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DISSERTATION

# GLOBAL TACTICAL ASSET ALLOCATION: S&P 500 VERSUS EMERGING MARKETS

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**CONTENTS**

## 1) INTRODUCTION

Global Tactical Asset Allocation is an active investment approach. It seeks to outperform a financial benchmark and improve the overall return per unit of risk through active management. In the early 1990s GTAA strategies developed with the growth of foreign futures markets and liquidity, as well as increasing evidence of global asset predictability. After a period of negative results for GTAA managers in the late 1990s, weak equity returns have renewed the interest in GTAA from 2000 and on.

In the present paper we intend to use GTAA strategies between S&P500 and the MSCI Emerging Markets (MSCI EM) index. Interest in emerging markets has grown considerably from the 1990s and on. These markets have important benefits when used in portfolios internationally diversified in contrast with developed markets which have a higher degree of correlation. Since 1980s, there have been changes in many aspects, for regions such as Asia and Latin America. These changes have turned the emerging markets into better investment opportunities than before and this has resulted in vast capital flows to and from these markets.

We create long-short portfolios between the MSCI emerging market index and S&P500 and implement our tactical strategies through the use of various economic variables and their predictive power on the relation between the two indices. These variables reflect the activity in sectors of the economy and include PMI indicators, Leading indicators, Industrial Production variables, Foreign Exchange rates and variables related to the interest rates' environment and to the general condition of the economy.

To be more specific we run a number of linear regressions for a period spanning from 1989:01 to 2007:02 to find variables statistically significant and with predictive power on the change of the relative performance between the MSCI EM index and S&P500.

Then we use these variables out of sample, from 2000:01 to 2007:02, through a binary probit model which gives us forecasts about the direction of the returns between the two indices. Using these forecasts we change our portfolios by going long in the market expected to perform better and short in the other market. We follow this procedure on a monthly basis. When the forecast made suggests that one of the markets is performing better for more than one month then we do not make any active change in our portfolios. Otherwise, we have to change our respective long/short positions.

The empirical results suggest that the use of these tactical portfolios between the MSCI Emerging Markets index and S&P500 creates excess returns relative to passive strategies of mixed portfolios of the two markets.

The rest of the paper is organized as follows. In section 2 we present a brief review of the literature about emerging markets and asset allocation. In section 3 we present the data and methodology used to implement our investment strategy. In section 4 we present the empirical results. Finally in section 5 we present our conclusions.

## 2) LITERATURE REVIEW

### *A) EMERGING MARKETS*

Emerging markets are capital markets in developing countries. A developing country is one that has a per capita GNP that would place it in the lower or middle-income category. The markets in these countries are thought to have a great potential of growth. Research on emerging markets has proposed a number of empirical regularities. First, they are characterized by high volatility. Second, they have low correlations with developed markets and within themselves. Third, an investor should expect high long-horizon returns and finally the degree of return predictability is greater than that of developed markets. Another point to be mentioned is the fact that they are more likely to experience shocks induced by regulatory changes, exchange rate devaluations and political crises. Important economic and political reforms are also typical of emerging markets and these reforms lead some observers to believe that historical performance data are irrelevant for the future of these markets.

Harvey (1994) suggested that emerging markets have a degree of return predictability. Conditioning information can be used to improve the process of portfolio optimization instead of historical return statistics. Harvey showed that ex post performance is enhanced when conditional information is used.

The potential for diversification provided by emerging markets is supported by Harvey's (1995) findings that the correlations between emerging and developed markets is less than 0,10. But we must pay attention to the fact that the correlations exhibit considerable variation across time and furthermore, Erb, Harvey and Viskanta (1994), Longin and Solnik (1995) and Strongin, Petsch, and Fenton (1997) observed that correlations in international equity returns increase during unfavorable market conditions. Specifically, correlations increase during global contractions and periods of high return volatility a finding which suggests that international diversification is least effective when it is most needed.

Barry, Peavey III and Rodriguez (1998) showed that the historical performance of emerging markets is inconsistent with the assertion that these markets can consistently produce high returns. They do offer though consistent diversification opportunities to global investors and regardless of the time period they are characterized by a high level of volatility.

