains additional information about the market. When all markets start at the same time, for instance, markets that crossed recently (i.e. later than other markets) are likely to have lower expected returns.

Thus, historical information about when the market began, what its past capitalization was when it started, and what its capitalization was when it last emerged may all be useful inputs to estimating expected returns. Here, the "recentness" of emergence is related to its drift, in contrast to the conditioning process in the BGR analysis, which is "memoryless." In the current analysis, the long-term memory of when and where the process began is crucial.

I.2 A Stylized Model

We now present a simple model which formalizes the above arguments. As Harvey (1995) shows, world markets differ in their systematic as well as unsystematic risk components. Consider a single-factor model excess log return generating process for the equity market for country k,

$$R_{k,t} = \beta_k R_{m,t} + e_{k,t} \tag{1}$$

where $E[e_{k,t}] = 0$, $E[R_{m,t}e_{k,t}] = 0$ and $R_{m,t}$ is the excess log return on the global market portfolio at time t. The mean zero term need not be pure noise, but it could be a function of some asset class that has no covariance to the global wealth portfolio, such as gold, or physical asset such as commodities that are known to have nearly zero betas. The log price level of market k at time t can be expressed as: $P_{k,t} = P_{k,0} + \sum_{\tau=1}^{t} R_{k,\tau}$, which converges to $P_{k,0} + tE[R_m]\beta_k$ as t increases. Thus, we expect prices to be distributed according to their beta values—for t big enough it matters little whether initial capitalizations differ.

Note that under our baseline model, expected returns are driven by exposure to the world market. This setup is akin to a "null hypothesis," where no market is mispriced. The only reason to invest in foreign markets is for diversification benefits—markets are perfectly "integrated." An opposite view is "segmentation," i.e. local factor(s) are priced, perhaps because of barriers to capital flows. We assume here that expected returns are driven by outside investors who are able to diversify idiosyncratic risk sufficiently for the standard models to apply. In particular, the prospect of market disappearance for local reasons is not priced, i.e. does not enter expected returns. What we will show is that, even under our null hypothesis of no mispricing, survivorship creates situations where emerging markets appear attractive for the wrong reasons.

We want to emphasize that it is unlikely that this simple model fully captures the dynamics of emerging markets. Additional factors could be added to the model. Time variation in risk and structural changes could be also incorporated. These additions, however, would obscure the main message from the simulations: a simplistic model can generate, when submitted to selection through survival, complex patterns of biases and time-variation in returns.

I.3 Simulation Experiment

We simulate emergence among a group of markets as follows.

1. Annual returns for each simulated market are generated by the model in equation (1) as follows.

(a) We simulate 100-year histories of the global market $R_{m,t}$ using i.i.d. normal returns with an annual mean of 10% and an annual standard deviation of 20%, which are typical of stock market data.

(b) We simulate the local factor, $e_{k,t}$, with i.i.d. draws from a normal distribution with a mean of 0 and a random standard deviation drawn from a uniform distribution between 10% and 30%.

(c) β_k, the constant loading on the global market index, is drawn randomly from a uniform distribution between 0 and 2.

2. Markets begin randomly with starting dates drawn from a random uniform distribution over the interval $t = 1$ to $t = 99$. This random starting date is more realistic than usual models where all markets start at a fixed point in time. All markets start at one standard deviation of $R_{k,t}$ below the capitalization threshold.

3. We construct capital appreciation returns for each market, assuming no dividend payments and cumulate each index from its inception until the last period, to create stock market indices for 100 markets.

4. We "censor" the markets by dropping those which are below the threshold *at the terminal date.*

This model is quite general. Both beta and residual risk differ to make the model more realistic, as we would expect markets to differ in terms of expected returns and risk. The time of market founding is also random - markets start at any time within the 100 year interval. The important assumptions are that (i) no market is mispriced, (ii) expected returns are constant through time, and (iii) markets are arbitrarily censored if they end up below the threshold.

This procedure is repeated 2,500 times, for 100 markets each time. This results in 187,954 simulated price paths of "survived" series. For each simulation, we save a number of variables, including the year the market began t_1, the year it last emerged t_e, conditional and unconditional summary statistics; *conditional* statistics are those recorded after the last emergence. Of particular interest to emerging market investors is the difference between the mean annual return of the series *since the time of last emergence* less the expected return of the series, i.e. the true market beta times the global market return realization since emergence. We define this as the "bias" in the annual mean return

$$Bias_k = [\frac{1}{T - t_e} \sum_{t=t_e+1}^{T} R_{k,t}] - \beta_k[\frac{1}{T - t_1} \sum_{t=t_e+1}^{T} R_{m,t}]. \quad (2)$$

We also wish to examine the relationship between conditional beta and emergence, R^2 and emergence, and finally, the additional information provided by the start date of the series in relation to the emergence date of the series. This last issue is important because it may be possible to develop heuristics for correcting the bias in the mean returns for recently emerged markets. One potentially useful piece of information for this purpose is the length of time that the market has existed. For example, given any two markets that emerged ten years ago, the market with a longer history should have a lower mean, and therefore a greater bias than the market with a shorter history. We examine this issue via simulation results.

II Simulation Results

II.1 Survival Effects

The simulations reveal two effects: survival and sorting effects. Relative to the BGR results, the sorting effects are novel. First, we find that the more recent the emergence of the market, the higher the bias in the mean return. Figure 2 shows the relationship between the bias in the mean and the time of last emergence.

The figure shows quantiles of the distribution of the bias, as defined in equation (2). Notice that for early emergence, that is, for markets that emerged in the early part of our hypothetical century, there is virtually no bias in the distributions—the difference between the sample average annual return and the *ex ante* returns is typically zero. For very recent emergence, that is for markets which last emerged only five years ago, the bias is as high as 10% per year, with values over 20% per year not unusual. Even for markets that emerged a decade ago, we still see a substantial return bias, averaging about 5% annually.

BGR find that survival bias is greater when the price level is near the lower bound. In the context of our simulations, recent emergence implies a proximity to the bound and thus a more acute survival bias, since we constructed the sample so that the price never fell below the threshold after emergence. BGR also show that the bias increases in the residual variance of the series. Our regressions confirm that the bias is positively related to the residual risk of the series. In addition, we find that the effect is greatest for recently emerged markets. This provides an interesting possible application. For two markets emerging at the same time, we expect the one with the highest residual variance to have the largest bias. Empirically, this relationship between bias and residual risk may appear as though the local market factor is "priced," i.e. that the expected return is positively related to the portion of the variance not correlated to global factors.

II.2 Sorting Effects

Our simulations reveal another effect, which is in addition to the usual survival story. By conditioning on last emergence, we are sorting markets according to their last crossing time through a barrier. Indeed, Figure 3 shows the average beta of each market, sorted on the year of last emergence. It shows that recent emergence is negatively correlated with the loading on the global market factor. Markets that emerged near the beginning of the hypothetical century have an average beta of 1.2, while recently emerged markets have much lower average beta, around 0.9. Thus, the period of last emergence is informative about the unconditional expected return of the market—the more recent the last emergence, the lower the beta and consequently the lower the unconditional expected return. This relation between global factor loading and recent emergence accords well with the observation that emerging markets have low betas.

Our simulations reveal a second empirical regularity due to threshold-induced sorting. Figure 4 shows the R-square from the market regression, sorted on period of last emergence. For markets that emerged early, the amount of variance explained by the market is high, about 60%. For markets that only recently emerged, the R-square is under 50%. Thus, by conditioning upon recent emergence, we should expect to find markets with higher ratios of idiosyncratic risk. This corresponds exactly to the observation that emerging markets seem to have low R-square with respect to worldwide factors. Indeed emerging markets are often sold to institutional investor on the basis of their substantial diversification benefits. Our analysis suggests that this is a legitimate argument for emerging market investing, as opposed to claims of high alphas.

Recall from Figure 1 that one implication of "last time up" conditioning is that the longer the market history before emergence, the greater the potential bias. The intuition is that markets that remain in the neighborhood of the boundary over time are also likely to be those that emerged and submerged repeatedly. When we condition upon having emerged early in the hypothetical century, we implicitly "pick out" those markets with positive drift. This in turn decreases the probability of being near the barrier for any length of time. This effect provides another possibly useful heuristic for adjusting mean bias for emerging markets. For any two markets that emerged at the same time, the one that began earlier should have the largest bias. The reason for this is that, if it began a long time previously and still only recently crossed the barrier, it probably has a low beta, whereas a newly formed market that quickly crosses the barrier is likely to have a high beta, and thus a high expected return.

Figure 5 shows precisely this effect. For each period we select all the markets that last emerged at that time. We regress the bias in the mean upon the starting date for the series. We find the relationship negative for all periods. That is, *the earlier* *the starting date, the higher is the bias in the mean.* For new markets, the bias is lower. Therefore the time since last emergence and the time since the market first began may be used to forecast expected returns.

The survival and sorting effects are related. When markets differ in terms of expected returns, sorting effects exacerbate survival effects. In the BGR analysis, for instance, the bias can be shown to be functionally related to the true expected return. Thus, while sorting effects and survival can be considered separately in the simulations, they interact to increase the magnitude of the bias.

II.3 Cumulative Average Returns: Emergence as an Event

Another approach to examining the effects of emergence conditioning is to treat the date of emergence as an event and to align the simulations around the event time. Figure 6 shows the cumulative and average returns for all markets that last emerged on a given year. The horizontal axis is aligned in event time, as opposed to calendar time, and market emergence is set to year 0. The figure shows a cumulative index of ten years of returns preceding and following the emergence date.

Notice the strong effect of conditioning upon emergence. Returns are nearly flat before emergence, despite the fact that the average returns in the simulation are positive. Following emergence, returns follow a positive trajectory, which is slightly convex.

