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The Asset Allocation of Emerging Market Mutual Funds

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Abstract

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Benchmark following and portfolio rebalancing effects have often been cited when trying to explain international financial contagion phenomena. Using a dataset containing the country allocation of individual dedicated emerging market equity funds, we assess the relevance of mean-variance optimization and benchmark following, finding strong evidence for both. We also present a framework to systematically extract useful information about market expectations from funds' holdings.

JEL Classification Numbers: G11, G15, F21

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I. Introduction

Gaining a better understanding of the behavior of international investors ranks high on the research agenda in international finance. Particularly in policy circles, the succession of financial crises in recent years has sparked an intense debate about the nature of contagion effects, the need for capital market regulation, and the role of multilateral financial institutions. Policy proposals in this area hinge, directly, or indirectly, on assumptions about the nature of investors' behavior. This paper contributes to explaining the portfolio choice of a specific and important group of international investors, namely dedicated emerging market funds. Using a unique dataset of the worldwide country allocation of hundreds of funds, it seeks to assess the explanatory power of a simple model with two ingredients that play a major role in many technical and non-technical descriptions of investor behavior: mean-variance optimization and benchmarks. Some observers have argued that herding among investors plays a crucial role in explaining contagion, and the fact that performance is measured against widely used benchmarks is often cited as an incentive to herd (Calvo and Mendoza, 2000). Others have pointed out that contagion effects can be the result of simple portfolio rebalancing within a mean-variance framework (Schinasi and Smith, 2000). We take one step back and, without directly addressing contagion issues, simply ask: to what extent is mean-variance optimization in fact a good description of the portfolio choice of these investors? How important is benchmark-following by emerging market mutual funds?

Finance theory has advanced much beyond simple mean-variance optimization, as originally developed by Markowitz (1959). However, the framework remains the most popular among practitioners, and continues to receive a lot of the attention in the finance literature (for recent examples, see De Roon, Nijman and Werker, 2001, and Ormiston and Schlee, 2001). Moreover, it remains the most widely used model to describe portfolio choice in open-economy macroeconomic models. To our knowledge, however, its applicability to emerging markets has not yet been studied using data on the asset allocation of individual portfolios. Before testing more sophisticated models, it is therefore appropriate to make use of our unique dataset to take stock of the usefulness of this most widely used framework. Our approach is related to Bohn and Tesar (1996), who try to assess the determinants of U.S. portfolio flows within a mean-variance model.[2] The important distinction in this paper is the use of microdata with information about a specific, interesting class of investors.

The overall philosophy of this paper is not to limit ourselves to any strict tests of the validity of the mean-variance model. In particular, we do not test for mean-variance efficiency of these portfolios. Tests of mean-variance efficiency often give rather black and white pictures—the model is either accepted or rejected—while we are more concerned with the *degree* to which the model can account for the observed data.[3] Rather, the idea is to obtain some goodness-of-fit measures that allow us to assess the extent to which the simple mean-variance framework can

[2]See also, among others, Frankel and Engel (1984).
[3]There are too many studies testing for mean-variance efficiency to be referenced. Interesting examples include Hsia (1986) and Rahman (1994), who illustrate two methods which rank the efficiency of a set of portfolios.

explain observed portfolio holdings and their evolution over time. For this purpose, we proceed in two stages.

We first compare actual portfolio weights with those derived from a Markovitz-type portfolio model with short-sale constraints, using historical moments to approximate expected moments. To better capture the real-world incentives of fund managers, their disutility is linked to the variance of the tracking error vis-a-vis a benchmark (see Roll (1992)) rather than to the absolute variance as in the traditional framework. However, since it is clear that the quality of the predictions depends critically on the realistic modeling of expected moments (in particular returns), we implement a different and innovative approach in a second stage. There, instead of second-guessing how fund managers form their views about expected returns, we only assume that fund managers believe that correlations will behave in the future as they did in the past. This allows us to derive the expected returns implicit in the investors' portfolio, which we then compare to actual returns.

We find that widely used benchmarks, such as the indices produced by the IFC and Morgan Stanley Dean Witter (MSCI) go a long way in explaining these funds' country allocation. For example, the simple correlations of actual with benchmark weights of the MSCI EMF indices range from 0.49 for funds investing worldwide to 0.89 for Latin American funds. A brief look at the performance of funds, however, shows that fund managers tend to add value, outperforming simple benchmark indices. Maybe more surprisingly, the simple mean-variance tracking error model with short-sale constraints based on historical returns has explanatory power *in addition* to that contained in the benchmark, especially for countries with high market capitalization. Overall, however, the benchmark indices are better than the model in explaining actual holdings and their changes over time. Finally, we find that the views on future returns implicit in the observed country weights, as interpreted with our mean-variance model, are strongly correlated with actual future returns. Although, as could be expected, we reject the joint hypothesis of rational expectations and correctness of our specific mean-variance model, this result nevertheless provides significant support for our model as an approximation to reality. Moreover, the findings do not seem to be driven by the impact of funds' flows on emerging markets' returns.

II. The Model

We model the problem of the fund manager as having to allocate total funds across a given set of emerging market countries. At this point one might ask why it is meaningful to focus on the *country* allocation by funds. After all, funds often claim to pick good individual *companies*, independently of their home countries. However, country factors are typically viewed as more important than industry or idiosyncratic factors in determining total returns, particularly in emerging markets (Serra, 2000), despite some recent evidence that industry factors have recently gained in relevance (Baca, Garbe and Weiss 2000 and Brooks and Catao, 2001).[4] Moreover, in many emerging markets, the number of big, liquid stocks is limited. Particularly for those

[4]See also Madura (1996) p.58, for a practitioner's view.

countries, it is a good approximation to focus on the country weights of equity funds and proxy their returns by market returns, as is done in this paper.

Since the performance of professional fund managers are often judged relative to a given benchmark, it is important to take this into consideration when constructing a realistic model. A variant of the standard mean-variance framework is the tracking-error variance model. The utility of the fund manager is tied to excess returns and the volatility of tracking error—the month-to-month variability of the difference between the manager's return and the benchmark's return—as opposed to absolute volatility of returns (Roll, 1992). The solution essentially involves maximizing the expected return relative to a benchmark while at the same time minimizing tracking error variance.

A typical fund manager has to allocate wealth across N risky assets to maximize his utility over portfolio returns and tracking error volatility, subject to a constraint against short selling. Under the assumption of a negative exponential utility with constant absolute risk aversion (CARA) and joint normality of asset returns, the optimization problem can be written as[5]

$$\max_{\mathbf{w}} \quad (\mathbf{w}-\mathbf{b})'\mathbf{u} - \frac{1}{2}A(\mathbf{w}-\mathbf{b})'\boldsymbol{\Sigma}(\mathbf{w}-\mathbf{b}) \tag{1}$$

subject to

$$\mathbf{w}'\mathbf{e} = 1 \tag{2}$$

and

$$w_i \geqslant 0 \quad \text{for } i = 1, ..., N. \tag{3}$$

A is the risk aversion coefficient, $\mathbf{w}$ an $N \times 1$ vector of portfolio weights, $\mathbf{b}$ the benchmark portfolio weights, $\mathbf{u}$ the vector of expected asset returns, and $\boldsymbol{\Sigma}$ the $N \times N$ variance-covariance matrix of asset returns. The problem is solved without a risk-free asset since most of these funds face restrictions on how much cash they can hold and also because cash holdings are generally quite small.

