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Portfolio Enhancement Using Emerging Markets and Conditioning Information

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This paper explores the implications of the low correlations of the emerging market returns with developed market returns and the relatively high degree predictability of emerging countres' returns in the context of conditional asset allocation strategies. It is well known that low correlations improve investment opportunities and my research provides out-of-sample validation of the improved performance. However, the most dramatic enhancement is generated by the use of conditioning information. Portfolio strategies that use conditioning information to predict emerging market returns produce out-of-sample performance that doubles traditional benchmark returns over the 1980-1992 period.

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1. Introduction

Many individual investors, as well as portfolio and pension fund managers, are reexamining their basic investment strategies. In the 1980's, fund managers realized that significant performance gains could be obtained with by diversifying into high quality global equity markets. However, these gains are limited by the fairly high cross-correlations returns in these markets.

While investment has traditionally been concentrated in developed markets, new interest has been sparked by the so-called 'emerging' capital markets. The emerging markets have at least three attractive qualities, two of which are their high average returns and their low correlations with developed markets. Diversification into these markets should result in higher expected returns and lower overall volatility.

In terms of portfolio theory, adding low correlation portfolios to an optimization enhances the reward to risk profile by shifting the mean-variance frontier to the left. However, this type of exercise may be misleading because it is based on ex post returns. This paper focusses on the performance of allocation strategies that optimize investment weights at the end of the month and hold the implied portfolio for the next month. Investment weights are then reoptimized and this strategy is continued throughout the 1980–1992 period.

However, the portfolio optimization problem requires important inputs – the expected returns and the variance-covariance matrix. In principal, all of these measures should be forward looking. That is, the returns, volatilities and correlations should be forecasted. The resulting investment strategy reflects current information.

The twist in this paper is that it utilizes the third desirable property of emerging market returns: they are predictable. Forecasting models are developed which provide one-step ahead forecasts for 41 markets (20 developed markets and 21 emerging markets).

Six portfolio strategies are evaluated. The first three examine traditional allocations based on (a) developed markets, (b) developed and emerging markets and (c) developed and emerging markets with a 20% cap on emerging markets. The allocations are traditional in that naive models, based on historical averages of the expected returns, variances and covariances, are used. For each case, two strategies are examined: (1) hold the global minimum variance portfolio and (2) hold the portfolio with a target volatility of 16% (annualized).

The fourth to sixth allocations use the same set of assets except conditioning information directly enters the optimization. With forecasted means, variances and covariances, new investment weights are calculated and the out-of-sample performance is evaluated and compared to the traditional asset allocation strategy.

Using the traditional asset allocation, there is some benefit to adding emerging markets to portfolios. However, the most dramatic enhancement comes with the introduction of emerging markets and conditioning information. Standard performance measures, such as ratios of expected return to volatility, more than double when both emerging markets and conditioning information are used.

The second part of the paper explores the risk of emerging markets. In the context of a global asset pricing model, each equity market has exposure to world risk factors. If the model provides a reasonable description of the expected returns, then each risk exposure is meaningful in that it is rewarded in equilibrium. Harvey (1993a) finds that there is no relation between emerging market returns and the risk sensitivity to the Morgan Stanley Capital International world portfolio. This study examines four additional factors: a world currency investment portfolio, the excess return on an investment in crude oil, growth in OECD industrial production and OECD inflation.

One weakness of previous analyses of emerging market returns is that static models are used. For example, risk exposures are often assumed to be constant. In the context of mature, developed economies, this might be an innocuous assumption. In the arena of emerging economies, it is unlikely that risk exposure remains fixed through time. Emerging economies are often characterized by shifting industrial structure which will induce changes in risk sensitivities. My research provides a first step examination of time-varying correlations between the emerging returns and the five risk factors.

The paper is organized as follows. In the second section, the unconditional and conditional portfolio optimization strategies are presented. The data are presented in the third section. In the fourth part, the results of the out-of-sample portfolio allocation are evaluated. The risk exposures of the emerging markets are explored in the fifth section. Some concluding remarks are offered in the sixth section.

2. Portfolio Strategies

2.1. Unconditional asset allocation

The usual problem that investment managers face is to maximize the expected returns of the portfolio subject to some target level of volatility. That is, investment weights are chosen to give the best possible performance for an expected level of standard deviation. The target standard deviation is determined outside the problem by the investor's tolerance for risk.

The solution to this problem,

$$\begin{gathered} \max_{\mathbf{w}} \quad \mathbf{w}'\boldsymbol{\mu} \\ \text{Subject to } \mathbf{w}'\mathbf{V}\mathbf{w} = \text{Target} \\ \mathbf{w}'\mathbf{1} = 1 \end{gathered} \tag{1}$$

where $\mathbf{w}$ represents a $N \times 1$ vector of investment proportions, $\boldsymbol{\mu}$ is a $N \times 1$ vector of expected asset returns, $\mathbf{V}$ is a $N \times N$ variance-covariance matrix, and N are the number of countries in the problem, is a standard quadratic program.

In this problem, the investment proportions are unrestricted in size but must sum to unity. This opens the possibility of extremely large short and long positions in any market. Given that thin trading is a problem in many emerging markets, it seem plausible that all short sales should be disallowed,

$$w_i \geq 0 \qquad \text{for } i = 1, \ldots, N. \tag{2}$$

This adds a third set of asset specific constraints to the problem (1).