The returns comprising the price path are also shown in Figure 6. The difference between pre-emergence and post-emergence returns is dramatic. The low returns preceding emergence are likely to be a consequence of conditioning upon the market being below the capitalization threshold. Simply knowing that a market crossed the threshold from below, and remained above until the end of the sample period helps to differentiate historical returns. Notice, also, that the largest return is in the year immediately following emergence. This is because year 1 is the year in which the market is closest to the boundary, and thus most likely to fail. As the market climbs away from the boundary, the chances of submerging decrease, and the survival-conditioned return decreases as well. If an econometrician only observes the history of a market since emergence, the simulation suggests that average returns will be greatest just after emergence.

II.4 Implications

The simulations, however stylized, provide some general guidance for investment practice. First, recent emergence by a market has the potential to be a strong conditioning factor that may affect *ex post* observed return distributions. Some of the effects are due to the fact that recently emerged markets are by definition near the lower threshold of capitalization. However, some of the effects are also due to actual differences in long-term expected returns, due to differing betas. This sorting also underscores the importance of detecting changing betas for emerging markets. Local or recent changes in expected returns may be sufficient to help a market avoid plunging below the lower threshold. The econometrics of conditional betas (cf. Harvey, 1995) would appear to be a crucial step in the analysis of future expected market returns.

These simulation results have strong implications for applications of mean-variance optimization to emerging market data, as is typically applied to strategic, or long-term, asset allocation. The brevity of emerging market histories induces a well-known uncertainty in the inputs to the mean-variance model, known as "estimation risk".[5] Our work shows that the problem extends beyond input uncertainty to input bias. Recently emerged markets typically have a positive bias in the mean and wider distribution. In a mean-variance framework, the *distribution* of the bias is as important as the average, because extreme values exert a large influence upon the composition of the optimal portfolio. Institutional investors seeking data on emerging markets for use in mean-variance optimization should use recently emerged market data with extreme caution.[6] As the number of emerging markets used in the optimization is increased, the likelihood of overweighing one with an extreme positive bias in the mean increases as well.

III A Look at History

III.1 Stock Market Histories

How well does the history of the global stock markets accord with the central premise of the simulation—namely that some markets have been around a long time, but only recently have emerged? Table 1 provides a partial list of the founding dates of the world's stock exchanges. It is based upon information in two well-known guides to global stock markets, Park and Agtmael (1993) and O'Conner and Smith (1992). Both of these sources collect information about market histories from currently operating stock exchanges around the world. Because countries that currently have no exchange are not included, this is presumably not a complete list of the markets that existed at one time. However even this partial list is interesting because it tells us just how much *we do not know* about equity markets. Of the forty markets that were founded before the twentieth century, only two, the U.S. and the U.K. markets, have been extensively analyzed over long investment horizons. This is not from lack of interest, but from lack of data. While econometricians in the U.S. and the U.K. have compiled reliable price information stretching back into the nineteenth and eighteenth centuries, it has only been recently that comparable information has become available for other markets such as Germany, France and Switzerland, albeit with notable gaps due to wars. Even so, this table is informative.

Table 1 tells us that *most* of today's stock exchanges have long histories. Many non-European markets began under the aegis of colonial rule, including Hong Kong, India, Pakistan, Sri Lanka, Indonesia, South Africa, Egypt and Singapore, and have continued with or without interruption to the present. Other markets only recently emerged from communist rule—Hungary, Czechoslovakia, Poland, Romania, Yugoslavia. Perhaps most surprising is the number of South and Central American countries with long market histories. Argentina, Brazil, Colombia, Uruguay, Mexico and Venezuela all have had equity markets for more than sixty years.

The League of Nations collected data on the capital appreciation of market indices in the period from 1929 through 1942.[7] This collection effort was continued by the United Nations. Interruptions in series were due to a number of factors, including wars, expropriation, hyperinflation, and political changes. The early price data indicate that hyperinflation closed the Danish and German markets in the early 1920s. While most markets remained open and functional through the Great Depression, World War II caused many of them to shut down in the 1940s. Some Eastern European markets remained open through the war, only to suffer expropriation after 1945. In total, Austria, Belgium, Shanghai, Czechoslovakia, France, Hungary, Japan, Korea, Luxembourg, Malaysia, the Netherlands, Norway, Poland, Portugal, Uruguay, Venezuela, Yugoslavia and Slovenia all experienced temporary or permanent shutdowns either in the war years, or in the occupation following the war. Many of the markets which shut in mid-century re-emerged after the war or after occupation.

Wars were not the only factors that created discontinuities in the price records.

Markets in Egypt, Lebanon, Portugal and Chile, for instance were shut down or barred to foreign investors due to political changes largely uncorrelated to outside global trends. Shifting legal factors have changed the attractiveness of markets such as Greece, Turkey and India to outside investors, and thus caused them to be regarded as "emerging" markets, despite long histories as capital markets. A turn of political fortunes can make a long-forgotten market suddenly of interest to outside investors.

A fair question is whether these events should be considered endogenous or exogenous—clearly some of these formerly emerged countries failed to maintain a social and political system which fostered steady industrial growth. While it is not the object of this paper to ask why these markets did not prosper in the same way as the U.S. and U.K. markets, it is reasonable to ask whether anything has changed. Have the political and economic forces that caused these markets to submerge been fundamentally altered? Can we expect the next sixty years of capital markets to be different from the last sixty years?

III.2 Evidence from Long-Term Markets

Later on, we will examine the empirical evidence on emerging markets using recent IFC data. These high quality indices, unfortunately, have a rather short history. This is why it is also useful to examine long-term histories of global stock markets.

Using the sources listed above, Goetzmann and Jorion (1996) collected a sample of capital appreciation indices for all equity markets for which data was reported at any point during the 1921 to 1970 period. All of these markets were followed continuously from the initial reporting period until 1995, at which time 32 were still included. The authors also compute a global index of stock returns weighted by GDP.

Most of these series have experienced some breaks. Defining emergence as the date after the last break, the question is whether price patterns since the last break are consistent with the simulations. We can use the global stock index to verify a key prediction of the simulation—that the systematic exposure of emerging markets will be less than that of developed markets. Figure 7 plots the global beta against time since the last break.

The graph clearly shows a negative pattern, which is consistent with that in Figure 4. The U.S. market has the highest beta; it also has the longest continuous history, going back to the beginning of the sample in 1921. Other markets, such as Peru, Portugal, and Argentina, have had long histories but are only recently re-emerged.

Their global beta is only around 0.40, suggesting their true expected return is lower than that of other markets.

The other major prediction of the model is the relationship between bias and recent emergence. Figure 8 plots the average return for each market against time since the last break (these are compound returns measured in excess of the Wholesale Price Index inflation.) The graph dramatically illustrates the importance of survival conditioning. As expected, shorter histories have greater dispersion, but also much higher returns. Whereas markets with long histories experienced real returns around 2 percent per annum, more recently emerged markets (but with long histories) displayed much higher returns, reaching 36 percent for Peru. These graphs confirm the intuition behind the simulations: markets with long histories but which only recently emerged are likely to have low betas and high returns. The simulations show that such results can be interpreted in terms of conditioning upon recent emergence.

IV Empirical Analysis of Emerging Markets

One of the obvious problems with evaluating survivorship bias in emerging markets is that the data may not be readily available before markets are considered to have "emerged." Yet a number of empirical regularities should be expected from the simulations. For instance, right after emergence, the bias should be greatest if markets that perform badly do not appear in the sample. This hypothesis is analyzed using a variety of approaches.

IV.1 Selection of "Emerged" Markets

The standard data source for emerging stock markets is from the International Finance Corporation (IFC), which is part of the World Bank group. In its laudable quest for promoting private equity investment in Less Developed Countries (LDCs), the IFC has developed the most comprehensive and consistent data base for Emerging Markets (EMs). The data base started in December 1980 with 9 markets, which were backfilled to December 1975 and has expanded to 25 markets as of December 1995 (Jordan was backfilled to 1978). Other markets are being watched by the IFC, then periodically added to their composite EM index. The IFC collects not only share prices, but also dividend and exchange rate information; this allows construction of a total return index that is consistent across all countries.

The term "emerging stock market" was coined by the IFC in 1981. IFC defines an emerging stock market as one located in a developing country. Using the World Bank's definition, this includes all countries with a GNP per capita less than $8,625 in 1993. The IFC states that "although IFC has no predetermined criteria for selecting an emerging market for IFC index coverage, in practice most markets added have had at least 30 to 50 listed companies with market capitalization of US$1 billion or more and annual value traded of US$100 million or more at the start of IFC index coverage." This definition clearly defines a size threshold that markets have to reach before official inclusion in the database.

IV.2 Backfilling in IFC Indices

In practice, different types of biases are imparted to IFC indices. The first issue relates to the backfilling of IFC indices. The early IFC indices were started in 1980 using companies that were in existence at that time and backfilled to 1975; more recently, the first data points generally predate the decision to include a market by one year or more. Backfilling a market explicitly conditions upon exceeding a threshold as of the decision date. Markets that were in existence in 1975, for example, but performed poorly in subsequent years are not included in the database. Therefore, markets that survived the backfilling period are likely to exhibit biases similar to those in the simulations.

Besides the country selection issue, another problem is the company selection. In 1980, for instance, the IFC indices were constructed using companies that were in existence at that time. As noted by Harvey (1995), the backfilling of the series to December 1975 creates a company-specific bias. This problem is not addressed in our simulations.

IV.3 Survival in IFC Indices

Another issue relates to using long-term market histories. To date, the IFC has never dropped a market from its sample. Does this mean that, absent the backfilling issue, the IFC database is not subject to survival issues? In other words, as long as the IFC follows all markets once they enter, isn't any potential survival bias eliminated? The answer is no. The fact that all the IFC markets have survived with continuous return records is not sufficient to prove that there is no survival effect in the series.