Bekaert, Erb, Harvey and Viskanta (1998) showed that emerging markets returns exhibit substantial deviations from normality. They found positive skewness and excess kurtosis for 1980s and 1990s and they examined how asset allocation decisions change with the presence of skewness and kurtosis. They found that investment weights are increased towards the asset with positive skewness, with kurtosis constant and that investment weights also increase as kurtosis increases, with skewness positive and constant.

When an investor decides to invest in an asset class the next step is to choose an index as a benchmark. Masters (1998) argues that emerging markets indexes are questionable benchmarks and that their disadvantages stem from factors inherent in the nature of the emerging markets. The main factor that leads to these problems is the spectacular swings in the performance of emerging markets and since the indexes are cap-weighted, country weights follow the rise and fall of these countries' markets. Furthermore, new countries are added to the indexes constantly while others are being removed and in each country many new company listings take place. All these changes affect cap-weighted indexes and as a result these indexes are not objective. The problems of these indexes make them inefficient portfolios and that provides the margin where an investor can create portfolios with better risk-return profile and add value through active management.

Conover, Jensen and Johnson (2002) focus their research on the performance of emerging equity markets relative to U.S. monetary conditions. Previous studies (Jensen, Mercer, and Johnson 1996, 2000; Patelis 1997; Thorbecke 1997) within the U.S. found that stock returns were lower during restrictive monetary policy by Fed and higher during periods of expansive policy. Conover, Jensen, and Johnson (1999b) extended this research to the international markets and found similar patterns in 14 of 15 non U.S. markets in the relation between equity returns and Fed monetary policy. Concerning emerging markets, their evidence indicate that these patterns do not prevail in emerging equity markets. An explanation could be the fact that the monetary authorities in developed markets are more coordinated while the authorities in emerging markets are less likely to align their policies with those of developed countries.

Another important issue regarding emerging markets is the degree of financial liberalization. By financial liberalization, we mean allowing inward and outward foreign equity investment. Foreign investors can buy or sell domestic securities without any restrictions and so can do domestic investors with foreign securities. The liberalization process is quite complex and there is no established economic model that adequately describes this process. Bekaert, and Harvey (2000a), and Henry (2000a) find that average returns in 20 emerging markets decrease after financial liberalizations and that the correlation and beta with the world market increase after equity market liberalizations. Bekaert and Harvey (1997) show that there is no significant impact on unconditional volatility. About the relation between financial liberalization and capital flows Bekaert, Harvey, and Lumsdaine (2002a) find that net capital flows to emerging markets increase rapidly after liberalizations and then level out after 3 years. Bekaert, Harvey, and Lundblad (2001, 2002c) find that economic growth increases post liberalization by about 1% a year over a 5-year period. Aggregate investment also increases significantly after liberalizations providing a channel for the economic growth mentioned above.

Harvey (1995) investigates the predictability of the emerging markets returns, using world and local information variables to forecast the returns. Three differences are found between the predictability in emerging markets and developed markets. First, in developed markets, the market's correlation with the U.S. return is closely linked to the degree of predictability while in emerging markets there is no significant association between correlation with the U.S. portfolio and predictability. Second, the amount of predictability in emerging markets is greater than that found in developed markets. Third, it is more likely that the emerging market returns are influenced by local rather than global information variables with one interpretation being the fact that some emerging markets are segmented from world capital markets to a degree.

Bilson, Brailsford, and Hooper (2001) investigate the extent to which macroeconomic variables are able to explain the variation in equity returns in emerging stock markets. The number of factors that influence equity returns has been a source of much contention. Trzcinka (1986) finds five dominant factors within returns for a sample of U.S. firms. Cho (1984) documents that the number of factors ranges between two and five on a range of U.S. industries. Cho et al. (1986) at the international level for 11 industrial economies report between one and five factors. Bilson, Brailsford, and Hooper (2001) use a multifactor model with a global factor proxied by the world market return and local variables. Specifically they find evidence that money supply, goods prices, real activity and exchange rates are significant in their association with emerging markets equity returns above that explained by the world factor. Also these variables are used to investigate the degree of commonality between emerging markets equity returns and the results show similar sensitivities to a number of these factors. Commonality is particularly evident when regions are considered. This finding suggests a limitation to diversification and the allocation of funds across, rather than within, regions.

