Emerging/Developed Market Portfolio Mixes

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Emerging markets have played an increasingly important role in international portfolios in the last decade. Many asset managers, however, have struggled with the question of what proportion of strategic or long-term holdings should be in emerging markets. Moreover, can that allocation be moved on a tactical basis? We propose a number of models to attempt to answer these questions.

There is a growing body of research that shows that emerging market equity returns have low correlation with developed country returns, high average returns, and high volatility. Indeed, with these ingredients, standard mean-variance analysis suggests that half or more of your portfolio should be composed of emerging market equities. A variety of practical factors, including the likelihood that future returns may be different from history, argue that the proper allocation be more modest. However, there is no doubt that, for most investors, their passive emerging market allocation ought to be significant, and possibly upward of 10% of their total portfolio.

In this article, we concentrate on active strategies that vary through time the weighting of emerging markets in a global portfolio. Active strategies have a high probability of success given the results of Harvey [1995], which suggest that emerging market returns have a relatively high degree of predictability.

DESIGN

Asset Universe

We approach the problem from the top down. We focus on two broad asset classes: world equity markets and emerging equity markets. The world equity market is represented by the Morgan Stanley Capital International world market index (WM). The emerging equity market is represented by the International Finance Corporation's global emerging composite index (EM). We examine strategies that weight these two indexes, along with a cash instrument represented by the United States' thirty-day Treasury bill (from Ibbotson Associates).[1]

Conditional Maximum Sharpe Ratio Strategy

Our first approach uses mean-variance analysis. We build forecasting models for the total returns on the WM and the EM. The predictive models build on the work of Harvey [1991, 1995] for developed and emerging markets, respectively.

Using the set of variables identified to forecast returns, we estimate a multivariate generalized autoregressive conditional heteroscedasticity (GARCH) model that follows Engle [1982] and Bollerslev [1986]. The GARCH model is widely used in the practice of asset management, especially in hedging applications. We also examine a simpler volatility model based on rolling variances and covariances. Our portfolio exercises deliver a measure of how much extra the GARCH model delivers relative to a simpler specification.

The specific GARCH model we use is the Baba, Engle, Kroner and Kraft (BEKK [1989]) model. This approach delivers time-varying variances of the EM and WM, as well as time-varying covariances. For two assets, there are five equations. The first two equations forecast the returns for the WM and the EM. The second two equations forecast the volatilities of these two portfolios. The final equation forecasts the covariances between the EM and WM. Formally, the BEKK model is:

$$r_{w,t} = c_w Z_{w,t-1} + e_{w,t} \quad (1)$$

$$r_{e,t} = c_e Z_{e,t-1} + e_{e,t} \quad (2)$$

$$h_{w,t} = b_w h_{w,t-1} + a_w e^2_{w,t-1} \quad (3)$$

$$h_{e,t} = b_e h_{e,t-1} + a_e e^2_{e,t-1} \quad (4)$$

$$h_{we,t} = b_{we} h_{we,t-1} + a_{we} e_{w,t-1} e_{e,t-1} \quad (5)$$

where the world market return is denoted by the "w" subscript and the emerging market return is denoted by the "e" subscript. The "Z" represents information known to forecast the returns. The "h" is the forecasted variance for the developed and emerging market returns. The "h" with the two subscripts is the forecasted covariance. This is called a GARCH (1, 1) because the conditional variance is a function of its first past value and the first past value of the squared residuals, e.

All of the model selection is performed on data through December 1989. We obtain forecasts of the expected returns, variances, and covariances for January 1990. We characterize the efficient frontier and add the cash asset. Because the thirty-day Treasury bill return for January 1990 is known at the end of December 1989, it is risk-free in the sense that it has a variance of zero. We select the most efficient mix of the two equity baskets and the cash instrument — the tangency portfolio. This is known as the maximum Sharpe ratio strategy. Exhibit 1 provides an example of this strategy for a 10% target level of volatility.

With the risk-free asset, Rf, we find the portfolio with the highest Sharpe measure, point A. As we are targeting a specific level of volatility, 10%, we choose point B. This portfolio is a mix of cash, WM, and EM. The exercise is repeated through every month.

Conditional Probability Strategy

This strategy focuses on the excess EM return, that is, the difference between the EM and WM returns. The strategy begins with a forecasting model for the difference. We then calculate the ratio of the forecast to the standard error. This gives us a measure of confidence of out- (or under-) performance. The confidence is obtained from a cumulative normal distribution. This confidence is directly mapped into a portfolio weight.

For example, if the forecasted excess return is 5% and the standard error of the forecast is 2.5%, the confidence rating (and the investment weight) for the EM index outperformance is 97.5%. We estimate the conditional variance of this portfolio using the BEKK model and selected equity/cash mix based on the target volatility.

Combining our conditional mean forecast of the

Exhibit 1
Maximum Sharpe Ratio Strategy

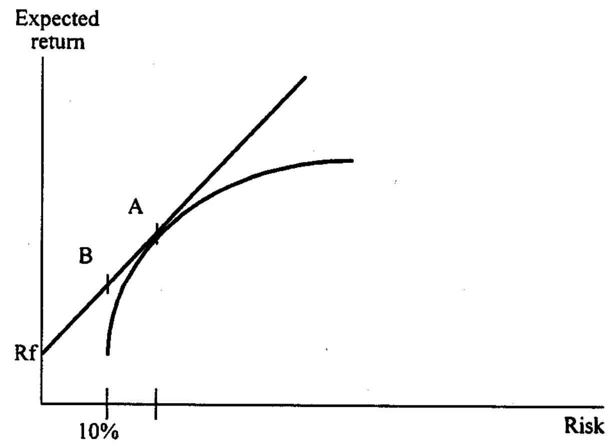
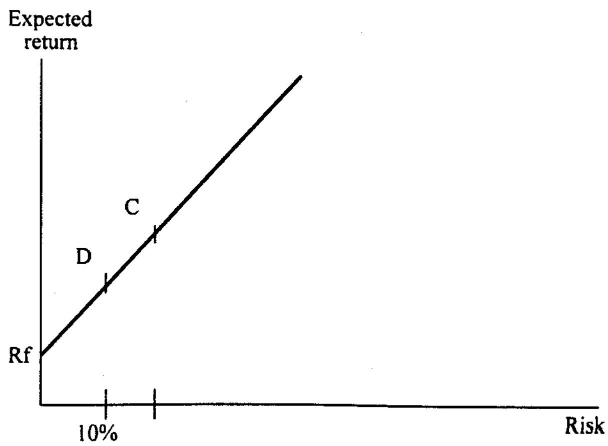


Exhibit 2
Conditional Probability Strategy



EM-WM difference with the estimate of the conditional volatility, we get point C, which represents a combination of the EM and WM. We adjust the position with cash to get the desired conditional volatility of the portfolio strategy (to point D), which in this example is 10%.

PERSPECTIVE

Point C is not necessarily efficient relative to the conditional mean-variance frontier in Exhibit 1. Indeed, only point A is efficient (C could be above or below point A). The conditional regime model, however, may give smoother weights that minimize transactions costs. C is likely in the region of A. The conditional probability model trades off weight volatility and efficiency.

The conditional probability strategy is also easily adapted to the conditional tracking error problem. That is, the deviation from benchmark weight can be determined from the conditional probability. A preset maximum deviation is usually selected, say 4%. If the conditional probability of the EM outperforming the WM is 75%, this would suggest an overweighting of the EM by 3%.