The strategies evaluated in this paper involve solving (1) at the end of each month and holding the implied portfolio for the next month. The sample is updated using a 60-month moving window and the portfolio is reoptimized at each point in time. In all strategies, transactions costs are ignored although it is straightforward to modify the problem to add proportional transactions costs. All strategies are evaluated on an out-of-sample basis over the 1980.12 to 1992.06 period. That is, the first allocation is based on data from 1976:12 to 1980.11.

Two basic strategies are evaluated. The first is to choose the minimum-variance portfolio. That is, the investment weights match the weights implied by the minimum variance portfolio over the previous five years. These weights are used to form a portfolio and it is held over the next month. The second strategy involves choosing a portfolio with a target level of volatility of 16% (annualized). This volatility is roughly the volatility of holding the Morgan Stanley Capital International (MSCI) world market portfolio [see Harvey (1991)] which is a common benchmark.

In solving the problem, there is always a minimum-variance portfolio. However, there is not always a portfolio with the 16% target volatility because of the short-sales constraints. In the case where the 16% can not be attained from below, the maximum-variance portfolio is chosen. When the 16% cannot be attained from above (on the positively sloped section of the mean-variance frontier), the minimum-variance portfolio is chosen.

Three sets of equity groups are considered. The first restricts the assets to 21 equity markets in the MSCI universe. The second group adds 20 emerging equity markets from the International Finance Corporation. The third group includes the 41 countries but imposes the additional constraint to (1) and (2) that the sum of the weights in the emerging markets must be less than or equal to 20%. This precludes the possibility that an unreasonable proportion of the portfolio is placed in emerging market assets.

The strategy is considered *unconditional* because of the way of expected returns, variances and covariances are chosen. The expected returns are the mean returns over the previous 60 months. Although these mean returns change through time as the 60-month window moves, using the average returns assumes that the best forecast of the equity return is its past average. This is consistent with a random walk model of stock prices with drift. This model implies that there is no other information relevant for forecasting next months stock *price* other than the previous price. In other words, stock *returns* are not predictable.

The unconditional strategy also places restrictions on other inputs to the problem. The variances and covariances are assumed to be the unconditional variances and covariances over the previous 60 months. This precludes the possibility that these measures move in more complex ways.

All strategies are developed and implemented in U.S. dollar terms. This assumes that no currency hedging takes place. Implementing the problem in local currency terms would be consistent with perfect foresight currency hedges being initiated for each country. This assumption is tenuous for developed markets and unreasonable for the emerging markets. As a result, the evaluation is done in a common numeraire currency.[1]

2.2. Conditional asset allocation

In the mean-variance problem in (1), three sets of inputs are needed: means, variances and covariances. At the end of the month, the investor is trying to design the portfolio that guarantees the highest possible expected return for the level of volatility that is consistent with the risk tolerance. In solving the unconditional problem, a set of portfolio weights are obtained that guarantees the highest ex post returns for a level of volatility – over the past five years. In other words, the unconditional mean-variance problem delivers a set of investment weights that 'work' – but only over the past history.

The only way for the manager to obtain an efficient portfolio (highest expected return for a level of volatility) in the unconditional problem is to hold the

[1] Harvey (1993b) studies the international asset allocation problem and argues that the portfolio selection should include currency portfolios (in the form of local deposits or loans). The solution to the quadratic program will deliver the optimal asset allocation as well as the optimal currency hedges.

investment weights implied by the actual data! Suppose that a manager is being evaluated over the 1981.01 to 1985.12 period. In 1980.12, the manager begins to manage the portfolio. Evaluation is measured in terms of how close the manager is to the efficient frontier. How can the manager obtain this efficient portfolio? – only on the basis of the knowing the data from 1981.01 to 1985.12 – which is obviously impossible.

In implementing the unconditional asset allocation strategies, managers will optimize their portfolio over 1976.01 to 1980.12 and hold the implied portfolio weights over the next period. These weights guarantee the portfolio is efficient over the 1976.01 to 1980.12 – not in the future.

So in practice, what is really required for the mean-variance problem is the best possible *forecasts* of the expected returns, variances and covariances *for the next period.* The past averages may not be that meaningful because the investment manager cares about the future and not the past. Past averages are only used if the means, variances and covariances are completely unpredictable.

The conditional asset allocation implements forecasting models for the inputs of the mean-variance problems. Linear regression models are built for the conditional means using a number of information variables,

$$E[r_{it}|\boldsymbol{Z}_{t-1}] = \boldsymbol{Z}_{t-1}\boldsymbol{\delta}_i, \tag{3}$$

where r_{it} is the return on country i over from $t-1$ to t, $\boldsymbol{Z}_{t-1}$ is a $1 \times \ell$ vector of ℓ global and country specific information variables that are known at time $t-1$, $\boldsymbol{\delta}_i$ is a $\ell \times 1$ coefficient matrix. The errors from this regression, ϵ_{it}, are assumed to be unrelated to the conditioning information, $\boldsymbol{Z}_{t-1}$.