### *B) ASSET ALLOCATION*

The goal of asset allocation is to achieve the best possible risk-return profile. Dahlquist and Harvey (2001) distinguish three levels of asset allocation. The first level is Benchmark asset allocation (BAA). It is a program that exactly replicates the investment weights of a benchmark index. Investors call this type of asset allocation indexing. BAA is characterized by very little change in investment weights and could be considered as passive asset management. The second level of asset allocation is Strategic asset allocation (SAA). This style of allocation is long-term in nature, usually with a five-year horizon. Investment managers make decisions based on their views of long-term performance of various asset classes. Managers may update their forecasts annually and rebalance their portfolios. This deviation from the benchmark induces tracking error, the strategic tracking error, which is the standard deviation of the differences between the benchmark return and the portfolio return. The third level of asset allocation is Tactical asset allocation (TAA). Here managers make short-term decisions, usually one month to one quarter and deviate from strategic weights. This form of investment induces also tracking error, the tactical tracking error, which is caused by the different weights between strategic and tactical allocation.

Here we must distinct between conditional and unconditional allocation. Unconditional implies that an investor bases the expected returns and the variance-covariance inputs into the asset allocation solely on past realizations of the returns. Conditional means that we use information available today, over and above the information in the past asset returns.

In BAA no conditioning information is used. In SAA we can either use long-horizon forecasting models with conditioning information or use an unconditional framework. In TAA conditioning information is always used to construct forecasting models that are the basis for weight changes.

Global Tactical Asset Allocation (GTAA) is an actively managed, multi-asset class strategy designed to produce alpha from a top-down investment discipline. GTAA differs from traditional bottom-up approaches because it seeks to achieve outperformance from macro or top-down decisions. This top-down distinction means that GTAA managers are not looking for inefficiencies between securities, but rather inefficiencies between entire markets and regions. Bottom-up managers must decide which individual securities to overweight and underweight while GTAA managers have to decide the same thing but with country indexes this time.

A brief history of GTAA starts from 1973-74 when bear market and the advent of cheaper stock index and bond futures drive institutional interest in exclusive market timing strategies. In the mid 1970s William Fouse at Wells Fargo begins to market "Tactical Asset Allocation". In 1987 well-positioned TAA managers outperform during the stock market crash. Later on, in the early 1990s GTAA strategies develop with the growth of foreign futures markets and liquidity, as well as increasing evidence of global asset predictability. At the end of the same decade the reputation of GTAA is tarnished by poor performance of some value-oriented managers who misjudge the equity boom. But from 2000 till nowadays weak equity returns, increasing liquidity in global derivative markets and increased familiarity of institutional investors with GTAA, have renewed the interest in the benefits of GTAA.

GTAA can provide alpha due to the fact that exploitable inefficiencies exist and there is an adequately broad investment universe in which an investor can find them. These inefficiencies probably will persist for fundamental reasons. The primary driver of macro inefficiencies is the segmentation of the global investment universe. Furthermore many investors, even sophisticated institutional investors, tend to have a large "home bias". As a result, inefficiencies within large markets disappear quickly but between markets they may continue to exist for some time. Another fact is that different countries have different economic drivers such as monetary and fiscal policy, investor rights. These differences can lead to disparity in performance and pricing between markets. As long as market fundamentals remain segmented, inefficiencies should persist at the macro investment level.

A clear definition for TAA has never been accepted. Arnott and Fabozzi (1988) define TAA in the following way: "Tactical asset allocation broadly refers to active strategies which seek to enhance performance by opportunistically shifting the asset mix of a portfolio in response to the changing patterns of reward available in the capital markets. Notably, tactical asset allocation tends to refer to disciplined processes for evaluating prospective rates of return on various asset classes and establishing an asset allocation response intended to capture higher rewards. In the various implementations of tactical asset allocation, there are different investment horizons and different mechanisms for evaluating the asset allocation decision."