Two IFC markets that had "near death" experiences illustrate this point. Both the Zimbabwe and Nigerian markets became quite small after inclusion in the database. The market value of Zimbabwe began at \$450 million in 1980, when it was introduced into the IFC database. It fell to \$40 million over the next four years and then increased to \$1.5 billion by the end of 1995. The drop in share prices after 1980 can reasonably be attributed to uncertainty regarding the future of the Zimbabwean economy in the early years of the new government. In 1984, there was a real possibility that the equity market would disappear, or become so thin that share prices would not be meaningful. Instead, we do observe a continuous series for Zimbabwe because of the ultimately successful transition to democratic rule. However, we completely eliminated from this sample the possibility that the market would not survive this crisis.

A related example is the Nigerian market, which fell to about a fourth of its initial 1984 capitalization of \$1.6 billion four years later. The Nigerian market emerged due to soaring oil prices in the early 1980s. The collapse of oil prices in 1986, however, certainly contributed to the subsequent economic crisis. President Babangida addressed the crisis by implementing drastic policy changes. These measures, which included the liberalization of trade and the privatization of agricultural markets, ultimately proved successful, and the market recovered to \$1.5 billion in 1995. Again, we have no record of what might have happened to the Nigerian equity market had the adjustment policy not worked?[8]

More generally, the fact that no market was dropped by the IFC does not imply that there is no survival effect. A sample of 9 markets over 15 years may not adequately represent the possibility of disappearance. The number of markets and the time span may simply be too low. A lack of sufficient cross-sectional observations of "disasters" does not prove their non-existence, nor does it prove that the bias imparted by such conditioning is non-existent.

There is further evidence on this point. Consider the sample of other markets also followed by the IFC. One of the largest ones was Kuwait, with \$10 billion in market capitalization in the late 1980s. This market was close to making the grade to "emerging" market. Had Kuwait been included in the IFC indices, the series would no doubt have been interrupted during the 1990 Gulf War. Here, no matter how diligent IFC researchers were, the interruption in price observations would not have been a matter of choice. Thus, with a larger sample, at least one market would have been dropped over the 1980-1995 period.

Our simulations should not be construed as a critique of the IFC database. In fact, the IFC has demonstrated an awareness of survival biases by following poorly performing markets, even when capitalization dropped sharply. This careful data collection certainly can reduce the magnitude of bias, although, as we have shown, it cannot eliminate it. Whenever a significant probability of market closure exists, any long-term historical series implicit conditions upon survival. This effect can be demonstrated in the context of the long-term history of the global markets, rather than from the perspective of an unusually placid 15-year period. Over the long-term, how frequent is market closure?

To answer this question, the following table describes the distribution of "lives" of stock markets starting at two points in time, 1929 and 1953. These dates correspond to times at which the League of Nations and the United Nations collected a large sample of market indices, which happened to number 29 in both cases (although the markets are not the same). We compute the "life" as the number of remaining years before an interruption in the series of at least one year using the same data sources.

Distribution of Stock Market Lives

1929 to 1995			1953 to 1995		
Life (years)	Count	Country	Life (years)	Count	Country
66	15	Others	42	22	Others
45	1	Mexico	32	1	Peru
44	1	Portugal	21	1	Mexico
42	1	Chile	20	1	Portugal
16	4	Germ.,Hung.,Neth.,Urug.	18	1	Chile
14	1	Romania	9	1	Egypt
11	1	Greece	4	2	Argentina, Lebanon
10	3	Austria, Czech., Poland			
9	1	Italy			
7	1	Spain			
Total:	29		Total:	29	

The distributions show that, over long periods, markets do suffer disruptions. Out of 29 markets existing in 1929, 14 did not last until 1995 without major interruption. Many markets, of course, were either closed or nationalized around World War II. But even more recently, starting in 1953, 7 markets out of 29 did not make it until 1995.

In the long run, it is fair to predict that markets will disappear and reappear. The lack of censored observations over a brief period in the history of global capital markets is not sufficient to prove the absence of survival effects. The question is whether any of the regularities we find in the simulation also appear in recent actual data.

IV.4 Performance of "Emerged" Markets

The IFC dataset has become the standard database for research on EMs and provides performance benchmarks for portfolio managers. As a result, the introduction of new markets is watched very closely by portfolio managers given that it affects the return on their "bogey." We consider the first date at which the IFC compiles a market index as the date of emergence.

Table 2 presents start dates and market capitalizations for the markets covered by the IFC. Prior to the IFC, the International Monetary Fund (IMF) also compiled stock index data, which were directly supplied by the central banks, or the stock markets themselves, and included no dividend data. The table also indicates the first date of record for monthly IMF data when it predated the IFC indices.

Next, Table 3 displays risk and return characteristics of emerging markets, expressed in percent per annum. For each market, the period covers the inception date until December 1995. The table shows that returns on emerging markets have been very high, both using arithmetic and continuously compounded averages. The return on the equally-weighted index, for instance was 24.8% per annum, on average, over the last twenty years, which is enormous. These markets display high volatility. Most of this risk, however, is diversifiable by global investors, as correlations with the world market are generally very low, averaging 0.155. As a result, many of these markets display superior "alphas", many of which are statistically significant. Apparently, the combination of these two features, high returns and low correlations with developed markets, makes emerging markets quite appealing. Could these be attributed to survival?

IV.5 Expected Returns after "Emergence"

In the first approach to measuring bias, we track the behavior of IFC indices right after emergence. Returns are measured in U.S. dollars, inclusive of dividends. As some of these markets have experienced hyperinflation, it is essential to measure returns either in a common foreign currency or in real terms, deflating by the local price index. Both approaches should give similar results in situations where Purchasing Power Parity holds, which is likely to be the case in inflationary environments.

Hypothesis 1: Expected returns will be higher immediately following emergence than later on.

To test this hypothesis, we adapt the event-study methodology used in the simulation above to the emergence of markets. We construct an equally-weighted index where returns are aligned on the emergence date. The advantage of this "portfolio" approach is that it fully accounts for cross-correlation between events, which is substantial in this case since 9 markets out of 25 emerge on the same date. Figure 9 plots the time-series of the emerging portfolio value; this portfolio is compared to that of a benchmark, which is constructed by replacing each market by the world index.

The graph shows that the slope of the line is greater immediately following emergence. This pattern is consistent with the simulation results. The emerging market portfolio also substantially outperforms the benchmark portfolio. The magnitude of the effect is confirmed in Table 4, which considers 36, 48, and 60-month windows after emergence. The portfolio performance is compared to that over the subsequent window of same length. The table shows that the performance is significantly greater immediately after emergence. The difference is striking: 15% pa using 60-month window, 29% pa with a 48-month window, and 24% pa with a 36-month window. These numbers are all statistically significant, as indicated by the t-statistics in the table. We also separated the sample into the initial pre-1980 group and others. In both cases, performance right after emergence is greater than later on, although the effect is most significant for the pre-1980 group. Therefore, as suggested by the simulations, we find a significant bias due to recent emergence.

There are other explanations for the price increase after emergence. One competing theory is the "price-pressure hypothesis." Official recognition of an emerging market by the IFC could induce purchases by foreign managers, leading to increased prices. In a similar context, Harris and Gurel (1986) report that additions of stocks to the S&P 500 list have led to price increases of about 3% over the 1978-1983 period. It is conceivable that given the thinness of some emerging markets, foreign purchases drive prices by much greater amounts. The price pressure hypothesis, however, should lead to reversals after the initial buying, since the pressure is temporary. However, reversals are not observed here.

Another explanation is changing economic conditions. Some markets emerge as a result of financial liberalization, which usually coincides with a changing political environment. We would then expect the best investment opportunities to come to the market first, spurring an initial growth that slows down as less profitable investments appear later. Whatever the explanation, it is clear that the long-run performance of markets right after emergence is not sustainable.

IV.6 Expected Returns around Emergence

An alternative approach to measuring bias is to recover market information from a completely different source. We take a sample of markets for which equity indices have been collected by the International Monetary Fund (IMF) since 1957. These indices are compiled by the local stock exchange and may not be consistent across countries. In addition, they often represent monthly averages, not end-of-month data. Still, comparisons are appropriate as long as the same IMF series is used before and after emergence. Additional data exist for a total of 7 markets, which are listed in Table 2. The shortest period before emergence is for Peru, for which we have data for two years only.

Hypothesis 2: Expected returns will be higher after than before emergence.

To guard against hyperinflation, we measure returns both in dollars and in real terms (deflated by the CPI as provided by the IMF). As before, returns are aggregated into an equally-weighted portfolio of seven markets aligned on the date of emergence. Figure 10 displays the time series of cumulative returns. The picture clearly indicates a break in trend, with returns after emergence sharply moving upward. This pattern is also consistent with the simulation results reported from our hypothetical market subject to conditioning upon emergence. In fact, Figure 10 is quite similar to Figure 7, which aligns simulation returns on the emergence date.

Formal tests of breaks in expected returns are presented in Table 5. Both real returns and dollar returns strongly indicate that average returns are higher right after emergence. The difference in real returns, for instance, averages 40% annually. Even with a very large standard error of returns of 89% annually, two years of data are sufficient to bring strong rejections of the null. Again, these results strongly suggest that returns are biased upward once a market is considered "emerged."

IV.7 Expected Returns before Emergence

A third approach considers markets that have not yet emerged. Besides its official list of emerged markets, the IFC also collects information on a sample of markets that have the potential to emerge. By the end of 1994, the IFC was watching 24 such markets. For these "non-emerged" markets, the IFC provides annual returns reported by local stock markets, exchange rates and market capitalization.[9]

Annual returns were collected for this sample of markets varying from 7 in 1985 to 19 in 1994. To compare their performance with that of established emerging markets, we constructed a value-weighted dollar return index which spanned ten years.[10] This index was compared to the IFC composite index, which is also value-weighted. To maintain comparability, both indices include only capital appreciation.

Hypothesis 3: Expected returns will be lower before emergence.