I use linear models for conditional means which is consistent with a number of previous studies.[2] The forecasting variables include a constant as well as

[2] See for example, Gibbons and Ferson (1985), Keim and Stambaugh (1986), Fama and French (1988, 1989), Harvey (1989, 1991), Ferson and Harvey (1991, 1993), Campbell and Hamao (1992), and Harvey (1993a) for some examples. Harvey (1992) compares the performance of linear models to general nonlinear alternatives and finds that linear models perform as well as nonlinear models in out-of-sample evaluation.

world variables such the lagged world dividend yield and lagged world returns and country-specific variables including lagged country dividend yield lagged country returns. All of the forecasting variables are financial variables to ensure data availability on the last day of the month.

The portfolio problem also requires the forecast of the variance-covariance matrix. Consider the covariance between asset i and j:

$$\mathrm{Cov}[r_{it}, r_{jt}|\boldsymbol{Z}_{t-1}] = E\left[(r_{it} - E[r_{it}|\boldsymbol{Z}_{t-1}])(r_{jt} - E[r_{jt}|\boldsymbol{Z}_{t-1}])\middle|\boldsymbol{Z}_{t-1}\right]. \tag{4}$$

Given the regression errors in (3), we can rewrite (4) as:

$$\mathrm{Cov}[r_{it}, r_{jt}|\boldsymbol{Z}_{t-1}] = E[\epsilon_{it}\epsilon_{jt}|\boldsymbol{Z}_{t-1}]. \tag{5}$$

The conditional covariance is the forecasted value of the product of the residuals for the regression models for asset i and asset j.

In principal, the conditioning information for asset i and asset j is different. In addition, the conditioning information on the product of the two residuals could be the intersection of the two information sets plus additional variables. For example, an autoregressive-conditional heteroskedasticity (ARCH) type model would include lagged values of the product of the residuals in the information set.

The approach of this paper is to use the unconditional mean of the product of the residuals as the forecasted variance-covariance matrix. This implicitly assumes that the product of the residuals is not predictable. This follows, in spirit, the approach of Solnik (1993). However, the matrix used in this paper is *not* the unconditional variance-covariance matrix. It is the average conditional variance-covariance matrix. Importantly, the $\boldsymbol{Z}_{t-1}$ variables are allowed to affect the means.

This approach greatly simplifies the estimation. Indeed, a full model of the variance-covariance matrix would require up to 820 forecasting equations when 41 markets are examined! In addition, the most important inputs for asset allocation are the expected values for the asset returns. The optimal weights are much more sensitive to a change in the means than to a change in the variances or covariances.

Similar to the unconditional asset allocation, the variance-covariance matrix is based on a 60-month moving window average of the product of the regression residuals through the sample. In the analysis, the regressions are estimated over the full sample which implies that the regression coefficients, $\boldsymbol{\delta}_i$, are constant. More elaborate models which using moving-window estimation for the conditional means are also possible. This would allow for out-of-sample forecasts at every step.[3]

In addition, to minimize the data snooping problem, a set of predetermined information variables were chosen before the data were examined. While the set of information variables resembles the set of variables used in potentially data-snooped studies of developed markets, no one has examined the predictability of emerging market returns. In addition, given the low correlations between emerging returns and developed returns, it does not necessarily follow that the variables that predict developed market returns automatically predict emerging market returns.

There is also the issue of survivorship biases in the emerging markets data which is examined in Harvey (1993a). The International Finance Corporation began publishing indices in 1981 – yet their data reaches back to 1975.12. In some of the markets, the indices were back-tracked. This induces a look-back bias in the sample. That is, the stocks in 1976 are the ones that survived to 1981. Harvey argues that it is not clear that this problem is serious. In addition, the asset allocation routine avoids the look-back by requiring that the market exist for five years before it is included in the allocation.

3. Data

3.1. Sources and summary statistics

Data are available on for 21 developed markets from Morgan Stanley Capital International and 20 emerging markets from the International Finance Corporation of the World Bank. Some summary statistics are presented in table 1.

The summary statistics are presented for the full sample period, 1976.01 to

[3] Harvey (1989) and Solnik (1993) examine the out-of-sample forecasts of the linear regression models and find that their performance compares favorably to the in-sample forecasts.

1992.06 and for a recent subperiod, 1985.01 to 1992.06. Both U.S. dollar returns and local currency returns are displayed. The statistics include the average (annualized) arithmetic and geometric return, standard deviation and autocorrelations. The developed market summary statistics are presented over different samples by other authors and appear for the purpose of comparison with the emerging returns.

The mean U.S. dollar returns for the emerging markets range from 72% (Argentina) to -6% (Indonesia whose sample only begins in January 1990). This sharply contrasts with the range of average returns in the developed markets. In the MSCI sample, no country has an average arithmetic return that exceeds 25%. In the IFC emerging sample, 9 countries (Argentina, Chile, Colombia, Philippines, Portugal, Taiwan, Thailand, Turkey and Venezuela) have returns that average above 25%.

It is important to present both the arithmetic and geometric average returns. The geometric average reflects the average returns to a buy and hold strategy. With high volatility, there could be large differences in the arithmetic and geometric mean returns. This is especially evident in the emerging markets sample. The most dramatic example is Argentina. The arithmetic average return is 72% and the geometic average is 27%!