While this is a very broad definition, Philips, Rogers, and Capaldi (1996) propose a more practical definition for TAA: "A tactical asset allocation manager's investment objective is to obtain better-than-benchmark returns with (possibly) lower-than benchmark volatility by forecasting the returns of two or more asset classes, and varying asset class exposure accordingly, in a systematic manner."

The performance of TAA is always measured against a benchmark. When the decisions of a manager lead to higher returns than the benchmark the manager delivers positive alpha. A measure in comparing various TAA strategies is the information ratio, which is the ratio of alpha to tracking error. What we seek is as high an information ratio as possible. Lee (2001) suggests another definition for TAA: "Tactical asset allocation strategies are strategies which attempt to deliver a positive information ratio by systematic asset allocation shifts."

MacBeth and Emanuel (1993) examine why investors may or may not want to adopt a tactical asset allocation strategy. The tactical strategies they consider are based upon three common measures of the aggregate value of the stock market. The first is the dividend yield, the second is the price/earnings ratio and last is the price/book ratio. The common theme of these strategies is that an investor's equity allocation should be reduced (increased) as the market becomes overvalued (undervalued), with overvaluation (undervaluation) signalled by a low (high) dividend yield or a high (low) price/earnings ratio or price/book ratio. An investment decision is a decision to select a probability distribution. It appears that the probability distribution of short-term equity returns changes over time. The shape of the distribution appears to change, rather than its location. When the dividend yield or price/book ratio indicates an overvalued (undervalued) condition, the frequency distribution appears to exhibit negative (positive) skewness. Contrary to the random walk hypothesis, equity investment opportunities appear to change over time. TAA may allow investors to select optimal probability distributions. Two of the three strategies employed, generate probability distributions better than a reasonable passive alternative.

Nam and Branch (1994) develop and test a model that incorporates currently available information into the tactical asset allocation process. They use logit analysis for the generation of state probabilities and then categorize each month as bullish or bearish. Investment timing may depend more on a proper forecast of the direction of the risk environment than on the magnitude. The estimated probabilities generated by the logit analysis are used to suggest the optimal allocation between the risk-free asset and the market portfolio. The results, to the extent that their models mimic the performance of actual tactical asset allocators, suggest that TAA may be able to add value. Risks are controlled and returns are enhanced. Also, the role of transaction costs is highlighted. Modest changes in the market risk environment should not lead investors who incur significant transaction costs to frequent shifts. Shifts in the portfolio tend to add value only when there is a relatively high degree of confidence in the assessment of the risk environment.

Weigel (1991), attempts to determine quantitatively the market-timing ability of a sample of 17 U.S. TAA managers who switch funds between large company stocks, long term bonds and cash equivalents, a so-called three way market timing strategy. The performance attribution methodology decomposes manager returns into three sources- returns to a static class mix, returns to market timing and returns to non market timing strategies such as security selection. The results showed that in aggregate the managers have significant positive market timing skill. Another finding is that there is a negative relation between market timing skill and other possible sources of ability. Finally, some managers exhibited considerable variation in market timing skill over time, a fact that could reflect changing capital market conditions.

Anson (2004) separates the concept of beta versus alpha classes. Beta drivers determine a fund's overall exposure to the financial markets. Their performance is linear, which means that their performance rises and falls with the financial markets. Beta risk is measured in relation to a financial benchmark. Alpha risk measures a fund's deviation from beta risk. It can be measured by actively managed accounts relative to a beta risk benchmark. Alpha drivers are used when markets are misaligned through a tactical bet to outperform the benchmark. These drivers are identified by their high tracking error to a benchmark and can have a performance distribution that is non-linear in nature. The two economic classes, alpha and beta drivers, are combined to form an asset allocation plan. The beta drivers are used to provide efficient exposure to the desirable asset classes while the alpha drivers provide the outperformance above the beta products. The results show that alpha drivers can be used to outperform a beta-driven portfolio and they can provide downside protection, protect against volatile downside movements of the financial markets. Alternatively, alpha drivers may offer upside potential and if used wisely the alpha class can offer both downside protection and upside potential.