Table 6 compares the performance of the two groups of markets, non-emerged and emerged. The table shows that the non-emerged group returned an average of 12.5% over these ten years, against 19.1% for the emerged index. This difference confirms, using an entirely different data set, biases in the performance of emerged markets. Emerged markets, on average, return 6.6% more than other markets. For comparison purposes, the table also reports the performance of the MSCI World index, a value-weighted index of developed markets. Over this period the average return was 14.0%, which also falls short of the performance of emerged markets. In our model, the 6.6% difference can be attributed either to the fact that non-emerged markets truly have low expected returns (low betas in our model) or to the fact that the sample selection process for defining emerging creates survivorship biases. The volatility of the series, unfortunately, is such that the t-test is unable to reject equality of mean returns. Most portfolio managers, however, would agree that an annual difference of 6.6% per annum over a decade is economically important.

V Conclusions

A general model of global markets that allows for differing expected returns provides the basis for simulations of selection of emerging markets. These simulations show an inverse relationship between the recentness of market emergence and the subsequently observed return. The model also shows that recently emerged countries have low covariance with the global market. These results are striking because they fit the empirical observation that emerging markets appear to have high returns and low correlations with other markets. In our baseline model, which assumes no mispricing of emerging markets, these high returns are partly due to survivorship biases.

The findings of these simulations are confirmed by our empirical analysis, which shows that average returns on markets that have just emerged are temporarily high. The history of emerged markets provides an overly optimistic picture of future investment performance. Therefore basing investment decisions on the past performance of emerging markets is likely to lead to disappointing results.[11]

Another fruitful line of research would be to examine the predictive power of measures for the probability of market upheaval, such as credit risk ratings or default spreads.[12] Indeed, Erb, Harvey and Viskanta (1995) find that, cross-sectionally, low credit ratings are associated with high average returns and low betas. As credit rating proxies for the probability of market failure, these results provide additional support for the survivorship story.

A major caveat of our analysis is that it is based upon a stationary model. Economies are never that simple. Global capital markets have been subject to dramatic changes over the twentieth century, and many nations with bright economic prospects in the 1920s subsequently failed to reward investors for their high expectations. It seems reasonable to condition expected returns in marginal markets on changing political, legal and economic environments. However, it is also important to learn from history. Market contractions and expropriations have occurred in the past, and are likely to occur in the future, even in the absence of a major event such as a world war. If we fail to account for the "losers" as well as the "winners" in the global equity markets, we may be ignoring important information about actual investment risk.

One way to account for losers is to gather additional historical data. Financial economists are accustomed to working with abundant and accurate data, but unfortunately it is strongly conditioned upon survival. For instance, we do not as yet have a quality data set for Argentina's equity market, even though it has existed since 1926—at which time Argentina was one of the world's major economies. Collecting long series of historical data will allow us to examine the behavior of markets in distress. Instead of blindly projecting returns from short-term historical data, investors should use the information in long-term histories to construct "stress-testing" of portfolios. This parallels the trend in the financial services industry, where methods based on historical risk measures, such as Value-At-Risk, are widely recognized as unable to capture unusual but highly disruptive events. This is why traditional risk measurement techniques must be complemented by *scenario analysis,* which ideally should rely on long histories of stock markets.

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Notes

[1] See for example, Bekaert and Harvey (1995a and 1995b), and Harvey (1995).

[2] For prior theoretical and empirical evidence on local pricing, see Stulz (1981) and Errunza and Losq (1985).

[3] In addition, survival induces all kinds of spurious relationships. Goetzmann and Jorion (1995), for instance, examine the predictability of stock returns based on dividend yields and find that survivorship biases the results toward finding spurious evidence of predictability. These effects are akin to the "peso problem" in the foreign exchange market, where forward rates appear to be systematically biased forecasts of future spot rates, essentially because they account for a non-zero probability of devaluation that may not be observed in the test sample period.

[4] We ignore emergence due strictly to increases in the number of listed firms. A case in point is China, in which the growth of the market has been a function of many new firms listing. Unless appreciation and issues of new securities are uncorrelated, price appreciation can be treated as an instrument, and the results we obtain are qualitatively valid.

[5] This problem is discussed in Michaud (1989). Jorion (1985) pointed out that the practical application of mean-variance optimization to international diversification is seriously hampered by estimation risk. Stambaugh (1996) provides a framework to analyze investments whose histories differ in length.

[6] For instance, Divecha et al. (1992) report that, over the five-year period ending in March 1991, the IFC Index returned 7.1% more than the FT World Index. With a correlation of 0.35 between the two indices, a mean-variance analysis reveals that investing 40% in EMs apparently would have increased returns by 4% annually relative to the World Index, with no greater risk.

[7] Countries with price indices compiled by the League of Nations include: Australia, Belgium, Canada, Chile, Colombia, Czechoslovakia, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Mexico, Norway, Netherlands, New Zealand, Peru, Portugal, Romania, Spain, Sweden, Switzerland, U.K., U.S., Uruguay, and Venezuela.

[8] In fact, Nigeria is a country for which the IFC was unable to construct a reliable index of investor return over the period since emergence. In 1993, the IFC started

a new series of "investable" indices which were designed to measure more precisely returns that were available to foreign investors, taking into account legal and practical restrictions. These series were reconstructed to 1988, but omitted Nigeria which was considered "closed" to foreign investors. In other words, while the Nigerian market "survived" its late-1980s crisis and bounced back from the brink of disaster, the return record was not reliable enough to be considered a fair representation of investor returns over the period.

[9] Countries watched by the IFC in 1994 include Bangladesh, Barbados, Botswana, Costa Rica, Ivory Coast, Cyprus, Ecuador, Egypt, Ghana, Honduras, Iran, Jamaica, Kenya, Kuwait, Mauritius, Morocco, Namibia, Oman, Panama, South Africa, Swaziland, Trinidad, Tunisia, and Uruguay. Of those, Costa Rica and Honduras have no stock price index, the series for Uruguay stops in 1991, and the series for Kuwait was interrupted from 1990 to 1993 because of the Gulf War.

[10] In the computation of the value-weighted index, we omit South Africa, because its market value would dwarf all others. As of December 1994, the market capitalization was $226 billion, while that of the next largest market is $10 billion.

[11] Along similar lines, Bekaert and Urias (1995) find that U.S. closed-end funds fail to provide the diversification benefits of corresponding IFC indices, which they ascribe to transaction costs, investment restrictions, and variation in fund premiums.

[12] Bailey and Chung (1995), for instance, show that the credit spread on Mexican sovereign bonds has predictive power for expected returns on the local stock market. They hypothesize that credit risk and political risk are positively correlated, which implies that credit spreads proxy for the probability of market upheaval.

TABLE 1. Time Line of Stock Market Founding Dates

This table compiles the founding dates of exchanges in cities currently within the borders of the identified countries, in chronological order up to 1975, when standard databases started. Only coutries who today have significant equity markets are included in the group, so this sample is subject to selection bias. For instance, it contains no information about Russian exchange(s) and Baltic exchanges. Sources are O'Conner and Smith (1992) and Park and Agtmael (1993), using country definitions as of 1993.

Netherlands	1611	Brazil	1877	Philippines	1927
Germany	1685	India	1877	Colombia	1929
UK	1698	Norway	1881	Luxembourg	1929
Austria	1771	South Africa	1887	Malaysia	1929
USA	1792	Egypt	1890	Romania	1929
Ireland	1799	Hong Kong	1890	Israel	1934
Belgium	1801	Chile	1892	Pakistan	1947
Denmark	1808	Greece	1892	Venezuela	1947
Italy	1808	Venezuela	1893	Lebanon	1948
France	1826	Mexico	1894	Taiwan	1953
Switzerland	1850	Yugoslavia	1894	Kenya	1954
Spain	1860	Sri Lanka	1900	Nigeria	1960
Hungary	1864	Portugal	1901	Kuwait	1962
Turkey	1866	Sweden	1901	Thailand	1975
Australia	1871	Singapore	1911		
Czechoslovakia	1871	Finland	1912		
Poland	1871	Indonesia	1912		
Argentina	1872	Korea	1921		
New Zealand	1872	Slovenia	1924		
Canada	1874	Uruguay	1926		

TABLE 2. Emerging Markets Covered by IFC

Historical information about the return series calculated for twenty-five equity markets designated "emerging" by the International Finance Corporation. "Start Date" indicates the month the series begins in the IFC database. "Capitalization at Start Date" and "as of Dec 95" indicates the IFC index market capitalization in millions of dollars at the start date and at the end of 1995. "IMF Coverage Start Date" is the date at which International Monetary Fund data are available for the market.

Country	IFC Start Date	Capitalization ($ million) Start Date	as of Dec 95	IMF Coverage Start Date
Argentina	Dec 75	83	22,148	
Brazil	Dec 75	8,469	94,615	
Chile	Dec 75	180	48,070	Jan 74
China	Dec 92	21,369	24,608	
Colombia	Dec 84	401	8,519	Jan 57
Greece	Dec 75	1,677	10,161	
Hungary	Dec 92	659	796	
India	Dec 75	527	57,753	Jan 57
Indonesia	Dec 89	2,254	27,610	
Jordan	Jan 78	335	3,484	
Korea	Dec 75	324	123,648	
Malaysia	Dec 84	9,523	142,494	
Mexico	Dec 75	677	60,419	
Nigeria	Dec 84	1,560	1,537	
Pakistan	Dec 84	498	6,482	Jul 60
Peru	Dec 92	2,081	7,353	Jan 88
Philippines	Dec 84	200	31,965	Jan 57
Poland	Dec 92	2,139	1,987	
Portugal	Jan 86	138	10,932	
Sri Lanka	Dec 92	1,082	1,249	
Taiwan	Dec 84	3,532	113,032	
Thailand	Dec 75	220	94,963	
Turkey	Dec 86	377	13,782	
Venezuela	Dec 84	505	2,483	Jan 57
Zimbabwe	Dec 75	215	1,517	

TABLE 3. Risk and Return of IFC Emerging Markets

Annualized risk and returns of IFC emerging markets, using the earliest start month (in table 2) until December 1995. The table reports the sample size, the arithmetic average, compound average, volatility, beta and correlation with the world market, and alpha from a market model in excess returns. The sample consists of 25 IFC-covered countries plus the IFC Composite Index and an equally-weighted average of all countries. All data are presented in annual terms in percent. Arithmetic returns and abnormal alphas are multiplied by 1200; compound returns use annual compounding; monthly volatility measures are multiplied by $\sqrt{12} \times 100$.

