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Value investing in emerging markets: risks and benefits

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Abstract

This paper identifies a subset of emerging markets that have higher than average expected returns and studies risk properties of this subset by investment simulations. It is found that: (1) the portfolio of 'value' emerging markets generates superior returns; and (2) statistical measures of its risk are close to the corresponding measures for the portfolio of all emerging markets. The statistical significance of these results has been checked by a bootstrap procedure. The results imply that the optimal share of emerging markets increases from 0% for an equally weighted portfolio to approximately 25% for the portfolio of undervalued emerging markets.

Keywords: Emerging markets; Investment

1. Introduction

Emerging stock markets were extremely volatile at the end of the 1990s, and brought only moderate returns. The developed countries seem to have systematically higher returns and lower volatilities, dominating emerging markets as an investment device. For example, the annualized gross return on the Morgan Stanley Emerging Markets Index for the period from August 1991 until August 2001 was less than 2.5%, with an annualized standard deviation of monthly returns equal to 10%, while the annualized gross return on the Morgan Stanley Developed Markets Index was

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9.8%, with a much lower standard deviation of 5.7%. Small returns could be acceptable provided the correlation of emerging markets with the rest of the portfolio is also small. Unfortunately, this does not seem to be the case. Simple unconditional CAPM implies expected 12% return for emerging markets,[2] while the historical return on the MS Emerging Markets Index is significantly lower. These observations awake a suspicion that investment in emerging markets is an otiose undertaking. An important question, thus, is whether the expected returns in at least some of the markets are sufficient to overcome their risks?

This paper identifies a subset of emerging markets that provides higher expected returns and studies their risk properties. The intuition is that some emerging markets appear to be risky and are undervalued while their objective statistical measures of risk are comparable to the rest of the market. Thus, these markets are better investment targets than an average emerging market.

I determine the choice of the markets by a valuation model and assess its quality by investment simulations. The returns found in evaluations are significantly higher than both the returns on random investments and the returns on benchmark indices. The simulations also show that more complicated methods of return prediction do not improve performance in investment simulations. Using country-specific models is also found problematic. A likely explanation for the failure of complex and country-specific models is the small time span of the available data.

Compared to developed markets, emerging markets have higher transaction costs and risks. I quantify the transaction costs by measuring average monthly turnover, and find that the transaction costs can only partially reduce the excess returns of the undervalued markets. To study risk of the undervalued markets, I measure it in several ways, which are either suggested in the literature or are popular in practice. The main finding here is that the risks of the undervalued markets are not significantly higher than the risks of benchmarks with respect to any risk measure.

Finally, I show that the higher risk-adjusted returns of the undervalued emerging markets are important for the representative US investor. The optimal share increases from 0% for the equally weighted portfolio of all EMs to approximately 25% for the portfolio of undervalued EMs.

The literature on this subject is rapidly growing and controversial. For example, Harvey (1995) gives evidence that investment in emerging markets can improve performance of the portfolio of the representative American investor. At the same time, Crowley (1999) has expressed doubts about the usefulness of international diversification. Goetzmann and Jorion (1999) partially reconcile these parts of literature by providing a theoretical explanation of why emerging equity markets bring high returns only immediately after emergence.

This paper differs from the previous research by using recursive investment simulations to evaluate a multifactor prediction method, by thoroughly measuring risk, and by using Monte Carlo bootstrap to determine the statistical significance of

[2] For the last 10-year period, the monthly beta of the Morgan Stanley Emerging Markets Gross Return Index with respect to US S&P500 index was 0.99. This means that implied expected return on the index must equal 12% according to a simple unconditional CAPM model in which 12% (US stock market return for the last 30 years) is assumed as the expected return on the investor's base portfolio.

the results. The conclusions tend to support the part of the literature that argues that investments in emerging markets are beneficial.

The rest of the paper is organized as follows. Section 2 describes the return prediction method. Section 3 explains how the method was estimated and evaluated, and then describes the properties of the portfolio of undervalued emerging markets. Section 4 computes the optimal share of undervalued emerging markets in the combined portfolio with the S&P500 index and Section 5 concludes.