Absent the short-sale constraint (3), the problem can be easily solved to yield a closed-form solution as follows. The Lagrangian for the problem is

$$L = (\mathbf{w}-\mathbf{b})'\mathbf{u} - \frac{1}{2}A(\mathbf{w}-\mathbf{b})'\boldsymbol{\Sigma}(\mathbf{w}-\mathbf{b}) - \boldsymbol{\lambda}\,(\mathbf{w}'\mathbf{e}-1)$$

with the first order condition

$$\frac{\partial L}{\partial \mathbf{w}} = \mathbf{u} - A\boldsymbol{\Sigma}\,(\mathbf{w}-\mathbf{b}) - \lambda\mathbf{e} = 0$$

or equivalently,

$$\mathbf{w} = \frac{1}{A}\boldsymbol{\Sigma}^{-1}\,(\mathbf{u}-\lambda\mathbf{e}) + \mathbf{b}. \tag{4}$$

[5]Throughout this paper $\mathbf{M}$ will denote a matrix and $\mathbf{m}$ a vector.

Pre-multiplying the last equation by $\mathbf{e}'$ and making use of constraint (2) yields a solution for λ which can then be plugged into (4) to obtain

$$\mathbf{w} = \frac{\mathbf{\Sigma}^{-1}}{A}(\mathbf{u} - \overline{u}\mathbf{e}) + \mathbf{b} \tag{5}$$

where $\overline{u} \equiv \dfrac{\mathbf{u}'\mathbf{\Sigma}^{-1}\mathbf{e}}{\mathbf{e}'\mathbf{\Sigma}^{-1}\mathbf{e}}$, the expected return on the global minimum variance portfolio. Note that as the risk aversion coefficient rises, the optimal weights get closer to the benchmark because managers become more concerned about deviating from it.

Practical implementation raises two key issues. Firstly, since in practice mutual fund managers are generally precluded from selling an asset short, this important constraint has to be taken into account because its impact on optimal weights is quite substantial. Doing so, however, makes the problem nonlinear, and the solution can only be obtained numerically through a quadratic programming algorithm. Secondly, it is well known that portfolio weights are quite sensitive to changes in asset means. This implies that sampling errors in estimates of asset means feed through to estimates of efficient portfolio weights (we use 5-year moving window of historical returns to compute moments). Although estimates of portfolio weights are also sensitive to changes in covariances, the estimation risk inherent in the former are more severe (see for example, Jorion (1985)). Horst et al. (2000) show that problems associated with estimation risk in expected returns can, to a certain degree, be alleviated by adjusting the risk-aversion parameter upwards. Accordingly, we carry out all calculations with risk aversion levels of 5 and 15 which are more typical, as well as a higher level of 75. Our main conclusions are not sensitive to the risk aversion parameter adopted.

III. Actual, Predicted, and Benchmark Portfolio Weights

A. The Data

The data used in this paper are from a comprehensive database purchased from eMergingPortfolio.com. It covers, on a monthly basis, the geographic asset allocation of hundreds of equity funds with a focus on emerging markets for the period 1996:1-2000:12. At the beginning of the sample, the database contains 382 funds with assets totaling US$117 billion; at the end of the period, the number of funds covered is 639, managing US$120 billion of assets. Note that, while the total number of funds increased over the period, some funds were dropped from the database if they discontinued providing information on their holdings. From this set, we concentrate on a subsample of global emerging and regional funds, excluding those that have a sizeable portion of their assets in developed countries as well as single-country funds. This subsample contains 184 funds in 1996:1 (managing around US$60 billion) and 428 funds in 2000:12 (managing around US$67bn).[6]

[6]For more details on the data, see Borensztein and Gelos (2000).

As for the indices, while there is cross-sectional variation in the benchmarks selected by funds, most use the MSCI or IFC global or regional indices as performance benchmarks. We use country weights of the IFC global investable emerging market index and the MSCI Emerging Markets Free (EMF) index when looking at global funds, the IFC East Asia as well as the MSCI AC Far East Free ex-Japan indices when focusing on regional East Asia funds, and the IFC Latin America and MSCI Latin America EMF indices when evaluating Latin American regional funds.[7] Some countries forming part of these indices, such as China, had to be eliminated from our analysis due to lack of sufficiently long historical data series, which are required to estimate covariance matrices. On the other hand, the funds in our sample also hold some assets in a variety of smaller countries that do not pertain to the indices, as well as some cash. We eliminate those funds that hold large amounts of cash or have large portfolio weights in non-index countries, and rebalance the portfolio weights of the remaining funds. In order not to loose too many funds in this process, however, we retain some countries in the global case that do not form part of the global indices, such as Israel and Singapore. We report only the results based on the MSCI indices since the results using IFC indices are very similar.

B. The Results

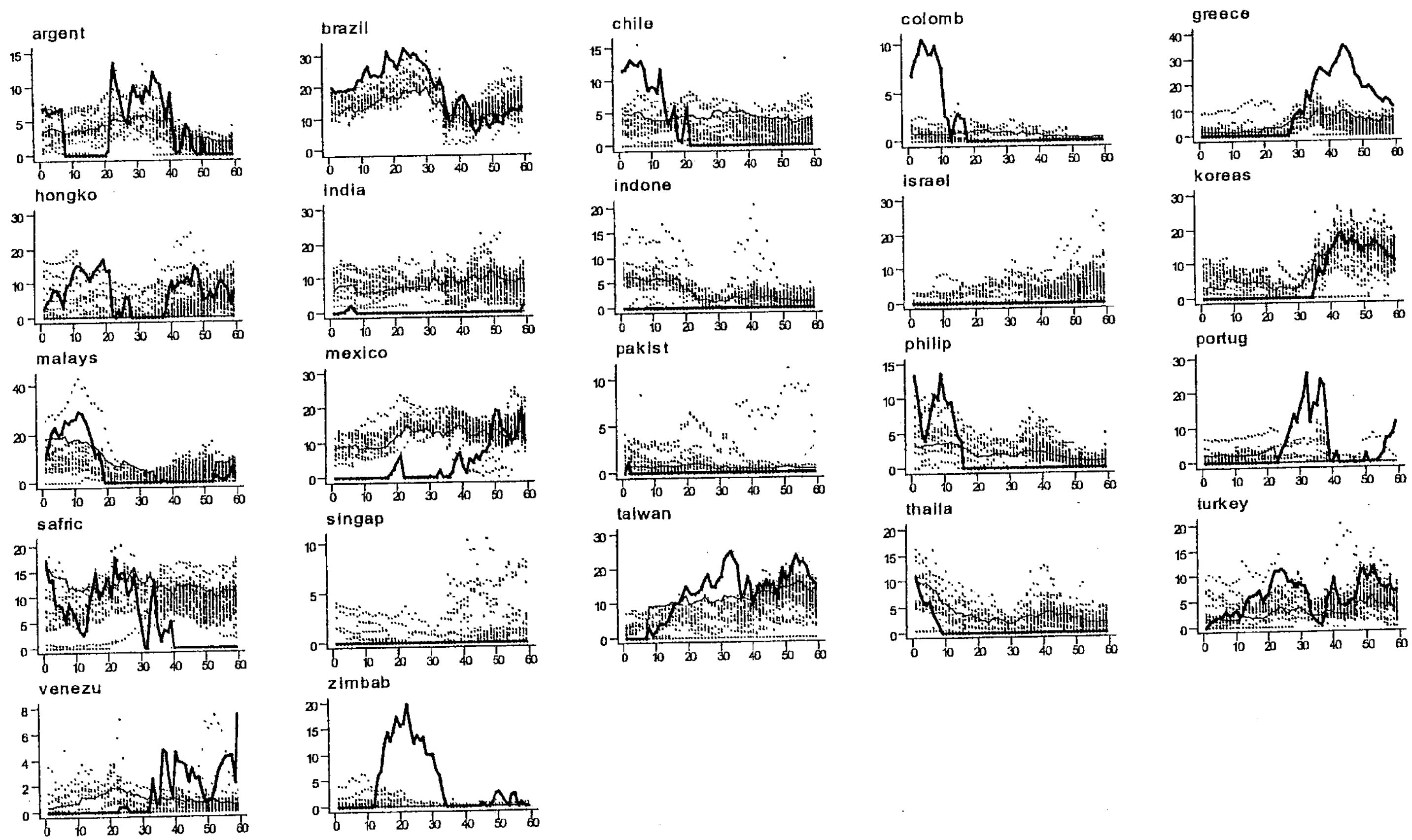
How useful is this model in describing the behavior of emerging market funds? Figures 1-3 plot the weights predicted by the model with risk aversion of 15 (the x-axis represents months starting from 1996:01) against the MSCI benchmark weights and actual holdings of the funds for the three regional groupings. The predicted weights follow the benchmark reasonably closely for Asia and Latin America, and less so in the Global case. More systematically, the performance of the model relative to the benchmark is examined in the following ways. First, we compare the actual portfolio weights of the three regional groups of funds with those predicted by the model using the root mean squared error (RMSE) and the Theil coefficient.[8] Second, we run panel regressions of actual on predicted weights for each country separately, with fixed fund effects. The fixed effects control for unobserved heterogeneity in funds' characteristics that do not change over time. We also conduct the analysis on differences, i.e. changes in weights, to investigate the relative performance of the model in predicting levels as oppose to changes in country allocations.[9] Lastly, we report the results from a regression for the pooled data. Given the fact that the weights need to add up to one, an interpretation of the coefficient is difficult, but