MODEL SPECIFICATION

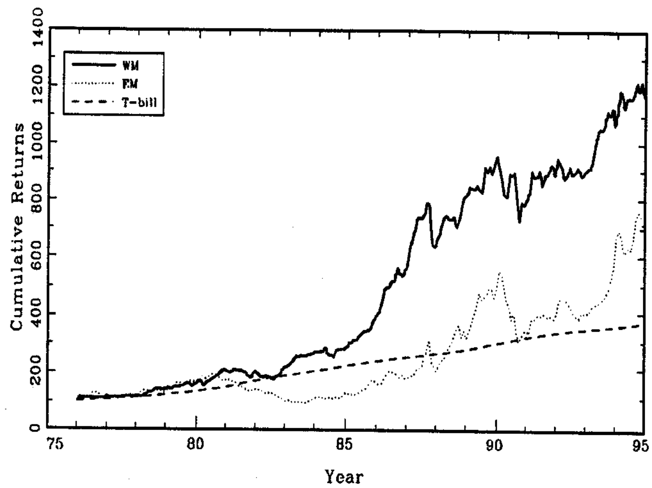
DATA

We use the Morgan Stanley Capital International (MSCI) world market portfolio and the International Finance Corporation (IFC) global emerging markets composite index. Both indexes represent total returns (dividends plus capital gains). The IFC index is only available from 1985. IFC data, however, begin in December 1975. We extend the IFC composite index back to December 1975 using the individual countries in the data base. The extended returns are value-weighted.

As a short-term instrument, we use the Ibbotson Associates thirty-day U.S. Treasury bill return.

Exhibit 3 presents the cumulative returns to investing $100 in each index on December 31, 1975. This graph clashes with generally accepted intuition about emerging market returns. It is well-known that emerging market returns have been, on average, higher than developed market returns. This is true if one begins the sample in 1985. However, we have recreated the composite index back to 1975. The first ten years do

EXHIBIT 3
CUMULATIVE RETURNS INDEXES — WORLD MARKET (WM), EMERGING MARKETS (EM), AND TREASURY BILL — DECEMBER 1975-DECEMBER 1994



WM IS THE MSCI WORLD MARKET TOTAL RETURN INDEX IN U.S. DOLLARS. EM IS THE IFC-GLOBAL TOTAL RETURN INDEX IN U.S. DOLLARS. T-BILL IS THE THIRTY-DAY U.S. TREASURY BILL RATE FROM IBBOTSON ASSOCIATES. THE SAMPLE IS 1976-1994.

not produce such impressive returns. A buy-and-hold for twenty years leads to a nine-fold increase in the initial investment in emerging markets. Over the same period, however, the developed market portfolio increased by a factor of twelve.

More summary statistics are presented in Exhibit 4. The WM portfolio has a higher mean return than the EM portfolio over the full sample. Since 1985, however, the EM average return is 19.9% and the WM return is 15.7%. In addition, the EM return is larger than the WM if the means are calculated beginning in 1990. Exhibit 4 also shows that the volatility of the EM is greater than the WM in every period.

Exhibit 4 also reports some additional distributional information. Consistent with the results of Harvey [1995], there is significant autocorrelation in the EM index and none in the WM index. The autocorrelation coefficient over the full sample for the EM portfolio is 0.19 with an approximate standard error of 0.06. For the WM portfolio, the same coefficient is 0.02.

Interestingly, there is little evidence against the hypothesis that both the WM and EM portfolios are normally distributed. While there is some excess skewness and a small amount of negative skewness, both the

EXHIBIT 4
SUMMARY STATISTICS

	ANNUALIZED MEAN (%)	ANNUALIZED STD. DEV. (%)	AUTOCORRELATION	SKEWNESS	KURTOSIS
FULL SAMPLE					
WM	14.04	14.02	0.02	–0.40	1.67
EM	12.21	20.65	0.19	–0.18	1.48
T-Bill	6.89	0.84	0.94	0.83	0.44
POST-1984					
WM	15.67	15.31	0.04	–0.52	1.88
EM	19.89	23.37	0.19	–0.49	1.47
T-Bill	5.32	0.51	0.92	–0.05	–1.18
POST-1989					
WM	5.25	14.85	–0.09	–0.06	0.10
EM	8.69	21.80	0.24	0.18	1.01
T-Bill	4.41	0.48	0.96	0.68	–0.85

WM IS THE MSCI WORLD MARKET TOTAL RETURN IN U.S. DOLLARS. EM IS THE IFC-GLOBAL TOTAL RETURN IN U.S. DOLLARS. T-BILL IS THE THIRTY-DAY U.S. TREASURY BILL RATE FROM IBBOTSON ASSOCIATES. THE SAMPLE IS 1976-1994.

WM and EM portfolios look remarkably similar with respect to these higher moments.[2]

PREDICTING RETURNS IN DEVELOPED AND EMERGING MARKETS

The regression models forecast both the WM and EM returns as well as the EM-WM difference. A number of steps minimize any data-snooping biases. First, the instruments (predictor variables) are largely drawn from previous research, such as Harvey [1991, 1995]. Second, models are estimated through December 1989.[3] All trading analysis is carried out on data beginning in January 1990. Finally, we attempt to make the models symmetric. That is, the same types of variables are used in both the WM and EM prediction models.

The predictor variables include three measures of the world business cycle: the U.S. three-month Treasury bill return minus the one-month return (short-term inflation, yield curve slope), the stochastically detrended long-term rate (expected real activity, longer-term inflation) ten-year U.S. Treasury bond yield minus the twelve-month moving average of the ten-year rate Treasury bill yield, and the default risk spread (expected real activity) Moody's Baa- minus Aaa-rated bond yields. These variables are common to all three prediction models. They are designed to reflect expectations about the strength of the world economy.

The fourth instrumental variable is a valuation indicator: the dividend yield. There is a long history of using this variable in prediction models (see, for example, Fama and French [1988] and Harvey [1991]). We considered using the price-to-book ratio. However, these data are only available from 1985 for the emerging markets, which would provide insufficient data to estimate our multivariate models. When forecasting the EM-WM difference, we use the relative dividend yield.

The final variable is a measure of the size of the trade sector. This variable has been shown to be linked to market integration and is a good proxy for expected returns in emerging markets (see Bekaert and Harvey [1995, 1997]). The size of the trade sector is defined as export plus imports divided by GDP in the IFC and MSCI markets. The variable is used in log form. When forecasting the difference, we use the relative size of the trade sector.

ADDITIONAL SPECIFICATIONS

When reporting prediction results, it is important to report all specifications that were investigated. This gives the reader valuable information regarding the extent to which data-snooping biases might affect the results.

We were initially concerned that the prediction model would generate forecasts that would lead to significant shifts in monthly weights, thereby inducing high transactions costs. We investigated a transformation of the dependent variable of the following form:

$$r^*_{i,t} = \sum_{j=0}^{11} \alpha^j r_{i,t+j}$$

The idea of this specification is to forecast a forward-smoothed return. The damping factor, α, assigns the greatest weight to the nearby returns. This model is used to obtain forecasts of $r^*_{i,t}$ based on information at time $t-1$. However, information through $t+11$ is used in the dependent variable. As a result, care must be taken in the out-of-sample exercise to make sure that the regression coefficients are known.[4] While this technique produces impressive results in trading simulations, we chose to focus on the direct forecasting techniques because they do not induce as much volatility in the investment weights as we had originally expected.