The emerging market returns are characterized by high volatility. Volatility ranges from 18% (Jordan) to 105.6% (Argentina). In contrast, the MSCI countries have range of volatility between 15% and 33%. There are 13 emerging countries with volatility higher than 33% (Argentina, Brazil, Chile, Greece, Indonesia, Mexico, Nigeria, Philippines, Portugal, Taiwan, Turkey, Venezuela, and Zimbabwe).

The autocorrelations are also presented in table 1. In the MSCI sample, there are only five countries with first-order autocorrelation that exceeds 10%. In the emerging countries, there are 12 countries with autocorrelations greater than 10%. Indeed, there are eight countries with autocorrelations above 20% (Colombia, Indonesia, Mexico, Pakistan, Philippines, Portugal, Turkey, and Venezuela). This suggests that the returns in these countries are predictable based on past information.

The second panel of table 1 examines the most recent subperiod. The same pattern in the summary statistics are evident. For example, one might think that the extraordinary 72% average return for Argentina might be a function of the a look-back bias because the data begins in 1975.12. However, in the most recent subperiod the average return in Argentina is 88%! Indeed, in the most recent subperiod, there are 10 countries whose returns exceed 33%. The predictability is also retained with 10 countries exhibiting serial correlation above 20%.

For comparison purposes, the statistics on the returns in local currency terms are also presented. The wild inflation in Argentina and Brazil is evident in the 228% and 156% average returns over the full sample. Other countries that have experienced severe inflation such as Colombia, Chile and Venezuela also have much higher local returns. Calculating the returns in U.S. dollars eliminates the local inflation. However, the U.S. inflation remains in the returns.

The cross-correlations of the emerging markets and the correlations of the emerging markets and the MSCI markets are presented in table 2. Panel A details the U.S. dollar return correlations within the emerging markets. These correlations are remarkably small. For example, the correlation between Argentina and Brazil is only -3%. The correlation between Pakistan and India is -10%. The correlation between Colombia and Chile is 0%. The correlations in the most recent subperiod (panel B) show the same characteristics. The correlation between Argentina and Brazil is still -4%.

Panels C and D present the correlations in local currency terms. Interestingly, the correlations do not change that much. For example, the correlation between the Argentina and Brazil returns increases to 15% when measured in local currency terms. Over the shorter sample, the correlation is 16%. The correlation between Colombia and Chile is -6%.

The correlation between the emerging and developed markets is presented in the next four panels. The average correlations are very small. Malaysia has the highest correlation with developed markets and Mexico has the second highest. For the other countries, the correlations are often less than 10%. For example, Argentina has correlations less than 10% for 18 of the 21 developed markets.

Korea has correlations less than 10% for 8 of the 21 developed markets.

The same holds true in the most recent subperiod. Argentina and Venezuela's correlations with each 21 MSCI markets are less than 10%. There are many countries that have negative correlations with a number developed markets.

Mullins (1993) argues that the low average monthly correlations could be due market imperfections such as lead and lag effects. Mullins shows that the annual correlations are higher than the month correlations. However, it is not clear that they are statistically higher. In my sample (excluding Indonesia), there are 171 cross-correlation coefficients for 19 returns. Using monthly data, 26 are significantly different from zero. With the annual data, only 5 are significantly different from zero. This evidence supports the position that the low correlations are real rather than an artifact of infrequent trading.[4]

The low correlations imply significant benefits are possible in diversifying into the emerging markets. Even though the volatility of the individual emerging markets is high, the low correlations should reduce portfolio volatility. This is evident in the work of Divecha, Drach and Stefek (1992), Stone (1990) and Wilcox (1992). Next, I will assess how these benefits translate into portfolio performance.

4. Asset Allocation

4.1. Performance of unconditional asset allocation strategies

The unconditional minimum-variance frontiers for each month between 1980.12 and 1992.06 are graphed in figure 1. The first panel presents frontiers based on the MSCI sample of developed equity markets. The second panel introduces the emerging markets into the optimization. Overlaying these two panels, it is evident that the introduction of the emerging markets greatly increases the investment possibilities. The frontiers move up (higher mean) and shift inward (lower standard deviation). This is evident even if the emerging markets are restricted to

[4] Using monthly data, there are 5 emerging countries that have significant correlation with the U.S. return. With annual data, only one country has significant correlation (at the 5% level of significance).

20% of the investment portfolio (in panel C).

Figure 2 presents the weights placed on the aggregate of the MSCI portfolios and the emerging portfolios for the two investment strategies. In the first panel, the weights for the minimum-variance strategy is shown. Through the entire sample, the weight on the developed markets decreases and the weight on the emerging markets increases. By the end of the sample, the optimizer wants to place over 90% of investment funds in emerging markets. The second panel shows the weights of the minimum-variance strategy when the investment in emerging markets is constrained to be at 20% or below. This constraint is binding in every month.

The next two panels show the weights for the 16% target volatility strategy. The weights are much more variable in this exercise. Indeed, the weight on the developed markets plunges from above 80% at the beginning of 1985 to zero for five months. Other than this one extreme swing, the same pattern persists: If the optimizer is unconstrained, it will place increasing weight on the emerging equities. The constrained optimization with the 20% cap, shown in the final panel, suggests that the constraint is binding after 1987.