Flavin and Wickens (1998) show that a TAA strategy that involves continuously rebalancing a portfolio in response to changes in the conditional covariance matrix permits a large reduction in risk over and above a portfolio based upon a constant covariance matrix. Flavin and Wickens (2002) develop a TAA strategy that incorporates the effects of macroeconomic variables. They show that information about the volatility, not the level of asset returns, plays a more significant role in portfolio selection models. Extending their previous analysis to allow for the incorporation of macroeconomic variables in determining the covariance matrix of returns allows further significant gains in risk reduction. They find that inflation has a significant impact on the conditional covariance matrix of asset returns. The negative covariance between inflation and excess returns generates a significant reduction in portfolio risk over and above what can be achieved by using a time-varying covariance matrix of excess returns alone.

Faber (2007) creates a simple quantitative method for managing risk for an asset class. A non-discretionary trend following model is used, and results to equity-like returns with bond like-volatility and drawdown, and over thirty consecutive years of positive performance. This means that the model acts as a risk-reduction technique but has limited to no impact on return. In addition an investor would have also been able to side-step many of the protracted bear markets in various asset classes.

Our goal is to implement a GTAA strategy between the S&P 500 index and the MSCI Emerging Markets index. We incorporate macroeconomic variables in our research and try to predict, by using a binary probit model, each month from 2000:02 until 2007:02 which of the two markets will perform better. Then, depending on our prediction, we take long position in the market expected to outperform the other and short position in the market expected to underperform.

## 3) DATA AND METHODOLOGY

### *DATA*

In the present study we use a variety of economic variables such as PMI (Purchasing Managers Index) indicators, Leading indicators, Industrial Production variables, Foreign Exchange rates and variables related to the interest rates' environment and to the general condition of the economy. Furthermore, we use various indexes such as some of the MSCI emerging markets indexes, main indexes of the most important emerging markets in US dollars and a few Dow Jones Wilshire Style indexes. These indexes are separated in small and large stocks based on capitalization and then the stocks are characterized as value or growth stocks based on a set of criteria. Six factors are used to determine whether a stock should be designated "growth" or "value." These are:

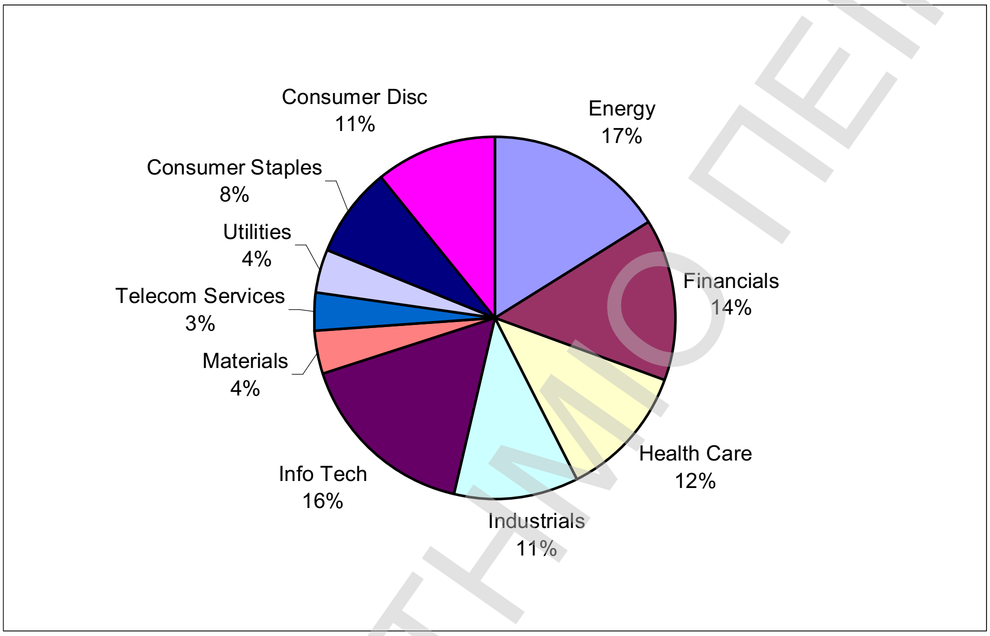
- Projected Price-to-Earnings Ratio (P/E)
- Projected Earnings Growth
- Price-to-Book Ratio (P/B)
- Dividend Yield
- Trailing Revenue Growth
- Trailing Earnings Growth