We considered using the dividend yields separately rather than the difference specification in the EM-WM regressions. Actually, the difference specification can be statistically rejected in favor of the separate variables. Parsimony is very important to us for the out-of-sample work, however, hence, we prefer a five-instrument model to one with six instruments. We similarly reject the idea of letting the trade to GDP measures enter the regressions separately.

We briefly considered the S&P dividend yield that has been used in previous research to forecast the world market return. Given that we are not using the S&P in the forecasting model, however, it made sense to use the MSCI dividend yield. As mentioned earlier, we also considered additional fundamental variables, such as price to book and price to earnings. Unfortunately, these data begin only in 1985 for the emerging markets.

We also looked at using a lagged return (MSCI or IFC) in the regression. This is an extremely volatile instrument and induces volatility in the forecasts — which leads large fluctuations in the investment weights and potentially high transactions costs. We tried three different smoothing algorithms on the lagged equity variable. While some of these transformations (e.g., six-month relative to three-month moving average) have some explanatory power, we were wary of data-snooping on the transformations and elected not to pursue this variable.

We considered two other variables. The first is the difference in the equity capitalization-weighted *Institutional Investor* country credit rating. Erb, Harvey, and Viskanta [1995, 1996] show that this variable has the ability to discriminate between high and low expected return countries. When aggregated to the level of the IFC and MSCI index, however, it has little explanatory power.

The final variable is a measure of foreign exchange rate changes. Ferson and Harvey [1993] find that an aggregated FX variable helps predict developed market returns as well as the world index. Harvey [1995] shows the same for emerging markets. This variable shows explanatory power in our 1976-1989 estimation sample. We did not use the variable, however, because, again, it induces great volatility in the forecasted values. We were also wary of some extreme values in this measure (due to dramatic devaluations in some emerging markets). Nevertheless, we think that future research should revisit the information in this variable.

Selection Criteria

We estimate the models through December 1989. We examine traditional measures of fit such as the t-ratios and R-square criteria. The highest R-square model is not necessarily the "best" model, however, if "best" takes trading costs into account. That is, the higher R-square model might produce excessive volatility in the investment weights that would lead to considerable transactions costs. Given this insight, we also calculate a measure of persistence of the forecasted values. High values of the first-order autoregressive coefficient on the forecasted values indicate that the forecasted values are very smooth. We use this measure as an additional criteria for model selection.

Prediction Results: Returns

Panel A of Exhibit 5 reports the regression results for the WM, EM, and EM-WM spread over the December 1976-December 1989 period (157 observations). Heteroscedasticity-consistent standard errors are reported in parentheses. During this period, 7.3% of

Exhibit 5
Prediction Models

	Intercept	3M-1M	10Y-1M	BAA-AAA	Div.	Trade	R^2	Adjusted AR1
Panel A. Through 1989								
WM	3.50	4.82	–1.12	–0.83	0.20	2.08	7.32	0.89
	(6.61)	(2.13)	(0.43)	(1.15)	(0.38)	(5.57)	[0.0343]	[6.17]
EM	7.50	7.66	–0.27	–4.13	0.15	2.54	9.52	0.61
	(1.79)	(2.68)	(0.43)	(0.91)	(0.28)	(1.44)	[0.0000]	[1.40]
EM-WM	3.80	3.45	1.04	–4.13	0.76	2.60	8.33	0.92
	(1.43)	(3.07)	(0.48)	(1.09)	(0.40)	(1.61)	[0.0001]	[8.33]
Panel B. Through 1994								
WM	–1.84	4.36	–0.89	–0.17	0.32	–1.77	5.07	
	(2.69)	(2.10)	(0.35)	(0.78)	(0.36)	(2.88)	[0.0114]	
EM	4.20	9.08	–0.49	–3.46	0.25	0.93	4.39	
	(1.20)	(2.75)	(0.41)	(0.93)	(0.25)	(1.36)	[0.0000]	
EM-WM	3.46	4.79	0.67	–4.01	0.76	2.12	5.23	
	(1.28)	(3.14)	(0.45)	(1.03)	(0.32)	(1.51)	[0.0004]	

Regressions are run on three dependent variables: the world market return, the emerging market return, and the difference between the emerging and world market returns. The predictor variables for the level regressions are: a constant, the excess return on a three-month U.S. Treasury bill, the ten-year–one-month Treasury yield spread, the Moody's Baa-Aaa corporate bond yield spread, the dividend yield, and the size of the trade sector. For the difference regression, we use relative dividend yields and relative size of the trade sector. AR1 represents the first-order autocorrelation of the fitted values, a measure of the smoothness of the forecasts (a coefficient of 1.0 would mean all values are constant). The half life is reported in brackets. Heteroscedasticity-consistent standard errors are in parentheses.

the variation in the WM can be explained with these five instruments. These results are consistent with the ones reported by Harvey [1991]. Over the same sample, 9.5% of the variation in the EM portfolio can be explained by the instruments. We also report (under the R-square) a test of the significance of the regressions. Each is significant. Note in these two regressions, that there are three common instruments. Using a different sample and different regressors, Harvey [1991, 1994] finds that 13.3% (10.3%) of the WM (EM) can be explained with global information variables.

The excess three-month T-bill enters both the WM and EM regressions with positive coefficients, which is consistent with Harvey [1991, 1994]. This variable measures changes in short-term inflationary expectations. As inflation expectations move downward, the three-month T-bill increases in price, leading to a higher excess return. Hence, lower inflation is associated with higher expected returns. This variable is linked to U.S. inflationary outlooks. The impact on both WM and EM market returns reveals the influence of the U.S. market on world equity prices.

The term structure spread enters both regressions with negative coefficients. This is consistent with the results in Ferson and Harvey [1993] for WM and Harvey [1994] for EM. The term structure is an indicator of the future strength of the U.S. business cycle. The term structure tends to be inverted (short rates higher than long rates) before recessions and normal (long rates higher than short rates) during expansions. This variable measures the influence of the U.S. business cycle on world and emerging equity markets.

The Baa-Aaa bond yield is also designed to move with the U.S. business cycle. During recessions, the yield spread takes on its highest values. Typically, during expansions, the spreads are low. This variable enters the EM regression with a significant negative coefficient. It is not significant in the WM regression.

The dividend yield is a specific, as opposed to a common, regressor. It enters the regressions with positive coefficients. This is consistent with the results reported in Ferson and Harvey [1993] for the WM, and Harvey [1994] for EM. The positive relationship between dividend yields and expected returns is well documented in finance (see, for example, Fama and French [1988]). A high dividend yield implies that stock prices are low and expected returns are high.

Trade to GDP is also specific to each composite. Higher trade to GDP is weakly positively associated with future returns in the WM. In the last five years, however, the trade variable is negatively related to WM. In contrast, the trade variable consistently explains the EM returns. It enters the regression with a positive coefficient. This indicates that a larger trade sector is associated with higher expected returns.

The final regression is the EM-WM difference. In this case, 8.3% of the variation can be explained by these five variables. The most important variables are the term structure spread, the Baa-Aaa bond yield, and the trade variable.

To get a sense of the persistence of the predicted values, we also report the coefficient from regressing the predictions on lagged values of the predictions. A coefficient of 1 would indicate perfect persistence (all fitted values identical). The higher the coefficient, the less variability there will be in investment weights.[5] The WM regression is very persistent with a coefficient of 0.89. The EW is less persistent with a coefficient of 0.61. Interestingly, the difference regression is the most persistent, with a coefficient of 0.92.