[7] Since we did not have access to all indices used by funds, we limited ourselvelves to the most widely used ones. This limitation will cause our computations to understate the predictive power of benchmarks and of our model. Note also that the term "global funds" here refers to those investing only in emerging markets worldwide.

[8] The Root Mean Squared Error (RMSE) and the Theil coefficient are defined as RMSE $= \sqrt{\frac{1}{T}\sum_{t=1}^{T}(w_t^p - w_t^a)^2}$ and Theil $=\text{RMSE}/\sqrt{\frac{1}{T}\sum_{t=1}^{T}(w_t^p)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(w_t^a)^2}$ where w_t^a and w_t^p stand for actual and model-predicted portfolio weights, respectively. The RMSE is the squared root of the averaged squared difference between actual and predicted weights. The Theil coefficient essentially rescales the RMSE as to bound it between zero and one. The lower the Theil index, the higher the accuracy of the model.

[9] Note that since the model portfolio weights are generated using actual historical returns, we are in essence looking at the out-of-sample performance of the model generated weights.

Figure 1. Actual vs Predicted Weights - Global



. Actual Weights — Benchmark Weights — Predicted Weights (Risk = 15)

Figure 2. Actual vs Predicted Weights - Asia

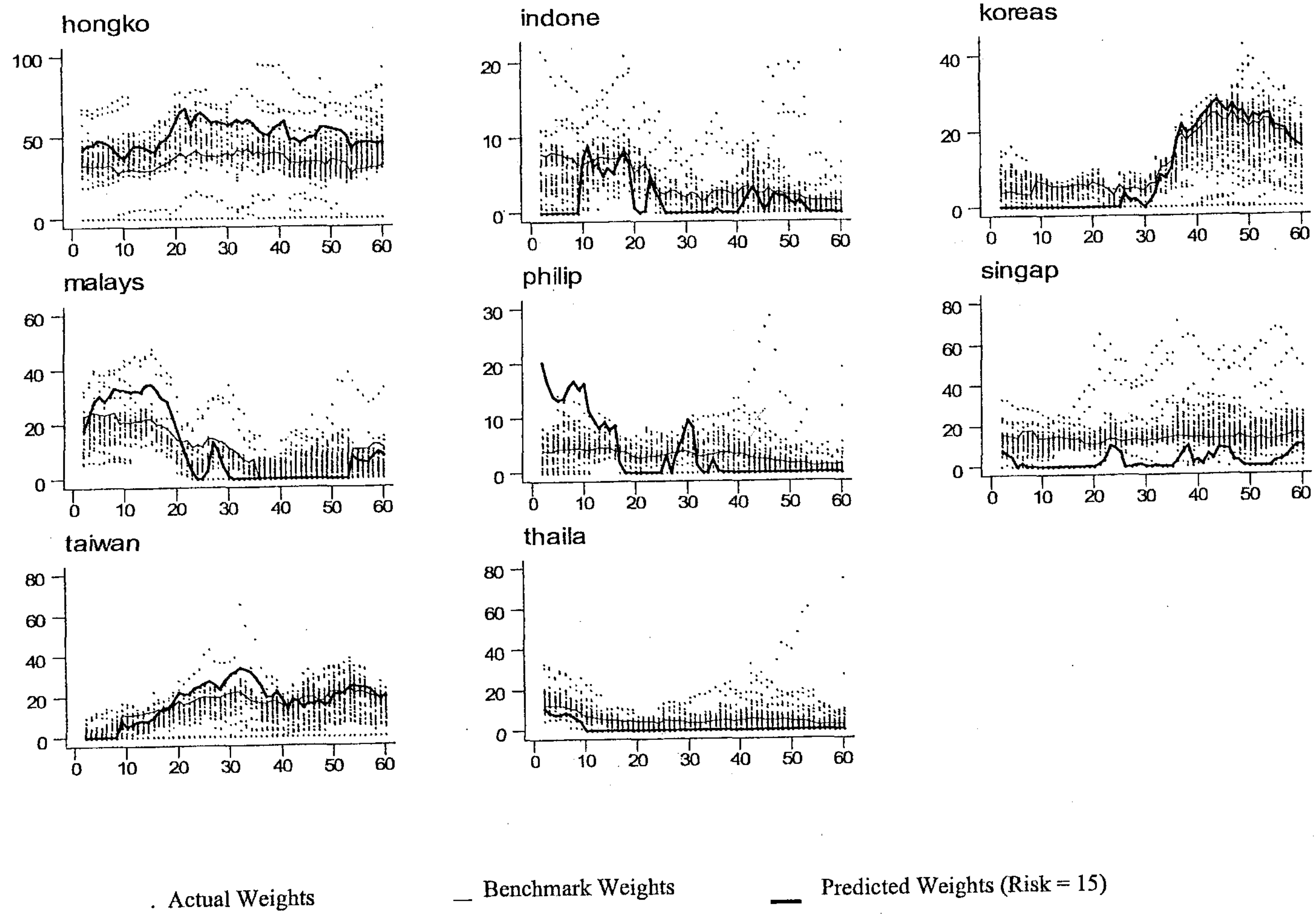
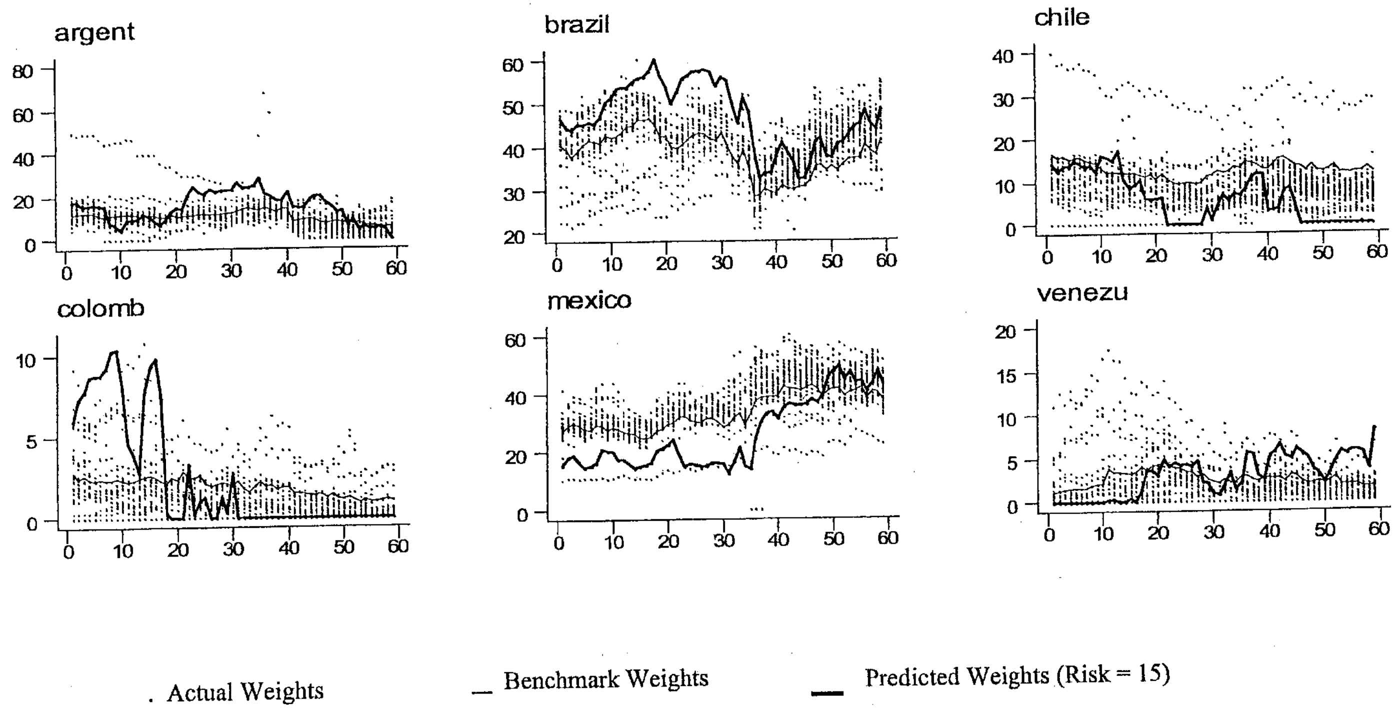