Our data are monthly and some of the series start as early as January 1960. We have observations until February 2008. These series have been acquired from Bloomberg database, Datastream database, the Fed of St. Louis and Ecowin database. In the appendix we present an analytical list of all the series used in this study.

Our strategy involves creating long/short portfolios between the S&P 500 index and the MSCI Emerging Markets index. The reasons for choosing these indexes are that they both are easily accessible to investors and do not suffer from the lack of liquidity that affects some segments of the broader market indexes. Any investor could access these two indexes through the use of Futures or ETF's (Exchange Traded Funds).

The S&P 500 is widely regarded as the best single gauge of the U.S. equities market. This world-renowned index includes 500 leading companies in leading industries of the U.S. economy. Although the S&P 500 focuses on the large cap segment of the market, with approximately 75% coverage of U.S. equities, it is also an ideal proxy for the total market. Here we show the sector breakdown of the index, a summary of index information and a linear graph of S&P 500 from 1959 to the present.

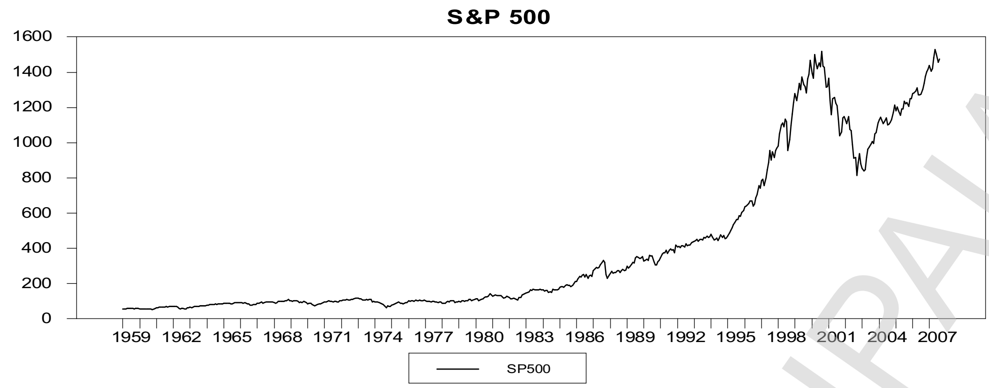
**Sector Breakdown**




**Summary Index Information**

| | |
|---|---|
| Number of companies | 500 |
| Adjusted Market Cap ($ Billion) | 11162,58 |
| Company Size (Adjusted $ Billion) | |
| Average | 22,33 |
| Largest | 465,65 |
| Smallest | 0,66 |
| Median | 10,41 |
| % Weight Largest Company | 4,17% |
| Top 10 Holdings (% Market Cap Share) | 19,53% |