Prediction Results: Conditional Variance

Exhibit 6 reports the estimation of the multivariate GARCH model. As we noted, the GARCH model has five equations. (1) and (2) are the regression equations for predicting the mean for the EM and WM. Equations (3) and (4) are the conditional variance equations for the EM and WM. Equation (5) is the conditional covariance between the EM and the WM. The BEKK specification reduces the number of parameters and makes the estimation tractable. This is particularly important because we implement this model recursively for our holdout sample. We make a further simplification. The first two equations we estimate separately by ordinary least squares (reported in Exhibit 5). This reduces the number of equations to three.

Exhibit 6
BEKK Model

	c	a	b
$h_{w,t}$	4.31	0.05	0.67
	(3.43)	(0.04)	(0.23)
$h_{we,t}$	4.71	–0.10	–0.65
	(1.92)	(0.05)	(0.11)
$h_{e,t}$	5.14	0.20	0.63
	(2.35)	(0.08)	(0.12)

The coefficients of the multivariate (BEKK) GARCH estimation. The first equation, h_w, represents the conditional variance of the world. The second equation, h_{we}, represents the conditional covariance of the emerging and world market returns, and the third equation, h_e, represents the emerging market return. The coefficient, c, is the constant; the coefficient, a, is on the lagged squared residual; and the coefficient, b, is on the lagged conditional variance.

Most of the parameters are significantly different from zero in Exhibit 6. Both the EM and WM have similar coefficients on the lagged variance, 0.67 and 0.63, indicating that the volatility is persistent. The EM portfolio has greater sensitivity to the square of the unexpected returns. The BEKK estimation indicates that there is strong negative correlation in the conditional covariances. The fitted conditional variances for the WM and EM portfolios are presented in Exhibit 7.

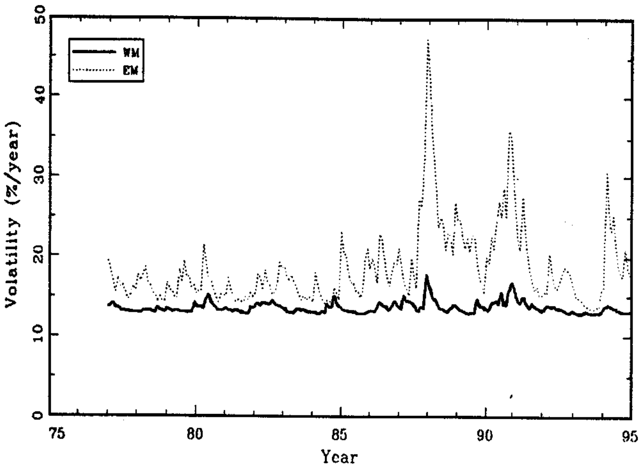
We consider an alternate model of the conditional variance: a sixty-month rolling variance. This measure's attractiveness is the ease of computation and that it forces the variance changes to be smooth (because of the rolling fifty-nine-month overlap).[7] This smoothness could be important in reducing transactions costs.

Conditional Standard Error of Forecasts

We have three models for the standard errors of the forecasts. The first is the usual formula that uses only the information from the regressions in Exhibit 5. The second uses a rolling sixty-month measure of the variance. The third uses the BEKK model's conditional variance.

EXHIBIT 7

EXPECTED VOLATILITY — WORLD MARKET (WM) AND EMERGING MARKETS (EM) — DECEMBER 1975-DECEMBER 1994



CONDITIONAL VOLATILITY FROM THE MULTIVARIATE GARCH(1, 1) MODEL. WM IS THE WORLD MARKET RETURN VOLATILITY AND EM IS THE EMERGING MARKET RETURN VOLATILITY.

RESULTS

CONDITIONAL MAXIMUM SHARPE RATIO STRATEGY

As with all of the trading analysis, we implement the models on an out-of-sample basis over the 1990:01-1994:12 period. The parameters of the models are reestimated at each point in time. Given estimates of the forecasted returns, variances, and covariances, the maximum Sharpe ratio strategy chooses the tangency portfolio. This portfolio is levered up or down to achieve four target levels of volatility: 10%, 12%, 14% and 16%. While transactions costs are ignored here, we present evaluations of strategies that include transactions costs later.

We focus our discussion on the model with 12% target volatility. Unambiguously, the worst model is the one that uses rolling means and rolling volatility estimates. This model just uses past averages of the returns and ignores the predictability in the returns. This model delivers only a 4.89% average return with 11.3% volatility.

The best strategy is the LS-BEKK model (least squares predicted returns and BEKK variances and covariance). The average return from this strategy is 9.9% with a standard deviation of 13.5%. The second best strategy is the LS-rolling model (least squares predicted returns and rolling variances). While this strategy only produces 6.3% average returns, the standard deviation is 10.4%. The Sharpe ratio of this strategy is 0.61, compared to 0.73 for the LS-BEKK.

Four benchmark returns are also included. Benchmark 1 is a 95% WM and 5% EM portfolio which is rebalanced monthly. Benchmark 2 is 100% WM. Each of these benchmarks are levered up or down to target volatility levels. We also present buy-and-hold returns and volatility for the 100% WM and the 100% IFC portfolios. These are not levered, so the returns and standard deviations are identical for all target volatility levels.

The benchmark portfolios are generally unimpressive compared to the dynamic trading strategies. For example, Benchmark 1 delivers a 5.2% average return with 10.8% volatility. LS-rolling, however, produces 110 bp of extra return with 50 bp of lower volatility. The Sharpe ratio of Benchmark 1 is 0.48. The Sharpe ratios of the two buy-and-hold portfolios are worse: 0.35 for the WM and 0.40 for the EM.

Exhibit 8, Panels A-D, present the investment weights for the three dynamic strategies and for Benchmark 1. Obviously, Benchmark 1 has the smoothest weights because the strategy targets 95% WM and 5% EM. Interestingly, the most volatile weights are from the rolling-rolling model, which performs the poorest. The second most variable weights come from the LS-BEKK model. The LS-rolling model has smooth weights for most of the sample.

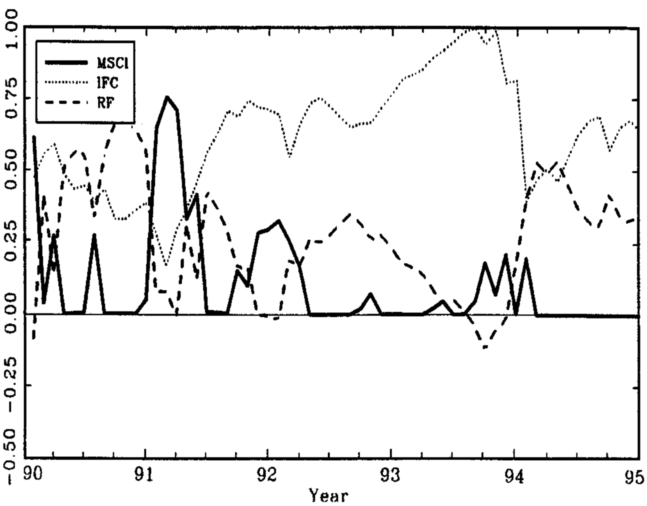
Even though the models are unconstrained, there are rarely any short positions. The LS-rolling and rolling-rolling models never have short positions. The LS-BEKK has a short episode in late 1993 where some borrowing (10% of equity) is required. The equity positions are never in a short position.