Table 3 presents the performance measures for each of the strategies. First, consider the minimum-variance strategy. When restricted to just developed markets, the out-of-sample performance amounts to 16.09% per year with a 15.39% standard deviation.[5] If emerging markets are added to the problem, the performance increases slightly to 16.35%. More dramatically, the volatility drops to only 11.63%. When the emerging markets are capped at 20%, the actual return increases to 17.02% and the volatility increases to 14.02% – however, this is still almost a full percent lower than the strategy that restricts investment to only developed countries. The Sharpe ratios (return in excess of the eurodollar rate[6] divided by standard deviation) for the three minimum-variance investment strate-

[5] For comparison over the same period, the MSCI world return was 14.32% with a standard deviation of 15.45%. The MSCI U.S. return was 14.96% with a standard deviation of 15.92%.

[6] Based on the average 30-day eurodeposit rate over the 1980.12 to 1992.06 period of 8.7%.

gies are: 0.48, 0.66 and 0.59. These results suggest an unambiguous benefit to diversifying into emerging markets. Interestingly, the benefit is mainly driven by lower portfolio volatility rather than higher returns.

The first three columns of table 4 detail the year-by-year performance of these strategies. The developed plus emerging markets with the 20% cap produces returns that are almost always better than the developed countries alone. The exception are the first 6 months of 1992.

The second panel of table 3 shows the results of the 16% target volatility strategy. All of the strategies have lower returns than the minimum-variance strategies. The highest return, 13.48%, is found in the developed and emerging sample. The Sharpe ratios for the three strategies are 0.23, 0.24 and 0.16.

The year-by-year performance is presented in the fourth through sixth columns of table 4. The 16% target strategy sustains serious losses in 1982, 1984 and 1990. An examination of the returns of the different 16% volatility strategies does not suggest that any one dominates the others.

Why doesn't the 16% target strategy perform better than the minimum-variance strategy? The answer has to do with the mean. In solving for the minimum-variance portfolio, you do not need the mean [see Roll (1977, eq. A.14)]. That is, the allocation is not affected by mismeasurement of the mean. However, the 16% target strategy needs an estimate of the mean. As a result, if the forecast of the return is poor, the 16% strategy will suffer. The minimum-variance strategy will be relatively immune to a misspecification of the mean. It now makes sense to examine the specification of the mean.

4.2. Predictability of returns

A number of world and local information variables used to forecast the returns on the 41 equity markets. Each variable is known at time $t-1$ when the forecast takes place. The world variables include a constant, the lagged world return, the lagged return on a 10 country currency index[7], the lagged MSCI world dividend yield,

[7] See Harvey (1993b) for details on the construction of this index.

the lagged MSCI earnings-price ratio, and the lagged Eurodollar rate. The local information variables include the lagged country equity return in local currency terms, the lagged change in the country's foreign exchange rate per U.S. dollar, the lagged country dividend and the lagged country's earnings-price ratio. For the emerging countries, the last two information variables are only available beginning in 1985. As a result, these two variables do not enter the regression forecasts until 1985.

The results of the U.S. dollar regressions are presented in table 5. In the overall sample, 14 of the 21 developed countries exhibit significant predictability. In 9 of these countries, the local information variables help predict the equity returns. A multivariate test of the predictability suggests that we can reject the hypothesis that the expected returns are constant at the 99% level of confidence.

The predictability of the emerging returns is detailed in the next panel. The regressions are significant in 12 of the 20 emerging markets. In addition, local information (lagged return, lagged FX) is important in 5 of these countries. There are 9 emerging markets whose R^2s exceed 10%. This contrasts to only 4 developed markets with R^2 above 10%. The multivariate test of predictability provides a strong rejection (99.9% level of confidence) of the hypothesis that the expected emerging returns are constant.

The next panel examines the most recent sample. In the developed countries, returns are predictable in 15 of the 21 countries. For the emerging markets, 13 of 20 regressions are significant. Local information is important in five developed countries. The local information (which now also includes a lagged dividend yield and a lagged earnings-price ratio) is important in 9 of the 20 emerging market regressions. In 18 of the regressions, the R^2s exceed 10%. Indeed, in 11 of the regressions the R^2s exceed 20%. The message from the table is that the emerging returns are predictable – and more predictable than the developed country returns.

4.3. The performance of conditional asset allocation strategies

Figure 3 draws the conditional mean-variance frontiers from 1980.12 to 1992.06. These frontiers are based on expected returns from the regression model (4). For the countries with all the conditioning variables, the full-period coefficient estimates are used for the expected returns. For the countries which are missing the dividend yield and earnings-price ratios before 1985, two models are estimated. The first model omits the dividend yield and earnings-price ratio and fitted values are obtained through 1984.12. The second model uses the most recent data and the full set of conditioning variables and the fitted values are obtained from 1985.01 through 1992.06.

All panels of figure 3 dramatically contrast with figure 1. The mean-variance frontiers shift across to a lower volatility range and upward to a higher expected return range. In almost every case, the parabola opens up indicating a wider range of investment opportunities. The frontiers are truncated between the annualized expected returns of -30% and 70%.

Comparing panels A (developed markets) and panels B (developed and emerging) for the 1981–1985 period, the shape of the frontiers looks similar. However, the frontiers have been shifted to the lower volatility range in panel B. The more dramatic differences appear in the 1986–1992 graphs. When emerging markets are added to the mean-variance problem, the frontier flattens out and moves to the lower standard deviation range. Even when the 20% cap on the emerging markets is binding (in panel C), this flattening out is evident.