**Linear Graph of S&P 500**



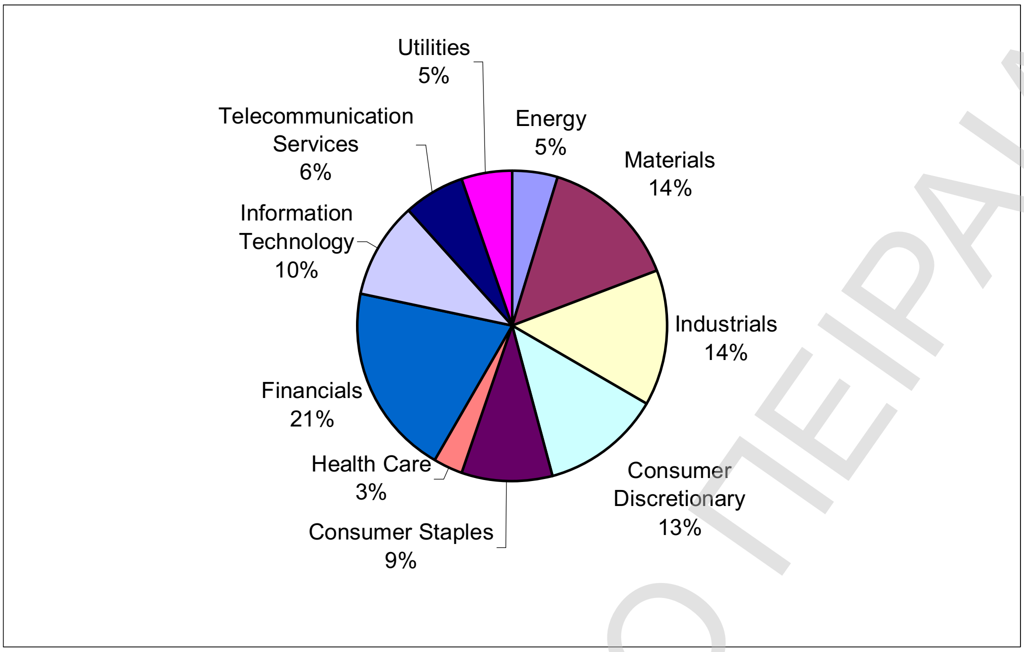

The MSCI Emerging Markets Index is a free float-adjusted market capitalization index. As of August 2005, the index consisted of the following 26 emerging market country indices: Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Israel, Jordan, Korea, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, Turkey and Venezuela. The index represents companies within these countries that are available to investors worldwide.

The MSCI Emerging Markets Index has a base date of December 31, 1987. As of August 31, 2005 it contained 823 constituents with a total market capitalization of USD 1,387,304 million. Next we present a summary of index information, the sector breakdown of the index and a linear graph of MSCI Emerging Markets from its beginning in 1987:12 until 2008:02.

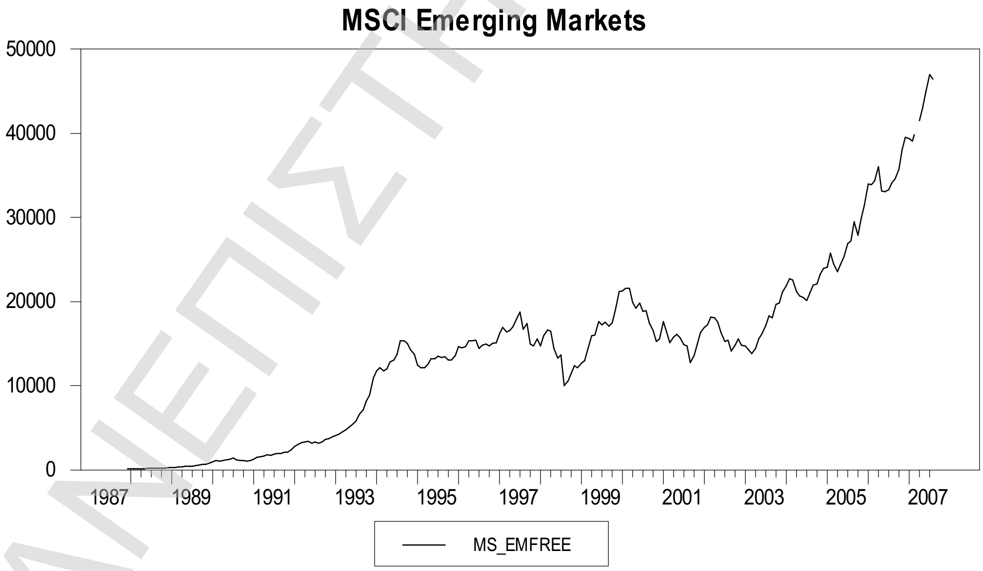
**Summary Index Information (As of August 31, 2005)**

| **Index Capitalization and Concentration** | |
|---|---|
| Total Index Market Capitalization | USD 1387304 million |
| Number of Constituents | 823 |
| Average Market Capitalization | USD 1685 million |
| Largest Stock | USD 61609 million |
| Smallest Stock | USD 30 million |
| **Financial Ratios** | |
| Price to Earnings (P/E) | 13 |
| Price to Book (P/B) | 2,1 |
| Dividend Yield | 2,8 |