CONDITIONAL PROBABILITY MODEL

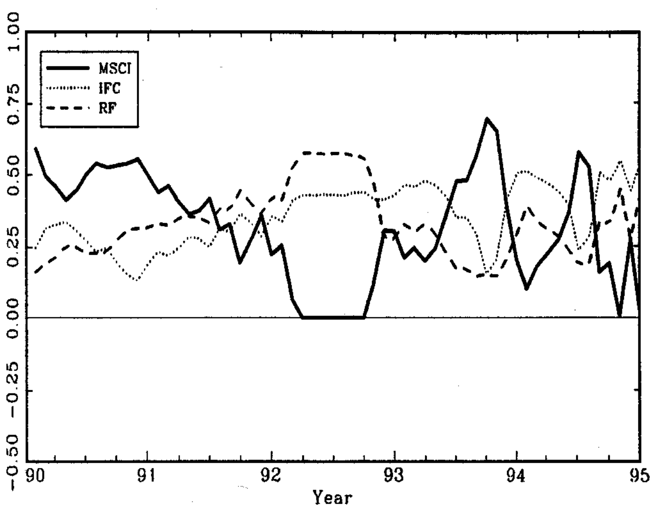
Exhibit 10 presents the full set of results for the conditional regime model. For this model, we have five trading strategies:

EXHIBIT 8
PORTFOLIO WEIGHTS FOR CONDITIONAL MAXIMUM SHARPE RATIO STRATEGY

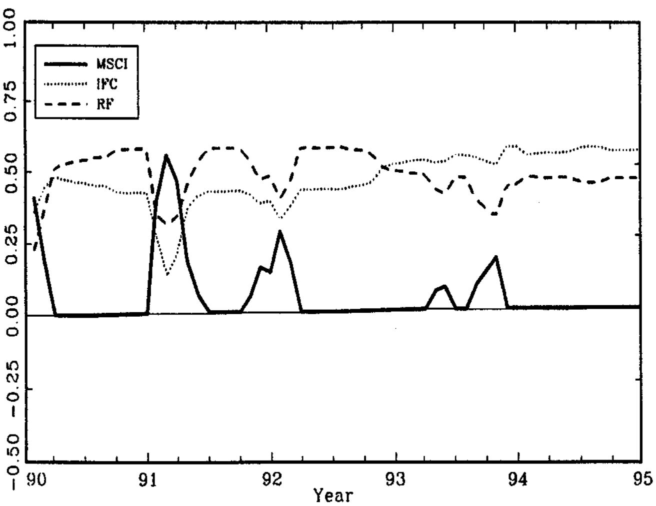
PANEL A. OLS MEANS-BEKK VOLATILITY: 12% TARGET VOLATILITY — JANUARY 1990-DECEMBER 1994



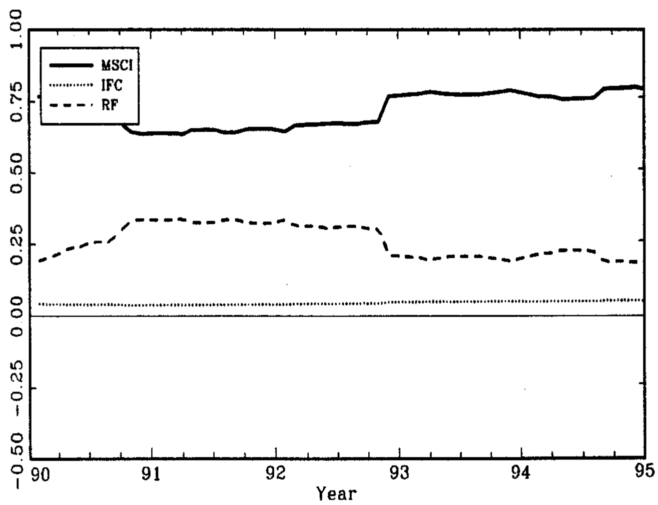
PANEL C. ROLLING MEANS-ROLLING VOLATILITY: 12% TARGET VOLATILITY — JANUARY 1990-DECEMBER 1994



PANEL B. OLS MEANS-ROLLING VOLATILITY: 12% TARGET VOLATILITY — JANUARY 1990-DECEMBER 1994



PANEL D. PORTFOLIO WEIGHTS FOR BENCHMARK 1 — 95% WM AND 5% EM: 12% TARGET VOLATILITY — JANUARY 1990-DECEMBER 1994



1. OLS means-BEKK variances-OLS standard errors.
2. OLS means-rolling variances-OLS standard errors.
3. OLS means-BEKK variances-BEKK standard errors.
4. OLS means-rolling variances-BEKK standard errors.
5. OLS means-rolling variances-rolling standard errors.

Given the results in the previous section, we do not pursue the model with rolling forecasts of the mean return. We present results for the post-1989 sample as well as disaggregated results for each year.

There are a number of observations. First, the

EXHIBIT 9
CONDITIONAL MAXIMUM SHARPE RATIO STRATEGY

	Target = 10			Target = 12			Target = 14			Target = 16		
	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Full Sample												
LS-BEKK	9.01	11.25	0.80	9.93	13.54	0.73	10.85	15.82	0.69	11.77	18.10	0.65
LS-Rolling	6.03	8.60	0.70	6.35	10.36	0.61	6.68	12.11	0.55	7.00	13.86	0.51
Rolling	4.81	9.39	0.51	4.89	11.30	0.43	4.98	13.21	0.38	5.06	15.11	0.33
B1	5.04	8.96	0.56	5.16	10.77	0.48	5.29	12.58	0.42	5.42	14.39	0.38
B2	4.90	8.90	0.55	5.00	10.70	0.47	5.10	12.50	0.41	5.20	14.29	0.36
WM	5.25	14.85	0.35	5.25	14.85	0.35	5.25	14.85	0.35	5.25	14.85	0.35
EM	8.69	21.80	0.40	8.69	21.80	0.40	8.69	21.80	0.40	8.69	21.80	0.40

SIMULATION RESULTS, JANUARY 1990-DECEMBER 1994, FOR THE CONDITIONAL MAXIMUM SHARPE RATIO STRATEGY. THIS STRATEGY USES OUT-OF-SAMPLE FORECASTS OF THE ASSET MOMENTS TO DETERMINE THE TANGENCY PORTFOLIO (MAXIMUM SHARPE RATIO). THIS PORTFOLIO IS LEVERED TO OBTAIN A TARGET CONDITIONAL STANDARD DEVIATION OF 10%, 12%, 14%, OR 16% ON AN ANNUAL BASIS. WE REPORT TWO MODELS: LS-BEKK REPRESENTS LEAST SQUARES FORECASTS OF THE CONDITIONAL MEAN AND GARCH FORECASTS OF THE VARIANCES AND COVARIANCES, AND LS-ROLLING REPRESENTS LEAST SQUARES FORECASTS OF THE MEAN AND ROLLING (MOVING WINDOW) ESTIMATES OF THE VARIANCES AND COVARIANCE. SR DENOTES THE SHARPE RATIO (ANNUALIZED). THERE ARE TWO BENCHMARK RETURNS. B1 IS 95% WM AND 5% EM. B2 IS 100% WM. EACH OF THESE BENCHMARKS IS LEVERED UP OR DOWN TO ACHIEVE THE TARGET LEVEL OF VOLATILITY. WE ALSO REPORT WM AND EM PORTFOLIOS THAT ARE NOT LEVERED UP (HENCE THE RESULTS ARE IDENTICAL UNDER EACH TARGET LEVEL OF VOLATILITY).