Country	Nb.of	Returns		Risk			Abnormal
	Months	Arithm.	Compound	Volat.	Beta	Rho	Alpha
Argentina	240	61.68	27.14	96.62	-.07	0.006	54.95*
Brazil	240	25.36	9.46	57.99	.35	0.089	15.63
Chile	240	35.34	32.72	37.98	.12	0.054	27.22*
China	36	1.83	-18.36	76.31	-.04	0.007	-1.69
Colombia	132	35.32	35.71	31.25	.08	0.045	28.75*
Greece	240	8.34	3.00	34.39	.45	0.191	-2.15
Hungary	36	-2.73	-8.40	36.89	.80	0.292	-16.67
India	240	16.89	14.11	27.39	-.03	0.012	10.03
Indonesia	72	6.88	2.18	31.02	.19	0.100	1.46
Jordan	215	12.27	11.22	18.12	.16	0.129	3.70
Korea	240	22.62	19.78	30.80	.52	0.243	11.65
Malaysia	132	15.73	12.74	26.91	.73	0.423	2.21
Mexico	240	25.65	15.87	44.15	.70	0.234	13.20
Nigeria	132	18.44	2.50	53.92	.30	0.087	9.58
Pakistan	132	16.52	14.60	24.62	.02	0.012	10.72
Peru	36	35.90	32.72	39.57	.75	0.252	22.70
Philippines	132	40.61	40.24	36.66	.71	0.299	27.41*
Poland	36	81.39	65.14	87.17	1.68	0.265	56.12
Portugal	119	29.66	23.71	43.23	1.06	0.392	14.80
Sri Lanka	36	5.68	0.75	32.08	-.29	0.111	4.94
Taiwan	132	31.09	20.93	50.05	.73	0.227	17.60
Thailand	240	23.62	22.02	26.90	.34	0.193	13.85*
Turkey	108	38.22	16.72	71.16	.08	0.017	32.39
Venezuela	132	20.53	8.90	47.88	-.37	0.122	19.00
Zimbabwe	240	13.99	8.55	34.21	.18	0.082	5.48
IFC Composite	132	17.03	15.42	22.76	0.46	0.317	6.42
EW Average	240	24.83	16.56	43.89	0.37	0.155	15.31

Note: * indicates significance at the 5% level.

TABLE 4. Returns after Emergence

This table reports statistics for returns for 25 IFC-covered markets in two equal-length sequential time periods following market emergence. Emergence is defined as the beginning of the IFC total monthly return series. Annual returns in percent. The t-statistic tests the equality of average returns in the first and second subperiods.

	First Period	Next Period	Difference
60 months			
Mean	30.77	15.74	15.03
Std.Dev.	(10.42)	(11.30)	
T-stat.			2.19*
48 months			
Mean	36.40	6.92	29.49
Std.Dev.	(10.66)	(10.11)	
T-stat.			4.01*
36 months			
Mean	37.28	13.41	23.87
Std.Dev.	(10.97)	(10.75)	
T-stat.			2.69*

Note: * indicates significance at the 5% level.

TABLE 5. Returns around Emergence

This table reports statistics for returns for 7 IMF-covered markets in two-year periods before and after market emergence. Emergence is defined as the beginning of the IFC total monthly return series. Returns are reported for real, CPI-deflated returns and U.S. dollar-converted returns. Annual returns in percent.

	Before Emergence	After Emergence	Difference
Real Returns			
Average	-2.09	44.60	46.69
Std.Dev.	16.52	21.27	26.93
T-stat.	-0.18	2.97	2.45*
Dollar Returns			
Average	1.23	50.43	49.20
Std.Dev.	15.00	22.82	27.30
T-stat.	0.12	3.13	2.55*

Note: * indicates significance at the 5% level.

TABLE 6. Returns Before and After Emergence

This table reports statistics for returns on IFC emerged markets and non-emerged markets. Returns are compared for the MSCIP world index, the IFC composite index and a value-weighted index of returns on markets that have not yet emerged. Annual returns are measured in dollars, without dividends, over the period 1985 to 1994.

	Non-emerged Market Index	Emerged IFC Composite Index	Difference	MSCIP World Index
Annual returns				
Average	12.5	19.1	-6.6	14.0
Std.Dev.	18.1	28.0	40.0	17.0
T-stat.	2.18	2.16	-0.52	2.61
Compound	11.2	15.7	-4.5	12.7

Fig.1. Emerging... or Re-emerging Markets?