2. A return prediction method

The return prediction method is based on an accounting valuation model, a model that goes back to Edwards and Bell (1961), Gordon (1962), and whose recent incarnation can be found in Ohlson (1995). I have adjusted it to capture return momentum. The method is as follows.

$$\ln R_t = a + b\ln\frac{B_t}{P_t} + c\frac{E_t}{B_t} + d\ln\frac{P_t}{P_{t-1}} + \varepsilon_t \tag{1}$$

where R_t is the asset return at month t, B_t is the asset book value, E_t is the asset earnings, and P_t is the asset price, so three factors influence the returns. The first factor is the potential to recover investment costs in the case of liquidation as measured by the ratio of the asset book value to the asset market value. The second is the potential of the value to grow, which is measured by the ratio of the earnings to the book value. And the third one is the momentum in asset prices.

Many important issues are neglected by this method. For instance, it does not allow for country-specific components or for time change in the parameters. With all its limitations, the method is a reasonable departure point since it utilizes nothing more than our basic intuitions. More complicated methods are problematic because their parameters have to be estimated from scarce and noisy data. The increase in the complexity of the method tends to decrease the precision of the parameter estimates and makes results more sensitive to specification mistakes. In the following empirical section, I explicitly address the question whether or not it is possible to improve this simple model.

3. Prediction method evaluation

3.1. Data

The data are from the International Finance Corporation (IFC) monthly country reports. The emerging markets used in this study are Argentina, Brazil, Chile, Colombia, Mexico, Peru, Venezuela, India, Sri-Lanka, Indonesia, Korea, Malaysia, Pakistan, Philippines, Taiwan, Thailand, China, Greece, Turkey, Hungary, Poland, Czech Republic, Romania, Russia, Slovakia, Israel, Egypt, Morocco, South Africa and Zimbabwe. The sample starts in January 1976 and goes through to October 2000. The length of the data series varies from country to country. The earliest data series starts in 1976, and the countries of Eastern Europe, Russia and China were added only in the middle 1990s. I add country indexes to the analysis during the month that they were first introduced by the IFC. All the price data are converted to US dollars.

3.2. Evaluation and estimation methods

The simple prediction method from the previous section has been evaluated by simulating an investment strategy. (Pesaran and Timmermann, 2000 suggest a similar approach.[3]) The period of evaluation is from January 1991 to October 2000, and the investment algorithm has been organized as a cycle. At each date, the model parameters are estimated with the data that were available at that moment; then forecasts are computed and an equally-weighted portfolio is composed from the markets having the best forecasts; then the return from the portfolio is recorded, and the process is repeated for the next date.

To illustrate this, assume the current date is the end of December 1990. Then we are to predict the returns for January of 1991. To do this, we run the regression of 1-month-ahead returns on the predictors using the data from the start of the sample to the beginning of December 1990. After we have estimated coefficients in this regression, we take the current (end of December) values of the predictors and compute the predicted return for each country. We take eight[4] countries having the highest predicted returns and invest in them equally. At the end of January 1991, we compute the return from the investment and proceed to the next cycle step. At the end of the data sample, we stop and analyze the returns on the strategy.

For estimation I have used feasible two-step generalized least squares to reduce the problem of heteroscedasticity in residuals. Also, the data are panel but the basic estimation model does not use fixed or random effects because evaluations of the corresponding models have demonstrated their inferior performance.

3.3. Excess returns

Table 1 represents the annualized total return for the simple prediction method in comparison with some benchmarks. It shows that the simple method performs very well. The investment rule based on its predictions generates a return that exceeds the return of the equally weighted portfolio by 10.6%.

The statistical significance of this excess return is supported by the Monte Carlo bootstrap. The bootstrap sample consists of 500 investment histories. Each history is randomly generated and includes each month from January 1991 until October 2000. Each month of every history corresponds to a set of eight randomly chosen

[3] The standard measures of forecast goodness, such as the sum of squared forecast errors, have been criticized in recent studies (e.g. Masters, 1998, and Granger and Pesaran, 2000). It has been argued that the forecast evaluation is meaningful only if it simultaneously evaluates an associated investment strategy. The reason is that an investor can have a loss function, which is irreducible to the sum of squares of one-period forecast errors.

[4] This number of countries was chosen as a half of the number of countries that were available at the beginning of the evaluation period. Variation in this number does not affect our inferences.

Table 1
Total annualized return of simple prediction method compared with benchmarks

Method	Annualized total return
Simple prediction method	24.0%
Investing in all emerging markets equally	13.4%
IFC Global Total Return Index.	4.3%
MS Emerging Markets Gross Return Index	6.8%
MS Developed Markets World Index Gross Return Index	12.9%
S&P 500 Price Return Index	15.8%

Note. Period is from January 1991 until October 2000.

countries. The returns from these investment histories could be obtained without any knowledge of return-generating mechanism. Therefore, statistical significance of our results by comparing them to these returns' distribution can be measured.