EXHIBIT 10
CONDITIONAL PROBABILITY MODEL

	Target = 10			Target = 12			Target = 14			Target = 16		
	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Full Sample												
LS-BEKK	8.42	11.64	0.72	9.22	13.99	0.66	10.03	16.35	0.61	10.83	18.71	0.58
LS-Rolling	6.35	9.18	0.69	6.74	11.05	0.61	7.13	12.92	0.55	7.52	14.78	0.51
LS-BEKK-BEKK	8.44	11.74	0.72	9.25	14.12	0.66	19.05	16.50	0.61	10.86	18.88	0.58
LS-Rolling-BEKK	6.41	9.22	0.70	6.81	11.09	0.61	7.21	12.95	0.56	7.61	14.84	0.51
LS-Rolling-Rolling	6.37	9.19	0.69	6.76	11.06	0.61	7.15	12.93	0.55	7.54	14.79	0.51
B1	5.04	8.96	0.56	5.16	10.77	0.48	5.29	12.58	0.42	5.42	14.39	0.38
B2	4.90	8.90	0.55	5.00	10.70	0.47	5.10	12.50	0.41	5.20	14.29	0.36
WM	5.25	14.85	0.35	5.25	14.85	0.35	5.25	14.85	0.35	5.25	14.85	0.35
EM	8.69	21.80	0.40	8.69	21.80	0.40	8.69	21.80	0.40	8.69	21.80	0.40
1990												
LS-BEKK	−12.80	14.00	−0.91	−16.78	16.83	−1.00	−20.76	19.64	−1.06	−24.75	22.45	−1.10
LS-Rolling	−11.03	12.82	−0.86	−14.67	15.40	−0.95	−18.30	17.98	−1.02	−21.93	20.56	−1.07
LS-BEKK-BEKK	−13.06	14.29	−0.91	−17.10	17.16	−1.00	−21.14	20.04	−1.05	−25.17	22.91	−1.10
LS-Rolling-BEKK	−10.89	12.93	−0.84	−14.50	15.53	−0.93	−18.10	18.12	−1.00	−21.70	20.72	−1.05
LS-Rolling-Rolling	−11.05	12.86	−0.86	−14.69	15.44	−0.95	−18.32	18.03	−1.02	−21.95	20.61	−1.07
B1	−8.16	13.46	−0.61	−11.22	16.15	−0.69	−14.27	18.84	−0.76	−17.33	21.53	−0.81
B2	−7.27	13.40	−0.54	−10.15	16.07	−0.63	−13.02	18.75	−0.69	−15.90	21.43	−0.74
WM	−15.62	22.47	−0.69	−15.62	22.47	−0.69	−15.62	22.47	−0.69	−15.62	22.47	−0.69
EM	−30.04	31.51	−0.95	−30.04	31.51	−0.95	−30.04	31.51	−0.95	−30.04	31.51	−0.95

EXHIBIT 10
CONTINUED

	Target = 10 Mean	Target = 10 Std. Dev.	Target = 10 SR	Target = 12 Mean	Target = 12 Std. Dev.	Target = 12 SR	Target = 14 Mean	Target = 14 Std. Dev.	Target = 14 SR	Target = 16 Mean	Target = 16 Std. Dev.	Target = 16 SR
1991												
LS-BEKK	14.38	11.35	1.27	16.22	13.63	1.19	18.05	15.91	1.13	19.88	18.18	1.09
LS-Rolling	11.73	7.85	1.50	13.03	9.42	1.38	14.33	10.99	1.30	15.64	12.56	1.24
LS-BEKK-BEKK	14.36	11.30	1.27	16.19	13.56	1.19	18.02	15.83	1.14	19.85	18.09	1.10
LS-Rolling-BEKK	11.71	7.84	1.49	13.01	9.41	1.38	14.31	10.98	1.30	15.61	12.55	1.24
LS-Rolling-Rolling	11.73	7.84	1.50	13.04	9.41	1.39	14.34	10.98	1.31	15.64	12.55	1.25
B1	12.65	8.73	1.45	14.13	10.48	1.35	15.62	12.23	1.28	17.10	13.98	1.22
B2	12.55	8.67	1.45	14.01	10.41	1.35	15.48	12.15	1.27	16.94	13.89	1.22
WM	18.63	15.75	1.18	18.63	15.75	1.18	18.63	15.75	1.18	18.63	15.75	1.18
EM	16.84	17.08	0.99	16.84	17.08	0.99	16.84	17.08	0.99	16.84	17.08	0.99
1992												
LS-BEKK	–0.99	6.56	–0.15	–1.84	7.88	–0.23	–2.69	9.20	–0.29	–3.55	10.52	–0.34
LS-Rolling	0.69	3.87	0.18	0.17	4.65	0.04	–0.35	5.42	–0.06	–0.87	6.20	–0.14
LS-BEKK-BEKK	–1.00	6.55	–0.15	–1.85	7.86	–0.24	–2.71	9.18	–0.30	–3.57	10.49	–0.34
LS-Rolling-BEKK	0.69	3.86	0.18	0.17	4.63	0.04	–0.35	5.41	–0.07	–0.87	6.19	–0.14
LS-Rolling-Rolling	0.75	3.87	0.19	0.24	4.65	0.05	–0.27	5.43	–0.05	–0.77	6.21	–0.12
B1	–0.79	4.84	–0.16	–1.61	5.82	–0.28	–2.43	6.79	–0.36	–3.24	7.77	–0.42
B2	–0.89	5.15	–0.17	–1.73	6.19	–0.28	–2.57	7.23	–0.36	–3.40	8.27	–0.41
WM	–4.39	8.97	–0.49	–4.39	8.97	–0.49	–4.39	8.97	–0.49	–4.39	8.97	–0.49
EM	1.54	15.50	0.10	1.54	15.50	0.10	1.54	15.50	0.10	1.54	15.50	0.10
1993												
LS-BEKK	37.71	10.47	3.60	44.70	12.57	3.56	51.69	14.66	3.52	58.68	16.76	3.50
LS-Rolling	26.64	7.91	3.37	31.42	9.49	3.31	36.19	11.07	3.27	40.97	12.65	3.24
LS-BEKK-BEKK	37.97	10.60	3.58	45.01	12.72	3.54	52.04	14.84	3.51	59.08	16.97	3.48
LS-Rolling-BEKK	26.69	7.96	3.35	31.47	9.55	3.29	36.25	11.14	3.25	41.03	12.74	3.22
LS-Rolling-Rolling	26.65	7.89	3.38	31.43	9.47	3.32	36.21	11.05	3.28	40.98	12.63	3.24
B1	16.47	7.49	2.20	19.21	9.00	2.14	21.95	10.50	2.09	24.69	12.00	2.06
B2	14.99	7.56	1.98	17.44	9.08	1.92	19.88	10.60	1.88	22.33	12.11	1.84
WM	21.59	11.49	1.88	21.59	11.49	1.88	21.59	11.49	1.88	21.59	11.49	1.88
EM	53.76	18.35	2.93	53.76	18.35	2.93	53.76	18.35	2.93	53.76	18.35	2.93
1994												
LS-BEKK	3.80	10.79	0.35	3.83	12.94	0.30	3.86	15.10	0.26	3.89	17.26	0.23
LS-Rolling	3.73	8.81	0.42	3.75	10.58	0.35	3.76	12.34	0.30	3.78	14.11	0.27
LS-BEKK-BEKK	3.93	10.84	0.36	3.99	13.01	0.31	4.05	15.18	0.27	4.11	17.35	0.24
LS-Rolling-BEKK	3.84	8.83	0.43	3.88	10.60	0.37	3.92	12.37	0.32	3.95	14.14	0.28
LS-Rolling-Rolling	3.75	8.82	0.42	3.77	10.58	0.36	3.79	12.35	0.31	3.81	14.11	0.27
B1	5.03	7.59	0.66	5.31	9.11	0.58	5.58	10.64	0.52	5.86	12.16	0.48
B2	5.14	7.45	0.69	5.44	8.94	0.61	5.74	10.44	0.55	6.04	11.93	0.51
WM	6.03	11.35	0.53	6.03	11.35	0.53	6.03	11.35	0.53	6.03	11.35	0.53
EM	1.37	18.71	0.07	1.37	18.71	0.07	1.37	18.71	0.07	1.37	18.71	0.07