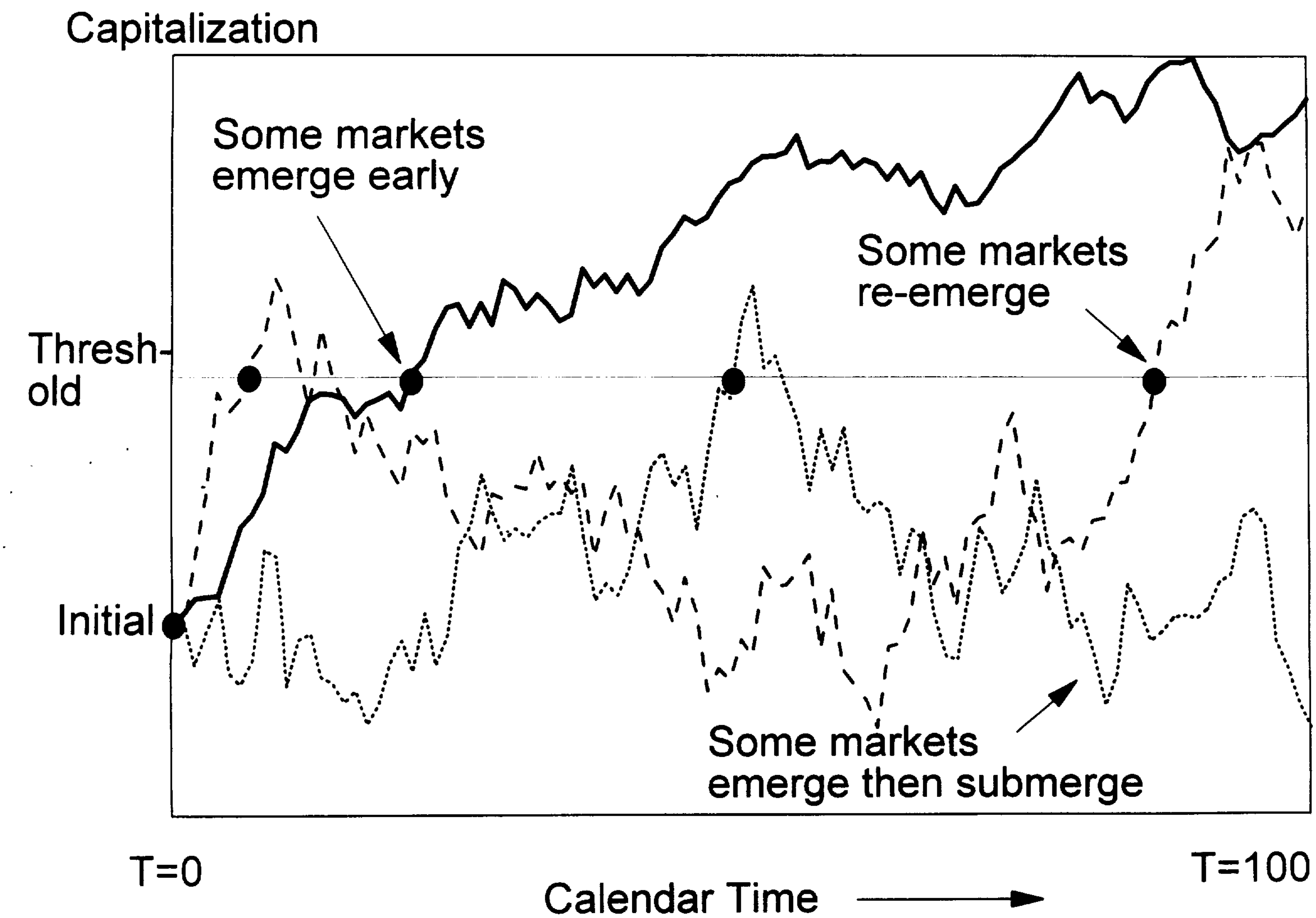

Fig.2. Bias vs. Year of Last Emergence

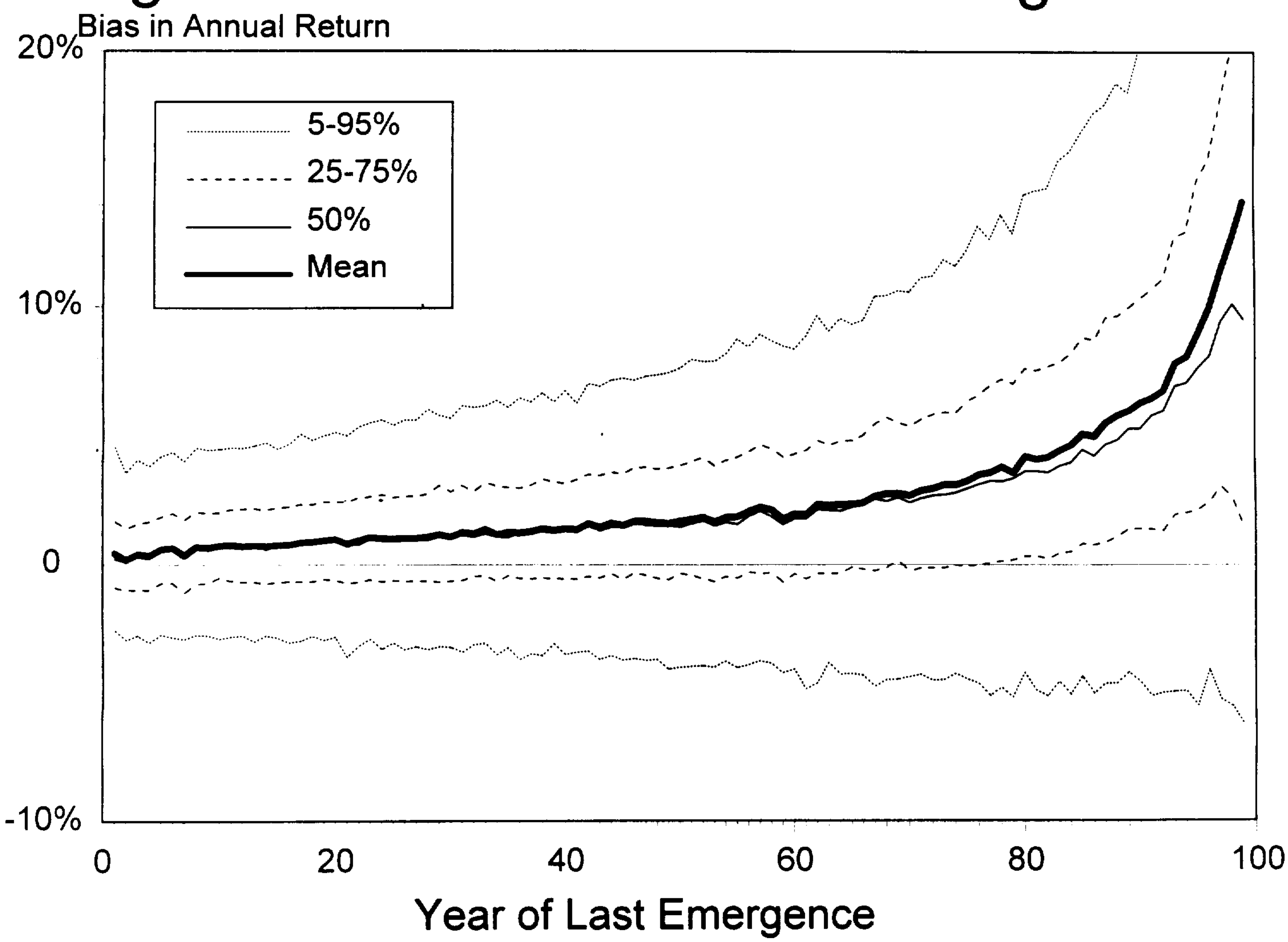

Fig.3. Beta vs. Year of Last Emergence

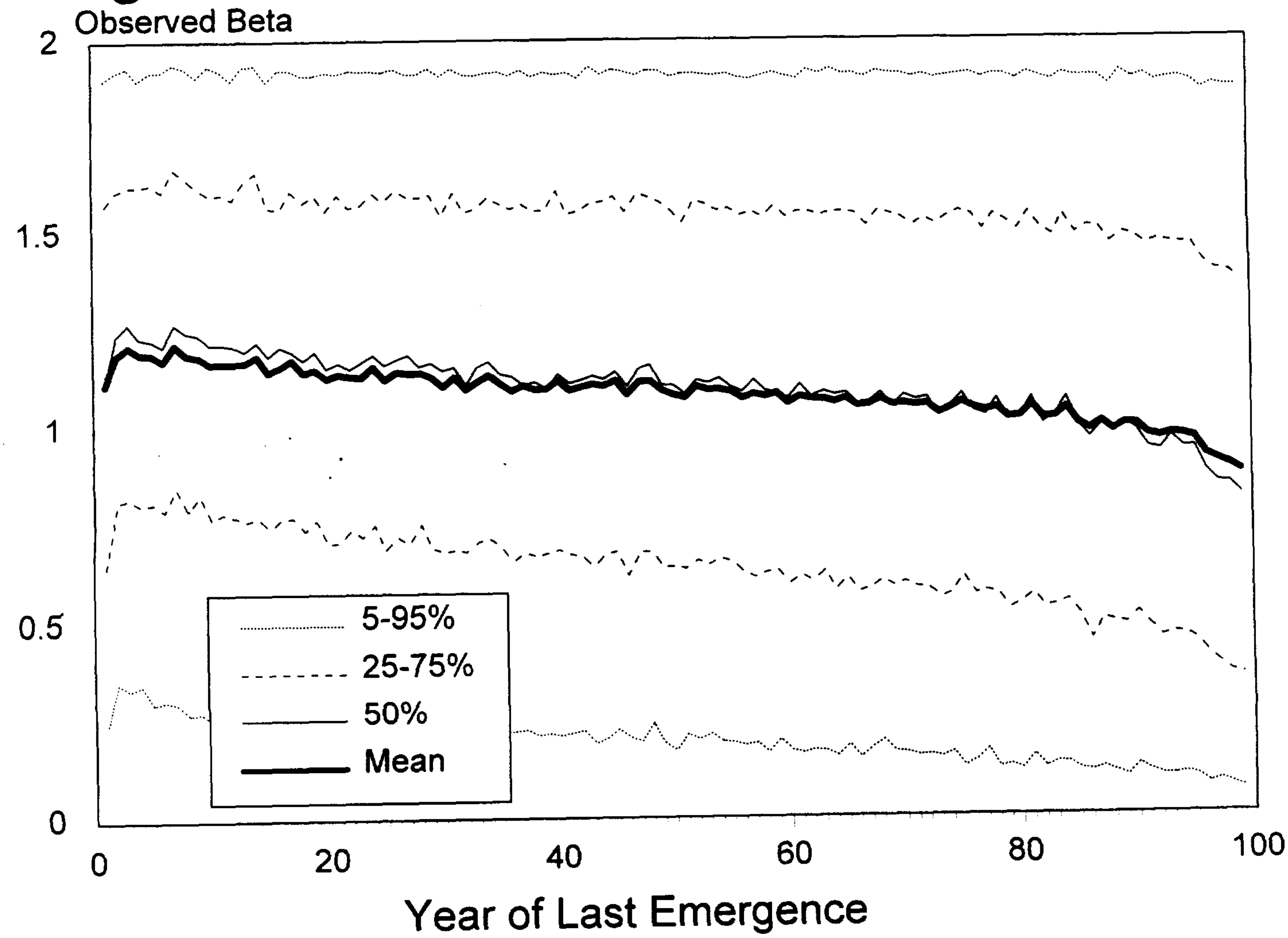

Fig.4. R-square vs. Year of Last Emergence