Figure 3. Actual vs Predicted Weights - Latin



such a regression will give us a different way of assessing the overall fit of the model and the benchmark indices.

The goodness-of-fit measures show that benchmark indices alone tend to explain a substantial fraction of the variation in holdings (Table 1), beating the model. The Theil coefficients are quite low and the benchmarks also appear to be highly correlated with the actual weights. The model's RMSE is always higher than the benchmark's and appears to be inversely related to the degree of risk aversion (recall that by construction, higher risk aversion results in better tracking of the benchmark). Overall across the regional groupings, the model performs best with respect to Latin America. The model and the benchmark do substantially worse in terms of capturing changes in portfolio weights. Note, however, that we did not exclude those countries for which the model predicts a large number of zero weights, thus handicapping the performance of the model as measured by the Theil coefficients.

The regressions tend to confirm these results despite the substantial heterogeneity in the importance of benchmarks across countries. Tables 2-4 presents regression estimates with a risk aversion parameter of 15. Looking first at the results when fund's holdings are regressed only on their respective benchmarks (the first column in Tables 2-4), the R^2 statistics suggest reasonable explanatory power in many cases and the coefficients are positive and significant for most countries, although there is substantial variation. This confirms our conjecture that funds pay close attention to the benchmark to which their performance is measured against, although clearly other considerations also play a role in their asset allocation decision. The second column in Tables 2-4 shows the results of regressions of actual holdings on the weights predicted by the model. The R^2's for the model with risk aversion coefficient of 15 are comparable to those of the benchmark and are generally higher than those obtained with a risk aversion of 5 (not reported). The estimated coefficients are generally lower for the model than for the benchmark and are positive and significant, except for the Global case where they are negative for some countries. Regressions of actual weights on model predictions (with risk aversion of 15) for the pooled samples of all countries (not shown) produced R^2's of 0.44 for the Global case, 0.74 for the East Asian funds, and 0.88 for the Latin American regional funds. Again, simple benchmark indices do somewhat better, with R^2's of 0.77 for Global funds, 0.82 for East Asia, and 0.95 for Latin America. (We omit statistics on the coefficient, whose interpretation is not straightforward, as mentioned above).

It should be noted, however, that this analysis does not differentiate between the relevance of market capitalization measures as opposed to merely technical changes in index composition. In other words, indices may explain funds' holdings well because i) their composition approximates market capitalization and the investor class that we examine on average holds the (regional) market portfolio; and ii) fund managers react strongly to technical changes in the composition of specific indices. This differentiation is interesting, but not the focus of our paper. More relevant is the finding that there seems to be predictive power in the model based on historical returns *beyond* the information contained in the indices (third column of tables 2-4). The coefficients on the weights predicted by the model, in regressions in which both the benchmark and the predicted

Table 1. Goodness-of-Fit Measures

Levels	**Global**	**East Asia**	**Latin**
Model with Risk Aversion=15			
RMSE	6.41	10.78	8.32
Theil Coefficient	0.42	0.27	0.17
Correlation	0.49	0.78	0.89
Model with Risk Aversion=5			
RMSE	9.81	14.32	15.20
Theil Coefficient	0.56	0.33	0.29
Correlation	0.23	0.74	0.72
MSCI Index			
RMSE	3.37	7.85	5.44
Theil Coefficient	0.25	0.22	0.12
Correlation	0.79	0.81	0.96
Differences			
Model with Risk Aversion=15			
RMSE	2.06	3.07	2.76
Theil Coefficient	0.69	0.63	0.62
Correlation	0.10	0.21	0.25
Model with Risk Aversion=5			
RMSE	3.69	4.04	4.81
Theil Coefficient	0.79	0.68	0.73
Correlation	0.03	0.12	0.11
MSCI Index			
RMSE	1.13	2.53	1.71
Theil Coefficient	0.62	0.63	0.54
Correlation	0.31	0.27	0.53

Note: The model's optimal weights are calculated using 5-year rolling averages of monthly returns, starting January 1991.

Table 2. Regressions of Actual on Predicted Weights - Global
(Risk Aversion=15)