It turns out that the average of annualized total returns across the sample of histories is 12.24%, and their standard deviation is 4.1%. Thus, the return from the simple method of prediction (24%) is greater than the mean of the null distribution by almost 3 S.D. The probability that the excess return is accidental is less than 1%.

The high return from the simple regression method is not sensitive to small changes in the specification of the prediction method and the investment strategy. Table 2 shows that the investment is still profitable if we take one country instead of eight in investment portfolio, if we predict a 6-month-ahead return instead of a 1-month-ahead return, if we rebalance annually instead of monthly, or if the months with the highest 1% of returns are removed from the sample. Inclusion of other predictive variables (such as dividend yield, long-run lagged returns, inflation, country-risk measures, relative market size and calendar dummies) does not change the performance of the model by a statistically significant amount.[5]

Table 2
Robustness of simple prediction method

Change in specification	Return
The first percentile of the highest returns is excluded	16.2%
Annual rebalancing[a]	19.6%
Investment in one country instead of eight	42.0%
Predicting 6-month-ahead returns instead of 1-month-ahead returns	21.8%

[a] The annual rebalancing return is the average of 12 returns for the strategies that rebalance in 1 of 12 months.

[5] This insensitivity of specification to small changes is not inconsistent with Durham (2000), which finds that no predictive specification is robust to addition of other variables. Durham's main implication is that the result of an automated search for the best specification depends on the set of initial variables. In contrast, by insensitivity of the specification, I simply mean that inclusion of additional variables does not significantly change performance of the model in the investment simulations.

Table 3
Total annualized return of prediction methods

Method	Annualized total return
The simple method: All data are pooled in a global regression. Predictors are logarithm of book to price ratio, earning to price ratio and 1-month past return	24.0%
The simple method with past returns excluded	21.0%
The simple method with fundamentals excluded	19.9%
Separate regressions for each country: Predictors are logarithm of book-to-price ratio, earning-to-price ratio and 1-month past return	12.0%
The simple method with added dividend yield, logarithm of 6-month interest rate, PPP, logarithm of market capitalization, and monthly growth in GDP	17.1%
The simple method + square of earnings-to-price ratio	20.1%
The simple model + interaction term between earning-to-price and book-to-price ratios	22.6%

The annualized total returns from some of the methods that have been tried are in Table 3. Many other methods have been tried, but are not tabulated for the sake of parsimony. The methods listed in Table 3 were selected for presentation because they illustrate some general ideas. First, note that both the recent price performance and the fundamentals have predictive power since the exclusion of either fundamental ratios or lagged price return decreases the predictive power of the model. Second, separate regressions for each country have performed unsatisfactorily. Third, the inclusion of other observables in the model does not improve predictive performance of the model. Fourth, the simple linear model performs better than the models with added non-linear terms.

To summarize, country returns can be profitably forecast using an unadorned model with lagged returns and value ratios as predictors. The next question is how the predictability of returns is counterbalanced by transaction costs and risks.

3.4. Transaction costs

I quantify transaction costs by measuring average monthly turnover. Turnover is defined as the ratio of absolute change in investment positions to the total value of the positions, so the maximal possible turnover under monthly rebalancing is 200%. It occurs then that all the positions from the previous period are closed and new positions in different countries are opened.

Turnover for different investment methods is shown in Table 4. This table illustrates that the turnover is the highest for the method that uses only momentum to predict returns. It is the lowest for the method that uses only fundamental ratios. Thus, value investing might be better than momentum investing because of the lower transaction costs.

Table 4
Average monthly turnover

Method	Turnover
The simple method: All data are pooled in a global regression. Predictors are logarithm of book to price ratio, earning to price ratio and 1-month past return	39%
The simple method with past returns excluded	27%
The simple method with fundamentals excluded	131%
Separate regressions for each country: Predictors are logarithm of book-to-price ratio, earning-to-price ratio and 1-month past return	50%
The simple method with added dividend yield, logarithm of 6-month interest rate, PPP, logarithm of market capitalization, and monthly growth in GDP	31%
The simple method + square of earnings-to-price ratio	38%
The simple model + interaction term between earning-to-price and book-to-price ratios	37%

It is also interesting to note that the method of separate regressions for each country has a relatively higher turnover. The possible reason is that arrival of new information can dramatically change estimated coefficients in the regression, which makes predictions more sensitive to new information. This supports the idea that the results of separate regressions are unstable because of the small time span of the data.