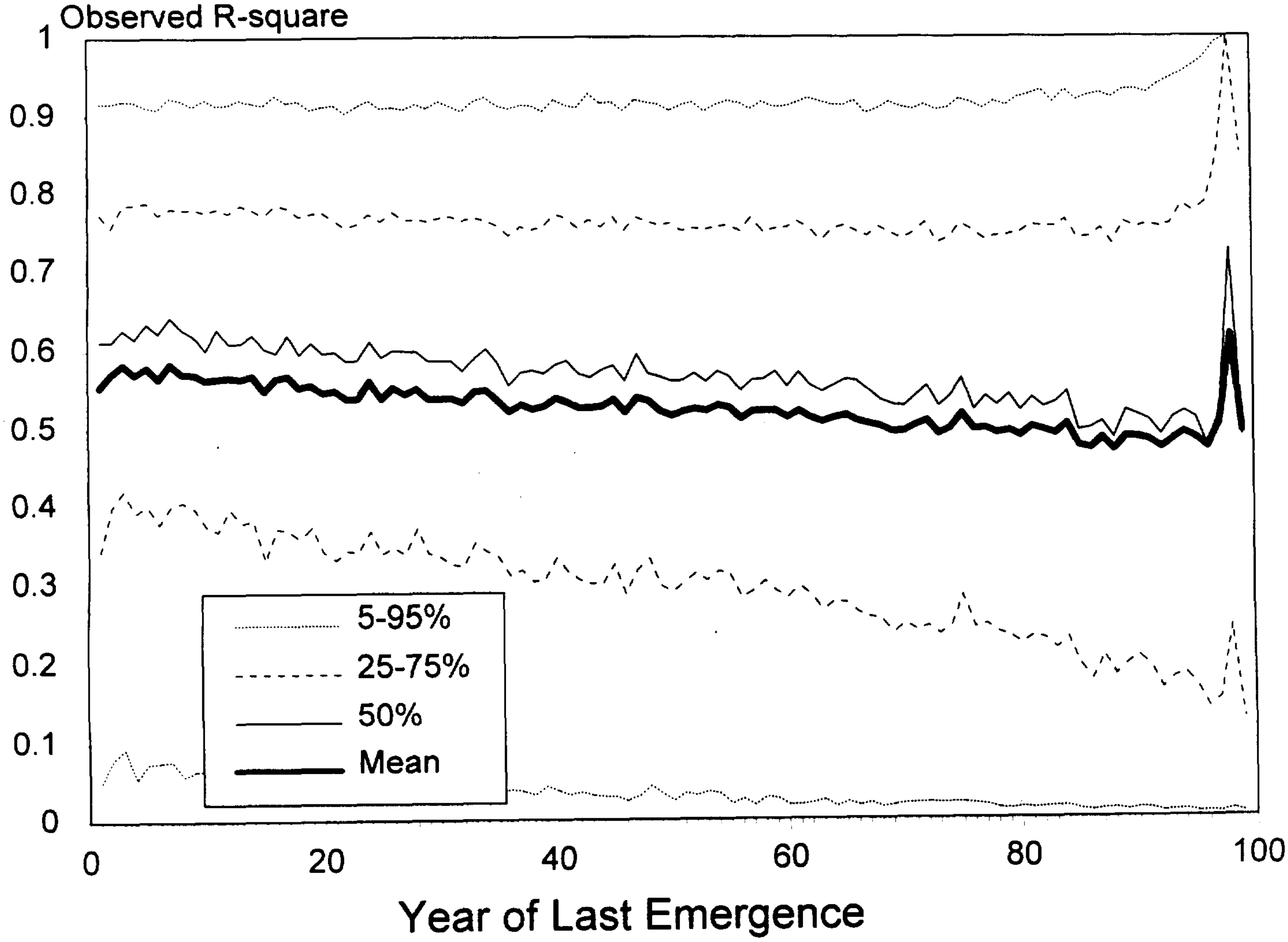

Fig.5. Betas of Bias on Start Date

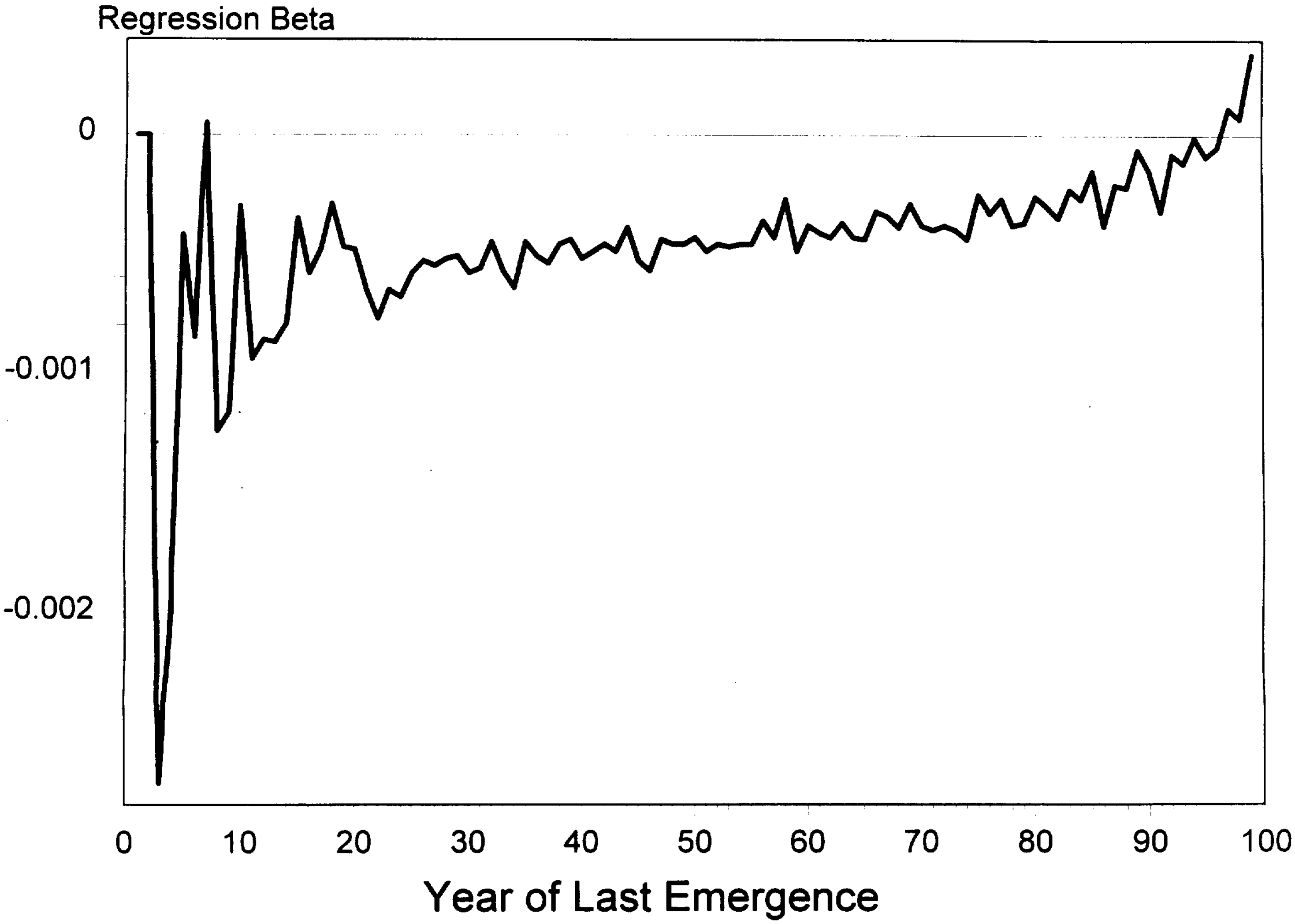

Fig.6. Average Returns Around Emergence

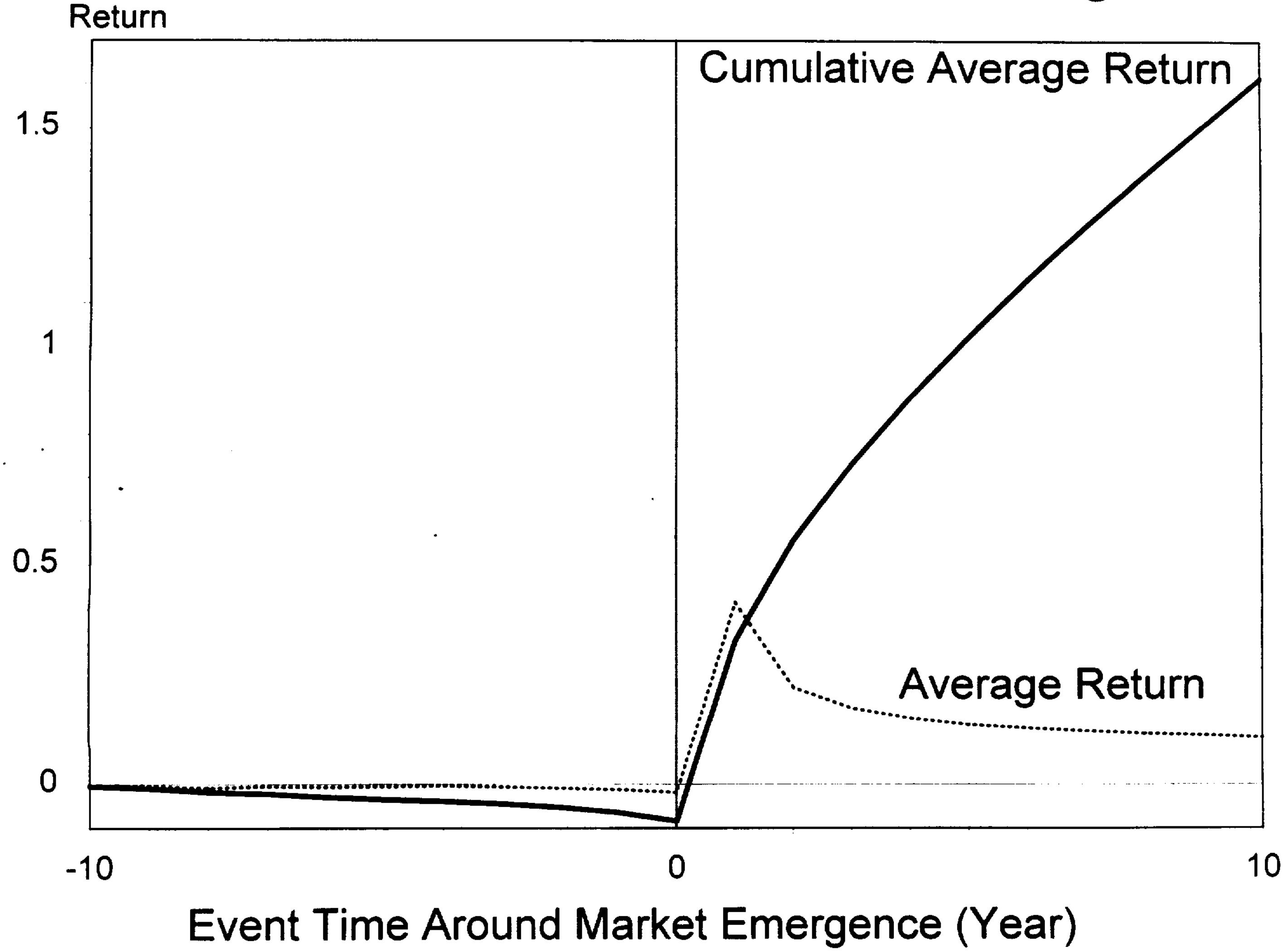

Fig.7. Global Beta and Emergence