	Levels			**Levels**			**Levels**			**Differences**	
Country	**MSCI index**	**R^2**	**Share of nonzero weights**	**Model**	**R^2**	**MSCI index**	**Model**	**R^2**	**Model**	**Return**	**R^2**
ARGENTINA	0.56	0.53	0.50	0.04	0.32	0.56	0.00	0.53	0.04	0.01	0.04
t-statistic	(14.73)			(4.06)		(13.92)	(0.00)		(5.10)	(6.59)	
BRAZIL	1.08	0.56	1.00	0.24	0.41	1.02	0.05	0.56	0.09	0.07	0.26
t-statistic	(27.82)			(12.43)		(22.60)	(2.93)		(4.84)	(19.80)	
CHILE	0.38	0.05	0.19	0.01	0.03	0.38	0.01	0.06	-0.01	0.00	0.00
t-statistic	(4.75)			(0.73)		(4.74)	(0.70)		-(0.41)	-(0.25)	
COLOMBIA	0.33	0.14	0.14	0.01	0.13	0.34	0.01	0.19	0.01	0.00	0.00
t-statistic	(5.87)			(1.33)		(5.97)	(1.67)		(1.22)	(2.39)	
GREECE	0.51	0.18	0.76	0.08	0.12	0.50	0.01	0.17	0.04	0.03	0.08
t-statistic	(17.44)			(6.70)		(15.81)	(0.69)		(3.55)	(9.81)	
HONG KONG	n/a	n/a	0.87	-0.02	0.01	n/a	-0.02	0.09	-0.03	0.01	0.01
t-statistic	n/a			-(1.85)		n/a	-(1.85)		-(2.76)	(3.32)	
INDIA	0.76	0.01	0.09	-0.17	0.00	0.76	-0.11	0.01	-0.17	0.06	0.12
t-statistic	(20.11)			-(1.97)		(20.04)	-(1.48)		-(2.08)	(14.04)	
INDONESIA	1.01	0.44	0.00	n/a	n/a	1.01	n/a	0.35	n/a	0.02	0.09
t-statistic	(16.95)			n/a		(16.95)	n/a		n/a	(12.21)	
ISRAEL	n/a	n/a	0.00	n/a	0.00	n/a	n/a	0.00	n/a	0.02	0.03
t-statistic	n/a			n/a		n/a	n/a		n/a	(6.59)	
KOREA	0.79	0.53	0.70	0.56	0.53	0.70	0.09	0.54	0.33	0.03	0.24
t-statistic	(25.72)			(21.80)		(12.68)	(1.95)		(10.00)	(9.94)	
MALAYSIA	-0.03	0.17	0.44	0.10	0.24	-0.10	0.13	0.17	0.07	0.02	0.09
t-statistic	-(1.37)			(6.13)		-(4.62)	(7.54)		(4.50)	(10.14)	
MEXICO	0.72	0.18	0.71	0.07	0.00	0.71	0.01	0.18	0.06	0.04	0.09
t-statistic	(14.77)			(5.40)		(13.70)	(0.87)		(4.45)	(10.36)	
PAKISTAN	1.39	0.12	0.01	-0.04	0.00	1.40	-0.08	0.12	-0.04	0.00	0.02
t-statistic	(8.80)			-(0.69)		(8.87)	-(1.29)		-(0.60)	(4.92)	
PHILIPPINES	1.22	0.48	0.13	0.01	0.28	1.22	0.02	0.48	0.02	0.01	0.04
t-statistic	(14.27)			(0.79)		(14.30)	(1.12)		(1.47)	(7.38)	
PORTUGAL	0.05	0.07	0.54	0.02	0.03	0.05	0.02	0.07	0.03	0.01	0.04
t-statistic	(1.41)			(5.13)		(1.50)	(5.14)		(6.35)	(4.62)	
SOUTH AFRICA	0.60	0.00	0.38	0.06	0.00	0.58	0.03	0.00	0.04	0.02	0.03
t-statistic	(11.53)			(3.61)		(11.08)	(1.98)		(2.10)	(5.11)	
SINGAPORE	n/a	n/a	0.00	n/a	n/a	n/a	n/a	n/a	n/a	0.00	0.00
t-statistic	n/a			n/a		n/a	n/a		n/a	(2.57)	
TAIWAN	0.36	0.31	0.94	0.03	0.23	0.36	0.00	0.31	-0.01	0.06	0.12
t-statistic	(10.85)			(1.82)		(10.60)	-(0.06)		-(0.46)	(14.23)	
THAILAND	0.79	0.36	0.07	-0.10	0.23	0.79	-0.12	0.36	0.11	0.02	0.07
t-statistic	(14.64)			-(1.32)		(14.69)	-(1.51)		(2.03)	(10.29)	
TURKEY	1.03	0.15	0.99	0.15	0.10	1.09	-0.07	0.15	0.01	0.04	0.26
t-statistic	(23.80)			(6.69)		(23.01)	-(3.12)		(0.34)	(21.77)	
VENEZUELA	0.39	0.08	0.74	-0.01	0.05	0.38	-0.01	0.09	-0.01	0.00	0.01
t-statistic	(5.75)			-(1.91)		(5.49)	-(0.97)		-(1.44)	(3.35)	
ZIMBABWE	n/a	n/a	0.74	0.01	0.03	n/a	0.01	0.27	0.01	0.00	0.01
t-statistic	n/a			(2.67)		n/a	(2.67)		(2.42)	(2.43)	

Note: Fixed-effects regressions, with fixed fund effects and Baltagi-Wu (1999) autocorrelation correction.

Table 3. Regressions of Actual on Predicted Weights - East Asia
(Risk Aversion=15)

	Levels		Levels			Levels			Differences		
Country	**MSCI index**	R^2	**Share of *nonzero* weights**	**Model**	R^2	**MSCI index**	**Model**	R^2	**Model**	**Return**	R^2
HONG KONG	0.6330149	0.02	1.00	0.26	0.01	0.64	0.00	0.02	0.15	7.27	0.05
t-statistic	(16.96)			(10.77)		(12.85)	-(0.08)		(6.40)	(8.09)	
INDONESIA	0.9427445	0.38	0.51	0.13	0.16	0.91	0.04	0.39	0.13	1.57	0.09
t-statistic	(23.08)			(7.28)		(21.25)	(2.44)		(7.95)	(10.62)	
KOREA	0.653367	0.56	0.72	0.54	0.56	0.35	0.28	0.57	0.35	3.03	0.17
t-statistic	(25.40)			(26.23)		(6.69)	(6.66)		(13.20)	(8.90)	
MALAYSIA	0.042816	0.40	0.51	0.17	0.49	-0.13	0.23	0.46	0.24	2.71	0.17
t-statistic	(2.05)			(10.94)		-(4.75)	(11.18)		(17.80)	(7.56)	
PHILIPPINES	1.231737	0.34	0.30	0.04	0.15	1.21	0.02	0.33	0.02	0.58	0.00
t-statistic	(17.01)			(2.67)		(16.27)	(1.56)		(1.91)	(2.88)	
SINGAPORE	0.512922	0.00	0.64	0.13	0.02	0.48	0.08	0.00	0.11	2.22	0.02
t-statistic	(10.15)			(5.46)		(9.26)	(3.45)		(4.89)	(3.64)	
TAIWAN	0.4487734	0.30	0.90	0.26	0.23	0.37	0.10	0.30	0.22	6.04	0.08
t-statistic	(14.60)			(10.88)		(9.34)	(3.24)		(9.52)	(9.64)	
THAILAND	0.9032153	0.33	0.13	0.19	0.27	0.91	-0.02	0.33	0.24	2.38	0.06
t-statistic	(16.92)			(3.43)		(16.28)	-(0.34)		(4.99)	(10.51)	

Note: Fixed-effects regressions, with fixed fund effects and Baltagi-Wu (1999) autocorrelation correction.