To get a better idea of how this level of turnover would influence our results, consider 1% one-way transaction costs. Then 30% turnover would decrease annualized total return by approximately $0.30\times 0.01\times 12 = 3.6\%$, so the simple trading strategy is still profitable. On the other hand, under 5% one-way costs, the reduction in return would be 18%, which would make our simple trading strategy unacceptable. This back-of-envelope calculation illustrates that the interpretation of our results depends on assumptions about transaction costs.

According to Willoughby (1997), transaction costs equal approximately 1% for emerging markets stock. Bekaert et al. (1997) estimate transaction costs as 1.1% across 21 emerging markets. Since our investment strategy is based on trading indexes, the transaction costs are likely to be even lower for those emerging markets that allow trading index futures. Overall, transaction costs are unlikely to be so high as to eliminate excess returns of our simple investment strategy.

3.5. Risks

Table 5 compares risk properties of the portfolio of the undervalued markets with the corresponding properties of benchmarks. The numbers in the second column are various risk measures, averaging over 500 investment histories when eight countries were randomly chosen each month. The numbers in the third column are the *t*-statistics for the test of the hypothesis that the risk measure of the portfolio of the

Table 5
Annualized total return and measures of risk for the portfolio of undervalued markets and various benchmark portfolios

	Simple method portfolio[a]	8-Random-Countries Portfolio[b]	*t*-statistic[c]	All EM	MSCI EM gross	IFCG total return index	MSCI DM gross	S&P500
Total annualized return[d]	24.0%	12.24% (3.7625)	3.1256	13.4%	6.84%	4.25%	12.89%	15.79%
Total risk	0.0712	0.0658 (0.0036)	1.4796	0.0579	0.0661	0.0643	0.0372	0.0379
Systematic risk	0.87	0.7801 (0.0909)	0.9888	0.7792	0.9918	0.8929	0.8326	1
Idiosyncratic risk	0.0631	0.0588 (0.0032)	1.3517	0.0498	0.0543	0.0547	0.0196	0
Maximal drawdown	54.6%	49.99% (6.8%)	0.6784	48.8%	56.01%	53.79%	13.45%	15.57%
Semideviation-0	0.0450	0.0442 (0.0043)	0.1877	0.0395	0.0485	0.0466	0.0233	0.0226
Semideviation-$\bar{r}$	0.0528	0.0487 (0.0035)	1.1706	0.0441	0.0509	0.0482	0.0282	0.0284
DownBetaW	1.9307	1.7100 (0.3223)	0.6848	1.6956	2.0342	1.8837	0.9358	1
DownBetaPW	1.8874	1.4865 (0.3648)	1.0991	1.5142	1.7336	1.6135	0.8379	1
VaR	−0.1686	−0.1576 (0.0161)	−0.6844	−0.1450	−0.1796	−0.1639	−0.0785	−0.0746
Skewness	−0.7515	−0.6826 (0.4587)	−0.1502	−1.0466	−1.1100	−0.7642	−0.6704	−0.6750
Coskew	−0.7738	−0.7319 (0.1375)	−0.3047	−0.8409	−0.8780	−0.8004	−0.6865	−0.6750
Curtosis	6.5348	6.4219 (2.2691)	0.0498	7.7030	7.8493	6.3030	4.2978	5.1577

[a] The portfolio is constructed of the eight countries with highest 1-month predictions. The portfolio is re-balanced monthly.
[b] These are averages over the 500 replications of the random portfolio of eight countries. These eight countries are chosen randomly each month. The

Table 5 *(Continued)*

	Simple method portfolio[a]	8-Random-Countries Portfolio[b]	*t*-statistic[c]	All EM	MSCI EM gross	IFCG total return index	MSCI DM gross	S&P500

numbers in brackets are the corresponding standard deviations.

[c] These are *t*-statistics for the test of the hypothesis that a measure of risk of the portfolio of markets with high predictions is generated by the distribution of the corresponding measure of risk of the random portfolio.