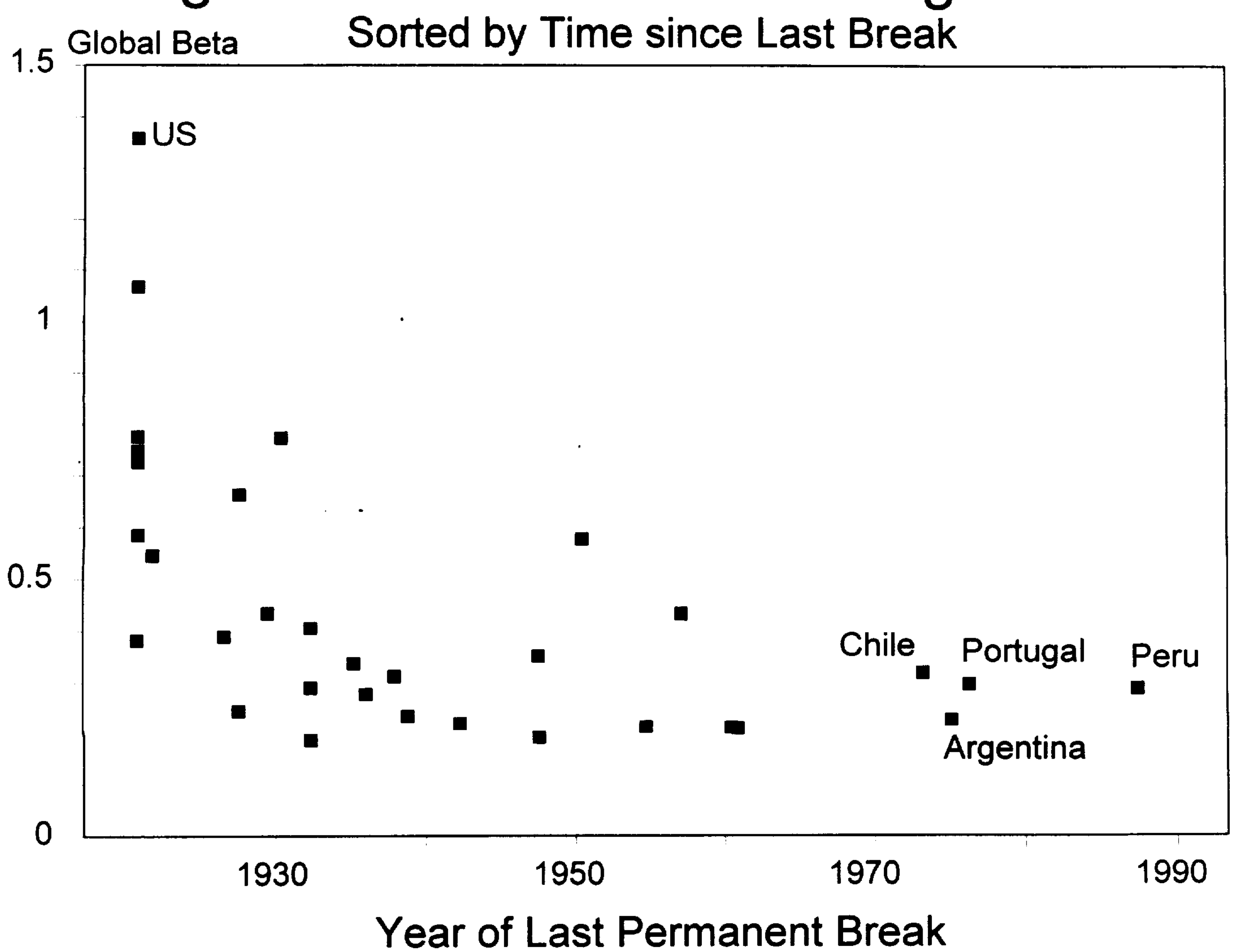

Fig.8. Real Returns on Global Stock Markets

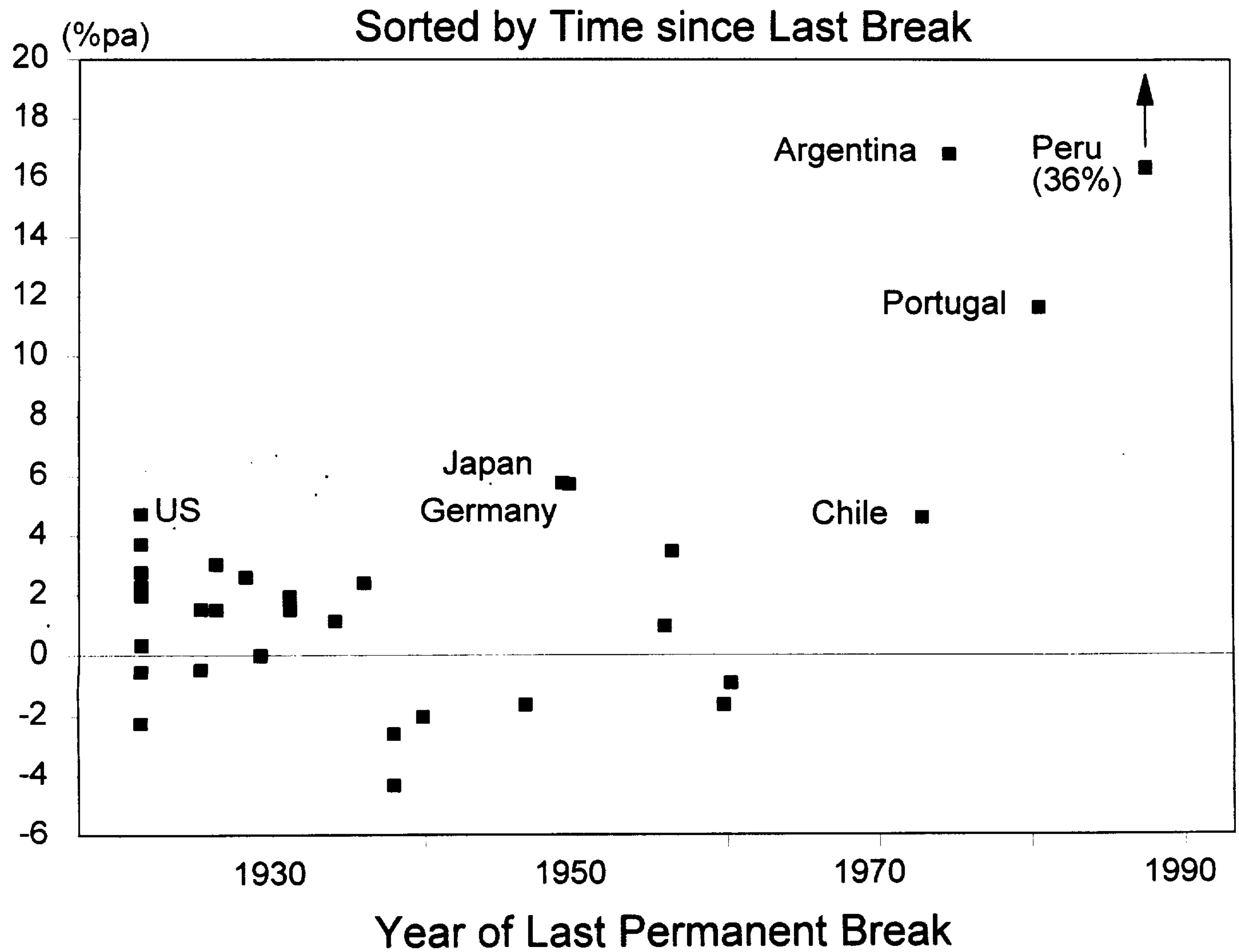

Fig.9. Performance after Emergence

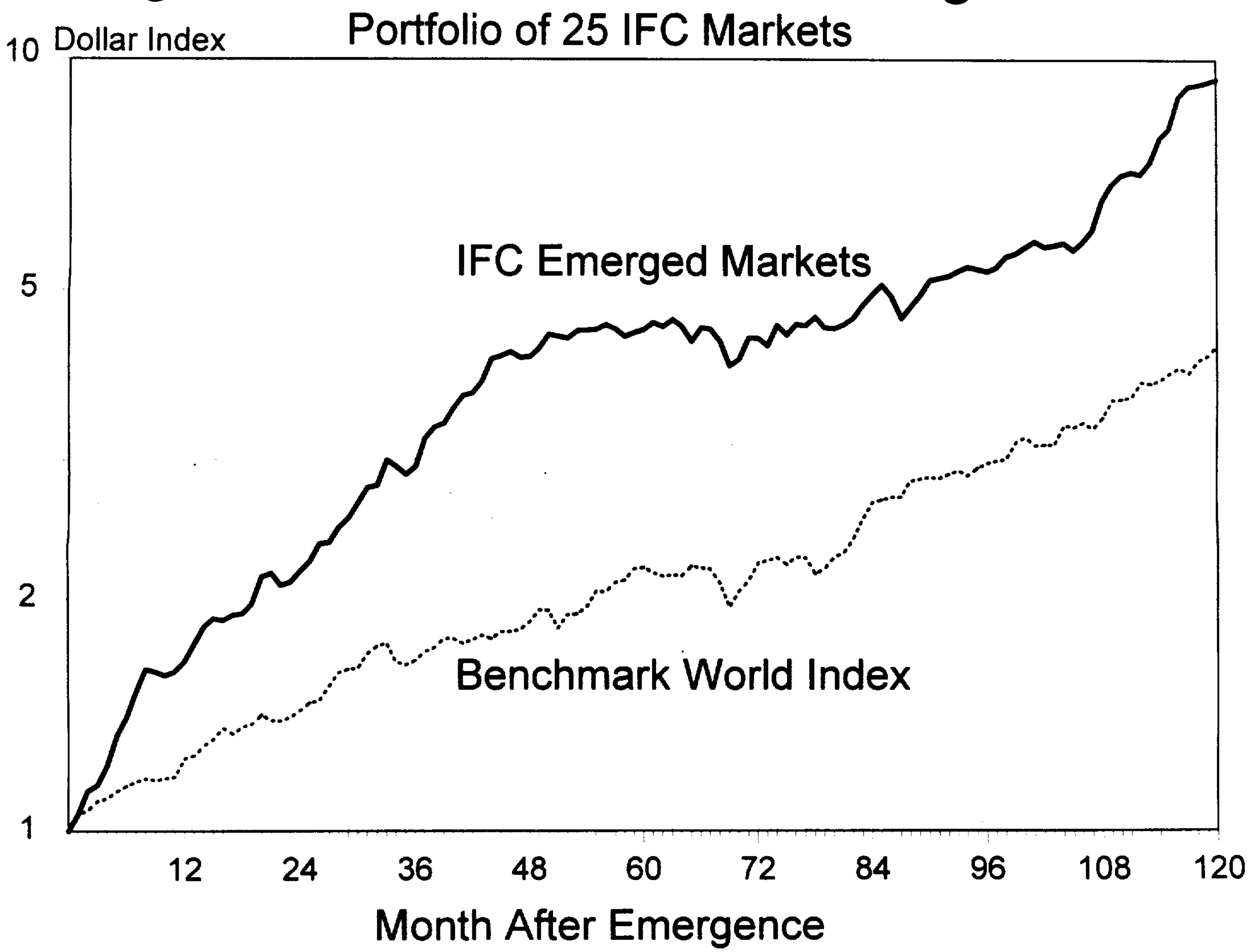

Fig.10. Performance around Emergence