Table 4. Regressions of Actual on Predicted Weights - Latin America
(Risk Aversion=15)

	Levels		Levels			Levels			Differences		
Country	**MSCI index**	R^2	**Share of nonzero weights**	**Model**	R^2	**MSCI index**	**Model**	R^2	**Model**	**Return**	R^2
ARGENTINA	0.74	0.29	0.97	0.03	0.11	0.76	-0.03	0.30	0.03	0.02	0.01
t-statistic	(19.69)			(2.24)		(19.60)	-(1.89)		(1.95)	(3.70)	
BRAZIL	1.01	0.28	1.00	0.47	0.19	1.02	-0.01	0.28	0.30	0.10	0.30
t-statistic	(30.66)			(20.63)		(20.32)	-(0.24)		(12.19)	(16.66)	
CHILE	0.75	0.02	0.57	0.07	0.05	0.75	0.01	0.02	0.05	-0.01	0.01
t-statistic	(16.60)			(4.15)		(16.06)	(0.40)		(3.08)	-(1.86)	
COLOMBIA	0.59	0.20	0.30	0.01	0.19	0.59	0.01	0.21	0.01	0.00	0.01
t-statistic	(10.76)			(1.13)		(10.78)	(1.24)		(0.89)	(3.73)	
MEXICO	1.01	0.53	1.00	0.35	0.40	0.96	0.03	0.53	0.30	0.02	0.13
t-statistic	(31.94)			(17.72)		(22.66)	(1.46)		(14.15)	(2.75)	
VENEZUELA	0.47	0.07	0.85	0.02	0.04	0.47	0.01	0.07	0.02	0.01	0.04
t-statistic	(9.76)			(1.43)		(9.68)	(0.70)		(1.67)	(8.47)	

Note: Fixed-effects regressions, with fixed fund effects and Baltagi-Wu (1999) autocorrelation correction.

weights are included, are significantly positive for most countries. This is particularly true for the countries with higher stock market capitalization and those for which the fraction of predicted zero portfolio weights is low. Turning to the last column which presents results for changes in weights, the performance of the model is generally poorer than in levels.

C. Relative Performance

Given that actual fund holdings appear to track the benchmark quite closely, a question that springs into mind is whether there is any value added from active fund management. While the focus of this paper is not on fund performance, this section briefly examines the relative performance of the benchmark with respect to actual and model predicted holdings. The information is presented in Table (5). The measures presented include simple time-averaged portfolio returns, the Sharpe ratio (the ratio of the portfolios average returns to its standard deviation), and the Jensen measure. The latter is the constant in a regression of portfolio returns on benchmark returns and significant positive/negative values indicate over/under performance relative to the benchmark.[10]

In terms of relative performances of the different portfolios, it turns out that for the Global and Latin America groupings, the actual portfolio of mutual funds perform best, followed by the benchmark, and then the model (with a higher risk aversion parameter improving the returns). In the Asian case, on the other hand, the model with the lowest risk-aversion parameter performs best, followed by actual fund portfolios, with the benchmark coming last. The underperformance of Asian funds can perhaps be attributed to the fact that the model is relatively underweight in the three worst performing markets—the Philippines, Indonesia, and Thailand— throughout the crisis years (1996-1998). The Jensen measure in Table (5) indicates that fund-managed portfolios yielded a monthly return that was, on average, 0.3, 0.08, and 0.1 percent higher than the benchmark for the Global, East Asia, and Latin American categories respectively.

From the perspective of average returns, those funds that deviate more from the benchmark have tended to be rewarded with better performance. The relationship between "closeness" to the benchmark index and funds' returns is examined through a regression of the rank of average returns on the rank of average distance from the benchmark as measured by the RMSE. For the Latin and Asian funds, the coefficient (0.54 and 0.4 respectively) is positive and significant at the 5 percent level. For Global funds, the coefficient (0.31) is significant at the 15 percent level.[11] The fact that actual fund performance is consistently superior to the benchmark and the model (in the Global and Latin American cases) suggests that managers add value to the model by conditioning their allocation on other information, public or private, which is not utilized in the simple mean-variance framework.

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[10]Note that, to be consistent, the calculations were not made with actual returns as reported by the funds, but with returns as measured by our approximation of total returns on the countries' indices times (rebalanced) country weights at the beginning of each period.

[11]The calculation is done for a balanced panel for the period from 1999:01-2000:12 to maximize the number of funds in the sample. Using the whole sample period yields qualitatively similar results.

Table 5. Performance Measures

Weights	Global			East Asia			Latin		
	Sharpe	**Mean Returns**	**Jensen**	**Sharpe**	**Mean Returns**	**Jensen**	**Sharpe**	**Mean Returns**	**Jensen**
Model:									
Risk=5	-0.1108	-0.0076	-0.0063	-0.0063	-0.0006	0.0028	0.0686	0.0071	-0.0032
Risk=15	-0.0834	-0.0059	-0.0042	-0.0221	-0.0021	0.0015	0.0876	0.0085	-0.0014
Risk=75	-0.0389	-0.0029	-0.0010	-0.0344	-0.0033	0.0004	0.0992	0.0093	-0.0003
MSCI Index	-0.0253	-0.0020	n/a	-0.0388	-0.0037	n/a	0.1024	0.0094	n/a
Actual	0.0041	0.0003	0.0030*	-0.0326	-0.0031	0.0008*	0.1121	0.0106	0.0010*

* Estimates significant at the one percent confidence level.
Note: Calculations were performed over the whole sample from 1996:02 to 2000:12.

IV. Implied Views

The first part of the paper argued that the tracking-error variance model contains some explanatory power with respect to the asset allocation of the funds in our sample over time. This section tries to get at the problem through an alternative avenue examining the views implicit in the funds' holdings. For a given variance-covariance matrix, these are the expectations of returns that fund managers must hold in order for the tracking-error-variance model to produce the particular asset allocation observed. The underlying assumption, which is quite defensible in our view, is that managers do not have strong views about the correlation structure of returns across countries, but rely on historical covariances for guidance. In other words, a fund manager may have reasons to expect the Mexican stock market to improve over the next months, but no reason to believe that Mexican returns will be more or less correlated with those of Korea than in the past. An advantage of this approach is that it avoids the problems inherent in using historical mean returns as a proxy for expected returns and relies only on computed historical variance co-variance matrix, where the estimation risk is less of a concern.

If fund managers have rational expectations, on average, their expected returns should not systematically deviate from actual returns and the managers' chosen portfolio weights should embody these rational expected returns. Thus, if one cannot reject rationality for the implied views backed out from actual portfolio holdings, then the underlying model used to calculate these views must also be a reasonably good representation of fund managers' behavior.[12]

We examine this issue using an approach based on the classic Fama (1976) methodology and now widely applied in international finance to examine the relationship between spot and forward exchange rates.[13] The basic idea, is that, on average, the realized return for country j in period $t+1$, $r_{j,t+1}$, should be equal to the implied views for period $t+1$ derived from asset weights observed in period t, $r^v_{j,t+1}$. Otherwise, fund managers are consistently over or under estimating returns. Econometrically, to test for prediction bias in the implied views, we run the following regression

$$r_{j,t+1} = \beta_j r^v_{j,t+1} + \varepsilon_{j,t} \tag{6}$$

and test the null hypothesis that $\beta_j = 1$. Rejection of the null implies rejection of unbiasedness of the implied views.[14] Note, however, that even if the hypothesis that $\beta_j = 1$ is rejected, evidence that β_j is significantly positive would indicate that implied views have power to predict actual future returns—ie. there is information content in fund manager's view about future returns. Thus a weaker test than strict unbiasedness is whether β_j is significantly positive. Estimation of

[12]Of course, this is a test of a joint hypothesis — that of the correctness of the model and of rationality. At the same time, failure to reject the joint hypothesis then constitutes strong supportive evidence for the model.

[13]See Obstfeld and Rogoff (1996) for a summary of the findings and Fama (1984) for application of the method to spot and future interest rates.

[14]A constant could be added to the equation, reflecting constant expected returns. As it turns out, the results reported below are not sensitive to the inclusion of a constant term.

(6) essentially attempts to measure the forecast power of information extracted from an *ex ante* variable with respect to the expected value of an *ex post* variable.