[d] The investment period is from 31 January 1991 to 31 October 2000. *Total annualized return* is computed as $(V_T/V_0)^{12/T}$ where V_T is the value of the portfolio in the end of the investment period and T is the number of periods in months. *Total risk* is the standard deviation of monthly returns. *Systematic risk* is the beta coefficient in the regression of monthly returns on returns of S&P500. *Idiosyncratic risk* is the standard deviation of the residuals in the regression of the returns on the return of S&P500. *Maximal drawdown* is the maximal percentage loss in portfolio value for the whole investment history. *Semideviation-0* is $\frac{1}{T}\sum_i 1_{r_i<0} r_i^2$ where r_i is the return on the portfolio. *Semideviation-r* is $\frac{1}{T}\sum_i 1_{r_i<r}(r_i - r)^2$. *DownBetaW* is the beta in the regression on the S&P500 restricted to the periods when the return on the S&P500 was negative. *DownBetaPW* is the beta in the regression on the S&P500 restricted to the periods when the return on both the S&P500 and portfolio was negative. *Value at Risk* is the average return of the lowest 5% quintile of the returns. *Coskew* is $\frac{1}{T}\sum_i (e_i f_i^2) / \left(\sqrt{\frac{1}{T}\sum_i e_i^2}\frac{1}{T}\sum_i f_i^2\right)$ where e_i and f_i are deviations of the returns on the portfolio and on the S&P500 from their means.

Table 6
Optimal portfolio minimizing variance

	Optimal share of emerging markets	Reduction in variance (percentage from initial value)
Undervalued emerging markets	9.0%	5.5%
All emerging markets	14.0%	8%

undervalued emerging markets could be generated by a portfolio of randomly chosen countries. As *t*-statistics show, it is not possible to reject the hypothesis that the risk of the undervalued emerging markets is the same as the risk of random investments.

The fourth column shows that the risk measures of undervalued emerging markets are higher than the corresponding risk measures of the portfolio of all emerging markets. This is not surprising because the portfolio of all emerging markets consists of 30 countries, while the portfolio of undervalued emerging is composed of only eight of them. Thus, this comparison may not be entirely appropriate.

The comparison with standard indices reveals that the undervalued markets have a somewhat higher total risk but a lower or similar systematic risk. The lower systematic risk means that the undervalued markets not only have a higher return but are also less statistically dependent on developed markets. All other measures of risk are similar or less for undervalued markets.

To summarize, the obtained evidence suggests that the undervalued emerging markets have risks that are not significantly higher than risks of benchmarks. Moreover, some measures of risk are lower for them than for the benchmarks.

4. Optimal share of undervalued emerging markets in a combined portfolio with S&P500

The results of the previous sections show that the portfolio of undervalued emerging markets have significantly higher expected returns than the portfolio of all emerging markets, while they have similar or lower risks. In this section, we explore what implications these findings have for the portfolio choice decisions of a representative US investor.

Table 6 displays optimal shares that minimize the variance of the combined portfolio and the corresponding decrease in the variance of the whole portfolio. It shows that the reduction in variance resulting from diversification is not large, whether the investor uses the standard value-weighted index or uses the portfolio of undervalued EMs.

The situation changes dramatically, however, if higher returns of the undervalued emerging markets are taken into account. Table 7 gives the optimal shares for the portfolio that maximizes the Sharpe ratio of the overall portfolio assuming the expected future returns and covariances are equal to their historical averages. For the purposes of the comparison, note that the Sharpe ratio of the S&P500 price

Table 7
Optimal portfolio maximizing sharpe ratio

	Optimal share of emerging markets	Sharpe ratio
Undervalued emerging markets	26.7%	1.21
All emerging markets	−0.16%	1.082

index is approximately 1.082 (with the risk-free rate set at 5%). This table shows that the share of undervalued emerging markets in the optimal portfolio is more than 25% of the whole portfolio, and that inclusion of the undervalued emerging markets in the portfolio significantly increases the Sharpe ratio of the joint portfolio.

5. Conclusion

Prediction of emerging markets returns by book-to-price ratio, earnings-to-price ratio and past change in price allows us to generate significantly higher investment returns. Transaction costs are unlikely to eliminate these excess returns. The risk of the markets with a high predicted return is not significantly higher than the risk of other emerging markets. Together these findings imply that the optimal share of the undervalued emerging markets is much higher than the optimal share of the portfolio of all emerging markets. Thus, investments in a group of temporarily undervalued markets are attractive despite the low returns and high volatility of an average emerging market.

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