Figure 4 plots the investment weights for the minimum volatility and the 16% target volatility strategies. Similar to figure 2, when there is no constraint on the weight of the emerging markets in the portfolio, the investment weight assigned to emerging markets increases through time. By 1992, the optimizer tells us to invest only 10% of our portfolio in developed country stocks. When the problem is rerun with the 20% cap on emerging markets, the constraint is binding from 1981.

The weights depicted in figure 4 for the 16% target volatility strategy are more variable but follow similar patterns to the ones experienced in figure 2. There is a huge reweighting to emerging markets beginning in 1986. Over time, when the participation in emerging markets is not constrained, the investment weights increase in these markets. By the last optimization, all investment is placed in emerging markets. The move to emerging markets is also evident in the constrained optimization. By 1986, the 20% cap is always binding.

Table 6 presents the returns of the portfolio strategies. The mean (annualized) return when only developed markets are included is 16.99% with a volatility of 15.14%. Similar to the unconditional strategy, when emerging markets are added to the problem, the mean return increases to 17.97% and the volatility plunges to 11.66%. Also similar to the unconditional strategy, when the emerging markets are capped at 20% the returns increase to 18.87% and the volatility increases to 14.05% – still more than a full percentage below the case where we are restricted to only developed markets' equities. The Sharpe ratios for the three strategies are: 0.55, 0.80 and 0.72.

The conditional minimum volatility (table 6) and the unconditional strategy (table 3) have striking similarities. The results are similar because, as mentioned earlier, the minimum-variance portfolio weights do not directly depend on the expected returns vector. The results are not exactly the same for two reasons. First, the problem is different than the one examined in Roll (1977) because of the no short-sales constraint. Second, and more importantly, the mean enters the problem indirectly through the variance-covariance matrix. In the unconditional problem, we use the unconditional variances and covariances. In the conditional problem, we use the average conditional variance and the average conditional covariance. The extent to which the conditional second moment measures differ from their unconditional counterparts will determine the degree of difference in the investment weights.

In the target 16% volatility strategy, the expected returns play a critical role. In the unconditional strategies in table 3, the historical average returns were used as the expected returns and the performance of this strategy was inferior to the minimum-variance strategy. For example, in the unconditional minimum-variance strategy with developed and capped emerging markets, the average expected volatility was 9.52% producing a return of 17.02%. In contrast, the unconditional 16% target volatility (whose average expected volatility was actually 16.19%), the return was only 12.09%. By taking on almost double the volatility, your returns go down. This might have seem surprising. However, as noted earlier, the intuition behind this result has to do with the expected returns.

The average historical mean is not a very good forecast of the expected returns in most countries. This is evident from table 5. In the minimum-volatility strategy, we get around the forecasting problem. However, in the target volatility strategies, you must use have a forecasting model. The results in table 3 suggest that implementing an asset allocation model using historical means as forecasts for the expected returns could have disastrous consequences.

The results in the second panel of table 6 use the regression forecasts for the expected returns. The average expected returns for the developed countries sample is 29.94% with a volatility of 18.33%.[8] When the emerging markets are added to the problem, the returns leap to 54.96%, however the realized volatility jumps to 24.40%. When the emerging markets are constrained to a 20% portfolio weight, the annual return is 39.30% with a volatility of 19.89%. The Sharpe ratio for strategy with the emerging markets capped at 20% is 1.53. This compares to a ratio os 1.16 if the investor is restricted to only developed markets and 0.23 for the strategy that does not use conditioning information.

The year-by-by returns of the six different investments that use conditioning information are presented in table 7. The minimum-volatility strategy returns are similar to the ones presented in table 4 in that losses are sustained in the first and last years. However, the choose 16% volatility strategies are much different from the unconditional ones presented in table 4. In the exercise with both developed and capped emerging markets, there is only one year with a small negative return

[8] These results are consistent with Solnik's (1993) study of 8 developed markets over the 1971.01 to 1990.08 period. His unconditional asset allocation produced returns of 18.2% with a standard deviation of 17.5%. Using the conditional means and the unconditional variances and covariances, the returns increased to 24.6% and with a volatility of 20.4%.

(1982, -0.49%). All other years have positive returns and there are five years where the returns exceed 30%.

The returns implied by the conditional asset allocation suggests that the main benefit of investment in emerging markets comes from the predictability of the emerging market returns. This predictability, combined with the low correlations within emerging markets and with developed markets, enhances portfolio performance.

Implicit in the mean-variance analysis are the assumptions that investors prefer higher expected returns and that the risk (which investors dislike) of the portfolio is captured by the overall variance. It is useful to characterize the risk of the individual markets. Indeed, in implementing portfolio optimization, it is commonplace to add constraints to limit exposure to certain types of risk. The problem that we face, in particular, is how do we characterize the risk of the emerging markets?