A. The Results

The derivation of expected returns form observed country weights poses some challenges. Although the presence of short-sale constraints prevents an analytical solution to the optimization problem, it is still possible to obtain the implied views given observations on actual portfolio weights. The key step is to recognize that the solution to the quadratic programming problem must be identical to the solution to the unconstrained problem maximized over the subset of assets contained in the final optimal short-sale constrained portfolio. Intuitively, the quadratic program yields an allocation over a subset of assets for which the short-sale constraint does not bind. If this allocation is to be optimal then, it must coincide with the optimal portfolio resulting from an unconstrained maximization since the latter is unique.[15]

Finally, the structure of the optimization problem is such that the implied views can only be derived in relative terms, i.e. up to a constant.[16] To pin down the returns while maintaining internal consistency of the approach, we set one of the asset returns equal to the actual one-period-ahead return of one of the countries. The country used to normalize was selected as that country in which all funds were invested in at all points in time throughout the sample. For the sample of Global funds and for the Latin American regional funds, this country is Brazil. For the East Asian regional funds, Singapore is used to normalize returns. Appendix (I) outlines the procedure of deriving implied views, which is quite involved.

We estimate equation (6) in two different ways. First, we carry out a month-by-month regression. Given that fund managers may not adjust their portfolios every month, we also estimate the relationship using end-of-quarter data. There, we interpret the implied views as the average monthly return expected by the fund managers for the next three months and compare them with the geometric average of the actual returns for the corresponding three months. We exclude the normalization country from the estimations. However, since we are using these countries' actual future returns to normalize the other returns, our estimation results will be biased upwards if cross-country correlations are positive. Therefore, in one set of regressions, we also augment equation (6) by including the actual return of the normalization country as an explanatory variable to control for this effect.

The results, presented in Table (6), are quite strong. The estimated β_j's are positive and highly significant, and the R^2's for the monthly data range from 0.16 to 0.36. Moreover, while the β_j's are mostly significantly different from one, they are quite high. The results are better for the East Asian regional funds than for the Latin American or the Global funds. Overall, the results for the quarterly estimations are weaker than those using monthly data, and the information contained in the future actual returns of the normalization country seems to be more important.

[15]See Tarrazo (2000) for an intuitive and more technical explanation of this result.
[16]Due to the adding up constraint, there are only $N-1$ independent equations in the system.

Table 6. Regressions of Implied Views on Actual Returns

Monthly data, simple

	Global		Latin America		East Asia	
	RA=5	RA=15	RA=5	RA=15	RA=5	RA=15
View	0.38	0.38	0.44	0.44	0.81	0.79
t-stat	54.27	54.69	51.59	51.92	57.96	57.01
R^2	0.17	0.17	0.36	0.36	0.33	0.32
Number of observations	19042	19042	6245	6245	11664	11664

Monthly data, including actual returns of normalization country

	Global		Latin America		East Asia	
	RA=5	RA=15	RA=5	RA=15	RA=5	RA=15
View	2.18	0.75	1.45	0.45	0.81	0.79
t-stat	12.09	12.55	5.21	4.97	59.07	58.23
NR	-1.81	-0.37	-1.01	-0.01	0.13	0.13
t-stat	-10.01	-21.90	-3.63	0.95	10.24	10.56
R^2	0.17	0.17	0.36	0.36	0.34	0.33
Number of observations	19042	19042	6245	6245	11664	11664

Quarterly data, simple

	Global		Latin America		East Asia	
	RA=5	RA=15	RA=5	RA=15	RA=5	RA=15
View	0.15	0.15	0.09	0.09	0.44	0.44
t-stat	15.64	16.20	8.40	8.54	27.36	27.08
R^2	0.05	0.05	0.04	0.05	0.24	0.24
Number of observations	6696	6696	2074	2074	3652	3652

Quarterly data, including actual returns of normalization country

	Global		Latin America		East Asia	
	RA=5	RA=15	RA=5	RA=15	RA=5	RA=15
View	0.59	0.59	0.04	0.04	-0.11	-0.88
t-stat	42.50	42.44	4.39	4.65	-5.24	-4.47
NR	0.08	0.09	0.49	0.49	1.21	1.18
t-stat	10.42	11.27	27.83	27.89	44.25	44.34
R^2	0.28	0.29	0.41	0.41	0.46	0.46
Number of observations	6696	6696	2074	2074	3652	3652

Note: The dependent variable is actual one-period-ahead returns. The reported errors are robust (Hubert/White).
RA stands for the risk aversion parameter. View denotes the implicit views about (on-period-ahead) returns.
NR denotes the actual (one-period-ahead) return of the normalization country (Brazil for Global and Latin American fur
Singapore for Asian funds.)

Figure 4 plots the forecast errors (actual returns minus implied monthly expected returns) for the case of Global funds and a risk aversion parameter of 15, with a superimposed normal distribution. On average, the funds tend to underestimate returns slightly (the mean and medians of -0.8 percent are both statistically different from zero), but one needs to bear in mind that this is dependent on the realized returns of the normalization country. The errors seem to be distributed symmetrically; in fact, skewness is relatively low (0.41), but due to the high kurtosis (5.09), normality tests are clearly rejected. Approximately 69 percent of the observations fall into the one-standard-deviation interval around the mean.

While the results reject the strong joint hypotheses of rationality and appropriateness of the model, we interpret them as indicating that (i) the model describes the funds' behavior to a reasonable extent, and (ii) fund managers' expectations as manifested in their holdings contains reliable information regarding future returns. Note that these findings are not an artifact of serially correlated returns. Returns are not autocorrelated in our sample, and estimations in differences yield even stronger results (not reported). An alternative explanation would be that reverse causation is at work: funds do not predict returns, but their flows into emerging market cause local stock prices to go up.[17] A direct way of examining this hypothesis is to regress country returns on changes in the funds' country weights. Such a regression, however, produces no significant results.

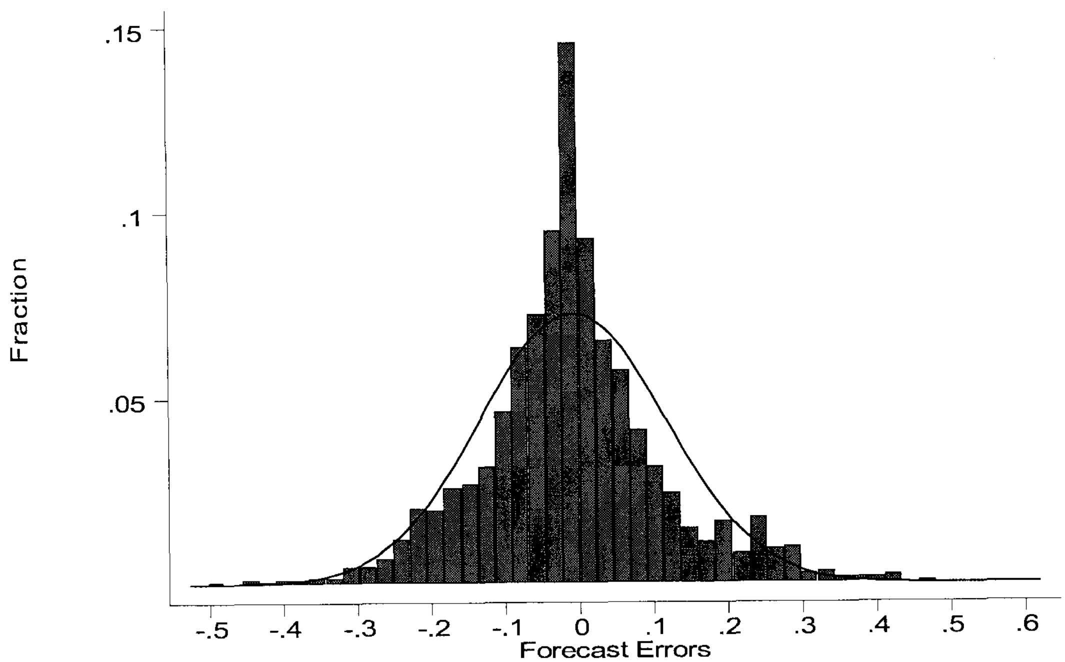
V. Conclusion

The results presented in this paper indicate that, as a first approximation, it is quite reasonable to model the behavior of emerging market equity funds as mean-variance optimization around benchmark indices. This finding provides empirical support for the relevance of rebalancing effects in explaining contagion effects, such as those originating from a shock to a particular country's expected return. The importance of benchmarks, as suggested by the evidence, is consistent with theories relating herding to benchmark-following. On the other hand, in line with evidence presented in Borensztein and Gelos (2000) who show that funds' behavior is driven by other factors than simple herding, mere benchmark-following alone explains only a fraction of the portfolio choice of these funds.