SIMULATION RESULTS, JANUARY 1990-DECEMBER 1994, FOR THE CONDITIONAL PROBABILITY STRATEGY. THIS STRATEGY FORECASTS THE DIFFERENCE BETWEEN THE EMERGING MARKET RETURN AND THE WORLD MARKET RETURN. WE DIVIDE THE FORECAST BY THE STANDARD ERROR OF THE FORECAST AND THEN USE THAT VALUE IN A CUMULATIVE NORMAL DISTRIBUTION TO DETERMINE THE WEIGHT PLACED IN EMERGING MARKET EQUITY. THERE ARE FIVE STRATEGIES PRESENTED: LS-BEKK REPRESENTS LEAST SQUARES FORECASTS OF THE CONDITIONAL MEANS, GARCH FORECASTS OF THE VARIANCES AND COVARIANCES, AND LEAST SQUARES ESTIMATES OF THE STANDARD ERROR OF THE FORECASTS. LS-ROLLING REPRESENTS LEAST SQUARES FORECASTS OF THE MEANS, ROLLING (MOVING WINDOW) ESTIMATES OF THE VARIANCES AND COVARIANCE, AND LEAST SQUARES ESTIMATES OF THE STANDARD ERROR OF THE FORECASTS. THE NEXT TWO MODELS LS-BEKK AND LS-ROLLING-BEKK USE THE GARCH MODEL TO CALCULATE THE STANDARD ERROR OF THE FORECAST. THE FINAL MODEL USES THE ROLLING VARIANCE ESTIMATOR TO CALCULATE THE STANDARD ERROR OF THE FORECAST. AS WITH EXHIBIT 9, WE REPORT THE IDENTICAL BENCHMARK RETURNS. SIMULATIONS ARE REPORTED FOR THE SAME FOUR LEVELS OF TARGET VOLATILITY. WE ALSO REPORT YEAR-BY-YEAR RESULTS AS WELL AS THE FULL FIVE-YEAR SAMPLE.

three methods to get the standard error of the forecast do not greatly affect the results. For example, the LS-rolling model is evaluated with LS standard errors (line 2), BEKK standard errors (line 4), and rolling standard errors (line 5). The performance is very similar. Each strategy produces a Sharpe ratio of 0.61.

Second, the trading models do better than the benchmarks. For example, the OLS-BEKK model with 12% target volatility produces a 9.2% average return with 14.0% standard deviation compared to a 5.3% average return for the WM, which has slightly higher volatility. This suggests that we could get 400 bp per year in extra return with the same volatility as the MSCI world using this active strategy (with no transactions costs assumed).

Third, the OLS mean and rolling variance models do fairly well. At a target 16% variance, the OLS-rolling model delivers a 7.5% annual return for 14.8% volatility. This compares to 5.2% mean and 14.9% volatility for the WM. This represents a 230-bp improvement. While this is not as dramatic as the LS-BEKK model, a final evaluation of the model needs to take transactions costs into account.

Fourth, the model consistently beats the benchmarks in every year except 1994. However, 1994 is not that bad. For example, in 1994 with a 12% variance target, the LS-BEKK delivered a 4.1% annual return with 12.1% volatility. The WM produced a 6.0% return with 11.3% volatility. While this 190-bp underperformance is significant, 1994 was a terrible year for emerging markets. The OLS-BEKK has significant emerging markets exposure and to underperform by 190 bp in 1994 does not seem too bad.

Fifth, the importance of the GARCH variance estimates become greater at higher target standard deviations. In these models, the equity/cash ratios are much higher.

Sixth, transactions costs are not included in the analysis. Hence, the smoothness of the weights is very important. The figures show the weight progressions of the LS-BEKK-LS and the LS-rolling-LS strategies. It is clear that the GARCH variances induce more variability in the weights. This concern led us to produce additional results that take transactions costs into account.

EXHIBIT 11
CONDITIONAL PROBABILITY MODEL WITH TRANSACTION COSTS

	Target = 10			Target = 12			Target = 14			Target = 16		
	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Full Sample												
Transaction Costs; 0.25, 1.50												
LS-BEKK	7.51	11.84	0.63	8.13	14.24	0.57	8.76	16.64	0.53	9.38	19.04	0.49
LS-Rolling	6.04	9.36	0.65	6.37	11.26	0.57	6.70	13.17	0.51	7.03	15.07	0.47
Transaction Costs; 0.75, 2.50												
LS-BEKK	7.06	11.56	0.61	7.59	13.91	0.55	8.12	16.25	0.50	8.65	18.60	0.47
LS-Rolling	5.90	9.70	0.61	7.59	13.91	0.53	6.50	13.64	0.48	6.80	15.61	0.44
Transaction Costs; 1.25, 3.50												
LS-BEKK	6.18	11.62	0.53	6.54	13.98	0.47	6.89	16.33	0.42	7.25	18.69	0.39
LS-Rolling	4.48	9.73	0.46	4.49	11.71	0.38	4.50	13.69	0.33	4.52	15.67	0.29

Simulation results, January 1990-December 1994, for the conditional probability strategy with three different levels of transactions costs. This strategy forecasts the difference between the emerging market return and the world market return. We divide the forecast by the standard error of the forecast and then use that value in a cumulative normal distribution to determine the weight placed in emerging market equity. There are five strategies presented: LS-BEKK represents least squares forecasts of the conditional means, GARCH forecasts of the variances and covariances, and least squares estimates of the standard error of the forecasts. LS-rolling represents least squares forecasts of the means, rolling (moving window) estimates of the variances and covariance, and least squares estimates of the standard error of the forecasts. The one-way transactions costs are 0.25% and 1.50% for world market and emerging markets respectively, 0.75% and 2.50%, and finally, 1.25% and 3.50%.

Conditional Probability Model with Transactions Costs

We impose three different assumptions on the one-way transactions costs for WM and EM: 0.25/1.50, 0.75/2.50, and 1.25/3.50. The 25 bp in transactions costs in WM is based on the fact that we can get high correlation with the WM in a managed futures strategy. There is no such strategy available in the emerging markets. As a result, the minimum transaction cost we consider is 150 bp.

The results with transactions costs are presented in Exhibit 11 for the full sample. Consider the medium transactions cost assumption 0.75/2.50. The 12% target volatility LS-BEKK strategy produces a 7.6% average return with 13.9% volatility. This compares to a 5.3% average return and 14.9% volatility for a buy-and-hold position in the WM. Even with the most extreme transactions costs, the LS-BEKK strategy produces higher average returns and lower volatility.

The results are even more impressive for the LS-rolling strategy. This strategy produces less variables weights and hence has lower transactions costs. This is evident in Exhibit 13. For example, the 12% target volatility strategy produces 6.4% average returns with 11.3% volatility. This compares to 6.7% average returns and 11.1% volatility when transactions costs are assumed to be zero.