5. Risk Exposure of Emerging Markets

5.1. Single factor models

If an efficient benchmark portfolio existed, then the risk of the individual market is measured by the covariance with the efficient benchmark. The expected return on that market would be exactly linear in the efficient benchmark [Roll (1977), Ross (1977)]. If the benchmark is not efficient (and even if it is very close to efficient), there may be no relation between the covariance and the expected returns.[9]

One potential benchmark is the MSCI world market portfolio in excess of the 30-day eurodollar deposit rate. Cumby and Glen (1990), Harvey (1991) Harvey and Zhou (1993), and Ferson and Harvey (1994) fail to reject the mean-variance efficiency of this portfolio within the set developed countries' assets. Harvey (1993a) shows that it is unlikely that this benchmark will adequately characterize the expected returns on emerging country assets.

[9] See Roll and Ross (1993).

Table 8 provides estimates of the one factor model for both the developed and emerging markets. The loading on MSCI world market portfolio is significantly different from zero in each of the developed countries.[10] However, in the emerging markets, only seven countries (Greece, Korea, Malaysia, Mexico, Philippines, Portugal and Thailand) have significant betas. In addition, only one of the countries has a beta greater than unity (Portugal 1.168) so it is unlikely that there is a strong relation between expected returns and this risk exposure.

In the more recent subperiod, the results are similar. Only six emerging markets have betas that are significiantly different from zero. Only a single country has a beta greater than one and two countries have negative betas. The R^2s of these regressions range from zero (in 13 countries) to 20% (Malaysia). Even if returns are calculated in local currency terms (last two panels), the significance is not altered.

The inability of the single factor model to characterize the emerging returns is a result of the MSCI portfolio being inefficient relative to the set of assets examined. Indeed, the low or negative betas are expected from the low and negative correlations that many of the emerging markets have with the developed market. The MSCI world market portfolio is really a developed world market portfolio.

The betas estimated in table 8 assume that the risk is constant throughout the period examined. Figure shows five-year rolling correlation measures of the country returns and the MSCI excess returns. Correlations are presented with and without the October 1987 observation. The graphs depict some interesting changes in the correlations. In Brazil, correlations have increased from zero in the early 1980s to 25% by 1992. There is no significant pattern in any of the other South American countries. However, the Mexican correlations have increased from zero in 1986 to 30% by 1991. In the East Asian countries, the correlations have been progressively increasing reaching 40% in Korea, 60% in Malaysia, 40% in the Philippines, 15% in Taiwan and 40% in Thailand. The correlation of India has

[10] Note that the table presents regressions of returns, not excess returns, on the MSCI world market portfolio. As a result, many of the intercepts are significantly different from zero.

been uniformly decreasing through time. The Greek and Portuguese correlations have reached 25% and 50% respectively by 1992.

The time-variation in the correlations suggest that the sensitivity of many emerging markets to the MSCI world portfolios is increasing. While there is only limited ability of the betas to explain the expected return variation across different countries (the cross-sectional adjusted R^2 is only 4% in the overall period),[11] it appears as if this cross-sectional R^2 may increase from the beginning of the sample to the end of the sample.

5.2. *Foreign exchange exposure*

The inclusion of a foreign exchange factor is motivated by the work of Solnik (1974), Sercu (1980), Stulz (1981) and Adler and Dumas (1983). The models presented in these papers provide an explicit role for exchange risk. I simplify the exchange risk into a single factor which represents the investment return on a portfolio of local deposits in 10 developed countries in excess of the 30-day eurodollar rate. The index is developed and analyzed in Harvey (1993b).

For developed market returns, the betas on the exchange investment index are significiantly different from zero in 12 of 21 countries in the overall period. The factor has marginal explanatory power in 8 of the 20 emerging markets (Greece, India, Jordan, Malaysia, Mexico, Pakistan, Taiwan and Zimbabwe). However, in 8 other countries the R^2 of the two factor regressions is zero.

In the most recent subperiod, the marginal explanatory power of the foreign exchange risk factor is not substantially altered. There are eight countries with t-statistics greater than 1.5 on the exchange portfolio. This portfolio has some ability to explain returns in Argentina and Chile as well as Thailand.

The significance of the foreign exchange risk factor in developed markets is not altered if the returns are calculated in local currency terms. Indeed, 17 of the 21 developed markets have significant exposures in local currency terms. In

[11] In contrast, the adjusted R^2 of the regression of the 21 developed country average returns on their betas is 30%.

addition, the explanatory power in the emerging markets is unchanged. Only 7 of the 20 countries have significant exposure to this factor when returns are measured in local currency terms.

Plots of the 5-year rolling correlations between the country returns and the foreign exchange portfolio are presented in figure 6. These measures are not the same as betas because the correlation with the world market portfolio is not being controlled for. However, the plots reveal interesting similarities to the ones in figure 5. In general, there is a tendency for the correlations to increase in absolute magnitude during the last seven years of the sample. This is the case in the South American countries and Mexico. The correlations are zero in the East Asian countries with the exception of Thailand. The correlation of the FX index and Greece is about 30% in 1992 and has risen to more than 50% for Portugal.

Again, although FX exposure does not explain the average returns[12] (measured over the entire sample, the cross-sectional R^2 is 7%), the graphs indicate that the cross-sectional relation may be strengthening through time.

5.3. *Multifactor models*

Three additional factors are examined: the return on a portfolio of crude oil less the eurodollar deposit rate, the growth in OECD industrial production and the rate of OECD inflation. The risk exposures for the five factor model are presented in table 10.

In the overall sample of 21 developed countries, 8 have significant exposure to oil, 2 have exposure to industrial production growth, and 5 have significant exposure to inflation. The adjusted R^2s of these regressions range from 3% to 71%.