A different implication is that, when trying to assess the reaction of capital flows to shocks, the information contained in historical return covariances is useful, since it seems to be used as input in fund managers' portfolio choice. However, the weak performance of the model based on historical averages of returns compared with the results of the second part of the paper once again highlight that modeling expected returns well is much more important than improving on the estimation of covariance matrices. As a side product, we present a systematic framework to extract useful information about market expectations from funds' holdings.

[17] See Froot and Ramadorai (2001) for an examination of the forecasting power of international portfolio flows for local equity markets.

Figure 4. Forecast Errors of Implied Views Relative to Actual Returns



APPENDIX I - DERIVING IMPLIED VIEWS

The last step in the quadratic program is equivalent to solving

$$\max_{\mathbf{w}} \quad (\mathbf{w}-\mathbf{b})'\mathbf{u} - \frac{1}{2}A(\mathbf{w}-\mathbf{b})'\mathbf{\Sigma}(\mathbf{w}-\mathbf{b})$$

subject to

$$\mathbf{w}'\mathbf{e} = 1 \tag{7}$$

and

$$w_i = 0 \quad \text{for } i = j, ..., k. \tag{8}$$

where j and k are, respectively, the first and last assets dropped (ie. those for which the short-sale constraint is binding). These assets have to be kept in the problem because they enter in the benchmark (note that $\mathbf{w}$ is of dimension $N \times 1$). The Lagrangian can be written as

$$L = (\mathbf{w}-\mathbf{b})'\mathbf{u} - \frac{1}{2}A(\mathbf{w}-\mathbf{b})'\mathbf{\Sigma}(\mathbf{w}-\mathbf{b}) - \boldsymbol{\lambda}(\mathbf{w}'\mathbf{e}-1) - \alpha_j(\mathbf{w}'\mathbf{m}_j - 0) - ...\alpha_k(\mathbf{w}'\mathbf{m}_k - 0)$$

where $\mathbf{m}_j$ is an $N \times 1$ vector with 1 in the jth row and zeroes everywhere else. The first order condition, $\dfrac{\partial L}{\partial \mathbf{w}}$, yields

$$A\mathbf{\Sigma}(\mathbf{w}-\mathbf{b}) = \mathbf{u} - \begin{bmatrix} \mathbf{e} & \mathbf{m}_j & \cdots & \mathbf{m}_k \end{bmatrix} \begin{bmatrix} \lambda \\ \alpha_j \\ \vdots \\ \alpha_k \end{bmatrix}$$

or more succinctly,

$$A\mathbf{\Sigma}(\mathbf{w}-\mathbf{b}) = \mathbf{u} - \mathbf{Ma}. \tag{9}$$

Note that $\mathbf{M}$ is $N \times (m+1)$ and $\mathbf{a}$ is $(m+1) \times 1$ where m is the number of assets for which the short-sale constraint holds.

Rearranging (9) for $\mathbf{w}$, pre-multiply both sides by $\mathbf{e}'$ making use of (7) and (8) gives

$$\begin{bmatrix} \mathbf{e}'\mathbf{\Sigma}^{-1}\mathbf{e} & \mathbf{e}'\mathbf{\Sigma}^{-1}\mathbf{m}_j & \dots & \mathbf{e}'\mathbf{\Sigma}^{-1}\mathbf{m}_k \\ \mathbf{m}_j'\mathbf{\Sigma}^{-1}\mathbf{e} & \mathbf{m}_j'\mathbf{\Sigma}^{-1}\mathbf{m}_j & \dots & \mathbf{m}_j'\mathbf{\Sigma}^{-1}\mathbf{m}_k \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{m}_k'\mathbf{\Sigma}^{-1}\mathbf{e} & \mathbf{m}_k'\mathbf{\Sigma}^{-1}\mathbf{m}_j & \dots & \mathbf{m}_k'\mathbf{\Sigma}^{-1}\mathbf{m}_k \end{bmatrix} \begin{bmatrix} \lambda \\ \alpha_j \\ \vdots \\ \alpha_k \end{bmatrix} = \begin{bmatrix} \mathbf{e}' \\ \mathbf{m}_j' \\ \vdots \\ \mathbf{m}_k' \end{bmatrix} [\mathbf{\Sigma}^{-1}\mathbf{u}+A\mathbf{b}] - \begin{bmatrix} A \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

or

$$\mathbf{M}'\mathbf{\Sigma}^{-1}\mathbf{Ma} = \mathbf{M}'[\mathbf{\Sigma}^{-1}\mathbf{u}+A\mathbf{b}] - \mathbf{c} \tag{10}$$

where $\mathbf{c}$ is an $(m+1) \times 1$ vector of zeroes with A in the first row. Denoting $\mathbf{M}'\mathbf{\Sigma}^{-1}\mathbf{M}$ by $\mathbf{X}$, solving (10) for a, and plugging into (9) yields

$$A\mathbf{\Sigma}\,(\mathbf{w}-\mathbf{b}) = \mathbf{u} - \mathbf{M}\mathbf{X}^{-1}[\mathbf{M}'(\mathbf{\Sigma}^{-1}\mathbf{u}{+}A\mathbf{b}) - \mathbf{c}].$$

Solving for the vector of expected returns gives

$$\mathbf{u} = [\mathbf{I} - \mathbf{M}\mathbf{X}^{-1}\mathbf{M}'\mathbf{\Sigma}^{-1}]^{-1}A[\mathbf{\Sigma}\,(\mathbf{w}-\mathbf{b}) + \mathbf{M}\mathbf{X}^{-1}(\mathbf{M}'\mathbf{b}-\mathbf{c})] \tag{11}$$

where $\mathbf{I}$ is the $N \times N$ identity matrix.

Since implied views can be backed out only for those assets which are held with positive weights in the final portfolio, the rows and columns in (11) corresponding to those m assets which are out of the portfolio must be eliminated. This yields a system of $(N-m-1)$ independent equations (because the weights sum to one) in $(N-m)$ unknowns. To pin down the level of expected returns, one of the assets returns (the jth asset say) is set equal to its actual historical value (r_j). This can be done by setting the jth row of $\mathbf{u}$ equal to r_j, replacing the last rows of $A[\mathbf{\Sigma}\,(\mathbf{w}-\mathbf{b}) + \mathbf{M}\mathbf{X}^{-1}(\mathbf{M}'\mathbf{b}-\mathbf{c})]$ and $[\mathbf{I} - \mathbf{M}\mathbf{X}^{-1}\mathbf{M}'\mathbf{\Sigma}^{-1}]$ by r_j and $\mathbf{e}_j'$ respectively, where $\mathbf{e}_j$ is an $(N-m) \times 1$ vector of zeroes with the jth row taking the value of one.

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