CONCLUSIONS

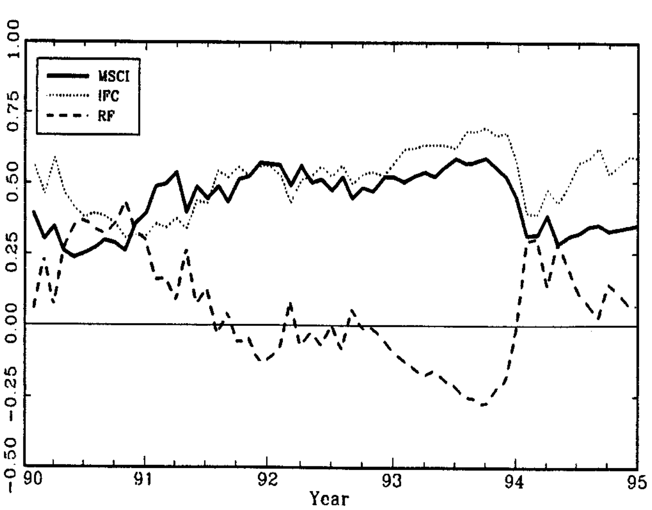
This article addresses the role of emerging markets in active portfolio strategies. Using a mix of a world equity portfolio, an emerging equity portfolio, and cash, we design a number of strategies that capture the predictability in the returns, volatilities and covariances. We present a number of models that appear to outperform the standard benchmarks for international investment.

It is sometimes the case that the best predictive model leads to volatile investment weight changes that induce high transactions costs. Our trading strategies attempt to take transactions costs into account. Even after transactions costs, our trading strategies outperform standard buy-and-hold benchmarks.

Our analysis indicates that there are predictable components in the means, volatilities and covariances of both emerging and developed market returns. The

Exhibit 12
Portfolio Weights for Conditional Probability Strategy

Panel A. OLS Means-BEKK Volatility: 12% Target Volatility — January 1990-December 1994



Panel B. OLS Means-Rolling Volatility: 12% Target Volatility — January 1990-December 1994

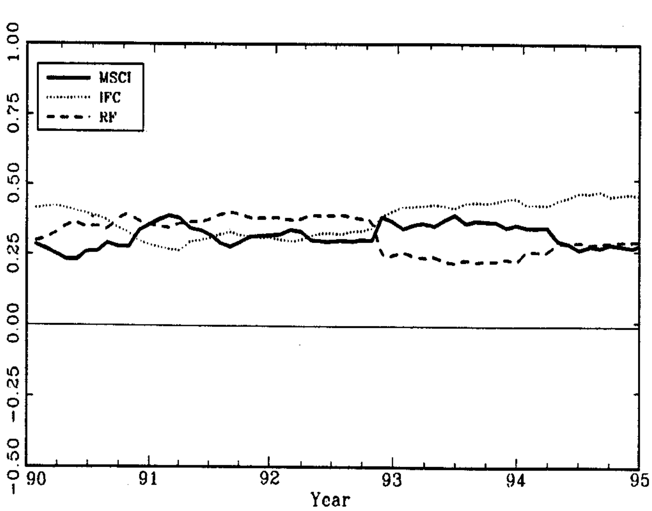
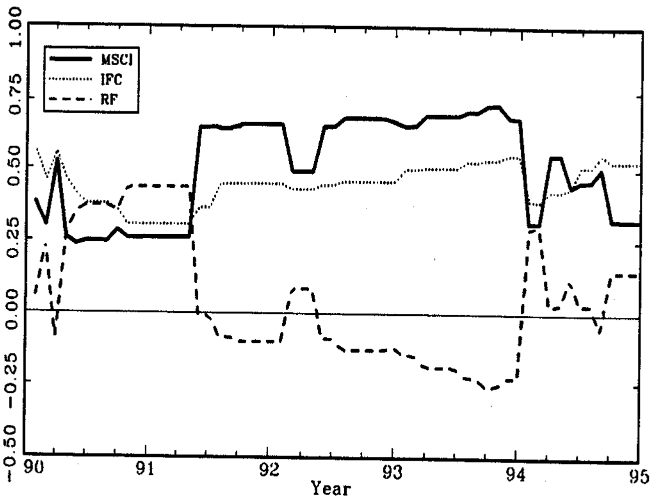
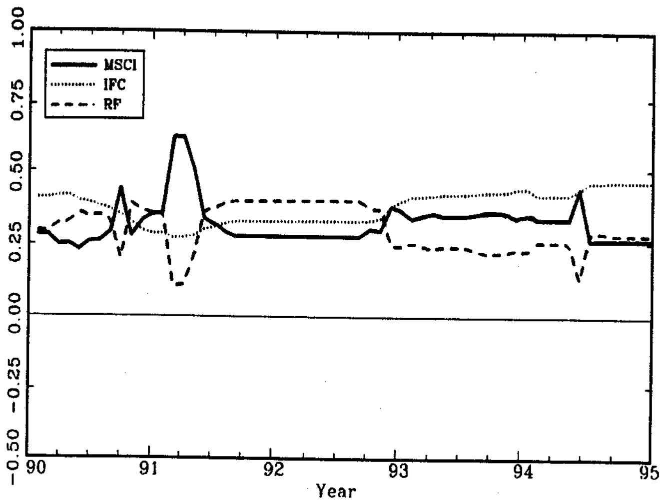


EXHIBIT 13
PORTFOLIO WEIGHTS FOR CONDITIONAL PROBABILITY STRATEGY WITH TRANSACTIONS COSTS

PANEL A. OLS MEANS-BEKK VOLATILITY: 12% TARGET VOLATILITY — JANUARY 1990-DECEMBER 1994



PANEL B. OLS MEANS-ROLLING VOLATILITY: 12% TARGET VOLATILITY — JANUARY 1990-DECEMBER 1994



active strategies that we examine attempt to capture this predictability. The buy-and-hold benchmarks ignore the predictable components. Our results support the notion that predictability is important in these strategies.

We present an ultra-top down methodology for deciding on regional exposure. One of the methods that we employ, the multivariate GARCH, is only feasible on a small number of regions or countries. Our results indicate, however, that the simpler rolling-variance-covariance model produces impressive results. For applications with more than five regions or countries, it is necessary to use the simpler methodology.

In our analysis, we calibrate our models through 1989 and perform out-of-sample analysis over the next five years. Currently, we are investigating the performance of our models in a period of substantial volatility in emerging markets, 1995-1997. Our preliminary results are very encouraging and reinforce the importance of attempting to capture the predictability of these asset class returns in portfolio management.

ENDNOTES

[1]We also carry out trading simulations using an equally weighted emerging market benchmark. Wilcox [1997] makes the case for this alternative weighting scheme. These results are available on request.

[2]This result is sample-specific to the 1976-1995 sample. Bekaert, et al. [1998] detail evidence of skewness and kurtosis in the IFC emerging market composite index using both the last ten years and the last five years of data.

[3]In Harvey [1991], the data extend through May 1989. Our prediction evaluation is based on data available after 1989.

[4]For example, the regression is estimated with the dependent variable dated through t + 11. These coefficients are used to forecast the return that begins at t + 12 (that is, out-of-sample forecast for t + 12 through t + 23).

[5]We also report a half life in months below the coefficient of persistence.

[6]That is, the prediction models are estimated and residuals are obtained. The residuals, e, are used in the last three equations. This reduces the complexity of the estimation.

[7]One observation is dropped and one observation is new, hence the overlap is fifty-nine observations.

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