The inclusion of these additional factors does not help explain the emerging market returns. Of the 20 countries, 5 have significant oil exposure. In four of these countries (Colombia, Jordan, Philippines, and Taiwan), the exposure is negative indicating decreasing returns when oil prices rise. In Venezuela, the exposure is

[12] For the 21 developed countries, the cross-sectional adjusted R^2 is 37%.

positive, as it is (albeit insignificantly) in Mexico and Nigeria. Only three of the emerging countries have significant exposure to world industrial production and four countries have significant loadings on world inflation. The adjusted R^2 of the five factor regressions range from zero (in six countries) to 25% in Malaysia.

Plots of the five-year rolling correlations with the final three factors are presented in figures 7–9. In most developed countries, the oil exposure is negative. Even producers like the United Kingdom and Canada have zero or negative exposure. In the emerging markets, there are a number of different patterns. For example, the Mexican exposure, while positive in the early 1980s, is now negative. It appears as if that economy's dependence on the state of the U.S. economy is more important than their oil holdings. India has a strange positive correlation with oil increasing from zero in 1987 to about 35% by 1992. Thailand's correlation has dramatically changed from 35% in the early 1980s to -35% by 1992.

Figures 8 and 9 show the correlation patterns for the growth in industrial production and the inflation rate. In seven of the emerging markets, the correlation with OECD industrial production has increased through time. In the other 13 markets, there are no detectable patterns over time. In addition, there are no obvious trends in the correlation with OECD inflation across all the emerging markets.

While the addition of the three factors increases the ability to explain the cross-section of expected returns[13] (adjusted R^2 rises to 10%), much is left unexplained. There are two ways to interpret these results. In one sense, the combination of the five prespecified factors can be considered a portfolio. The inability of the factor loadings as a group to explain the cross-section of average returns suggests that this portfolio is inefficient.

One can also view the results within the context of market integration. In an integrated global market place, the same exposure to risk in two different countries commands the same reward. The lack of a cross-sectional relation between the risk loadings and return performance could be symptomatic of market segmentation. As markets become more integrated, one would expect higher cross-sectional

[13] For the 21 developed countries, the adjusted R^2 is 29%.

correlation of risk exposures and expected returns.

Lack of integration opens up the possibility that equities are inefficiently priced in some emerging markets. Interestingly, the global investment manager may not care. The manager likes the opportunity of purchasing securities at a price lower than the implied value in an integrated world economy.

The notions of underpricing and overpricing are vague without explicit reference to an asset pricing model. To give an example, in many of the emerging markets there is a clear relation between average returns and volatility [see Harvey (1993a)]. In a globally integrated economy, covariance – not variance – is priced. Global investors can enhance their portfolio performance by taking on a high variance/high expected return emerging asset. The enhancement results from the extremely high contribution to portfolio expected return per unit of covariance (not variance). This opportunity is further attenuated by the significant degree of predictability in many of these emerging markets.

6. Conclusions

The idea of this study is to examine the impact of emerging equity markets on global investment strategies. Recently a number of researchers have documented the low correlations between emerging equity returns and developed market returns. In an active portfolio strategy, this means that the opportunity set has become larger: higher expected returns can be gained at lower volatility.

Portfolio simulations were presented to verify that the low correlations produced superior out-of-sample portfolio allocations. The out-of-sample allocation is important because portfolio programs usually produce weights that are *ex post* optimal. There is no guarantee that these weights will work with data outside the program (in the future). However, strategies that included emerging equity markets consistently outperformed strategies that were limited to developed markets.

While the low correlations with developed markets are important, the most striking advantage of investing in emerging markets relates to their predictability. Regression models were presented that show that the returns in a number of the emerging markets are predictable based on both global and country-specific information variables. When these regression forecasts are combined with a portfolio optimizer, the simulated portfolio performances sharply improve.

The final question address is what are the risks of investing in emerging equity markets. In real world portfolio selection, investment weights are chosen subject to a number of constraints such as the elimination of short-sales, caps on long positions in any market, and limits on the portfolio exposure to certain sources of risk. For the last constraint, estimates of each market's risk exposure is needed. These risk constraints eliminate the possibility of choosing a portfolio with a higher expected return than, say the Standard and Poor's 500, and the same volatility – but with an oil beta of -3.00 (compared to the S&P 500 oil beta of -0.30)!

Five sources of risk were examined: the world market equity return, the return on a foreign currency index, the change in the price of oil, world industrial production growth and the world inflation rate. Only a handful of emerging countries had significant betas on these factors. For example, only one of 20 emerging markets had a beta against the world market portfolio that exceeded unity.

One implication of the risk analysis is that many of the emerging markets are not well integrated into the global economy. However, the time-series evidence is suggestive of a number of countries becoming increasingly integrated. Models that allow for time-varying conditional integration of world capital markets are explored in Harvey (1993c).

On a more practical side, as long as the emerging market is investable, the portfolio manager may not care whether the market is integrated. Lack of integration can present opportunities for investors. High expected returns assets can be purchased at prices cheaper than comparable assets in developed countries. In addition, the lack of significant risk loadings to a standard set of global factors suggests risk target constraints would not be binding for the emerging equity markets.