**Sector Breakdown (As of August 31, 2005)**




**Linear graph of MSCI Emerging Markets**




About ETF's we must mention that they combine the advantages of both index funds and stocks. They are liquid, easy to use and can be traded in any quantity like stocks. At the same time an ETF provides diversification, market tracking and the low expenses of an index fund. One of the key strengths of the ETF as an investment tool is the wide range of products available and the sheer breadth of equity and fixed income benchmarks they track. They allow investors to easily gain exposure to a far deeper variety of asset class, including fixed income, sectors and additional countries and regions. The ETF's available cover a far broader range of indices than futures, giving investors more opportunity to action allocation tilts without the security specific risk that has an instrument that does not track the desired benchmark.

*METHODOLOGY*

Our intention in this study is to use a tactical approach between the S&P 500 and the MSCI Emerging Markets index. More specifically, we want to take advantage of the fact that each month one of the above indexes will outperform the other. To achieve that we need a model which is going to incorporate some economic variables and predict the direction of the change of the relative performance between the two markets.

As relative performance we define the following equation:

$$\textbf{RP = log (MSCI Emerging Markets/ S\&P 500)}$$

The change of the relative performance is defined as:

$$\boldsymbol{\Delta}\textbf{RP = \{RP – RP(-1)\}*100}$$

To develop a satisfying model we focus on the predictive ability of the variables used, on the change of the relative performance, out of sample. We do that by using a binary probit model through which we create monthly forecasts about the direction of the relative performance of the two markets. We pursue to predict the directional signal of the relative performance change each month.

Then we use our predictions to implement a tactical strategy. We make tactical switches, depending on the directional signal we receive each month from our model, and rotate long and short positions between the two markets. We go long in the market expected to perform better and short in the other one. If our signal indicates that during next month the other market is expected to perform better we change the positions in both markets. We will now present a step by step analysis of our methodology.

**A) Unit-Root Tests**

The first thing we needed to check was the fact that our series are stationary. A time series is called stationary if the mean and the variance of this series are not changing through time and if the covariance of the prices it takes between two moments depends on the distance between these moments. We want the series to be stationary otherwise they can not be used for our purposes.

The process we used to test our time series is the Dickey-Fuller test. It tests whether a time series has a unit root. More specifically we suppose that we have an autoregressive model like the following: $Y_t = pY_{t-1} + \varepsilon_t$ where,

p = the autocorrelation coefficient and,

$\varepsilon_t$ = the error of the regression

If $|p| \geq 1$ then the time series has a unit root and it is non stationary. As a result the variance of the specific time series is increasing through time and reaches the infinite. If $|p| < 1$ then the time series does not have a unit root, it is called stationary and it is proper for modeling.

**B) In sample regressions with economic variables**

The second step of our process is to find the predictive power of each variable alone, on the change of the relative performance. To achieve that we use one-factor regressions, with the method of ordinary least squares (ols). We run regressions for the period spanning from 1989:12 to 2007:02. For each variable we run regressions with 1, 2 and 3 lags. These regressions have the following form:

$$\Delta RP = c + \beta X_{(t-n)} + \varepsilon_t \quad \text{where,}$$

C = a constant,

$X_{(t-n)}$ = the time series of the differences of each variable with n lags and,

$\varepsilon_t$ = the error of the regression

After we complete these regressions and find the series that are statistically significant throughout the whole period, we repeat the regressions for the significant series but for the period spanning from 1989:12 to 2000:01 when our out of sample period begins. We do that because we want to ensure that the variables we will eventually use are significant at the beginning of our out of sample period. Otherwise we might end up using variables that became statistically significant sometime later. An investor who would try to employ our strategy at that time would not have that knowledge and we desire to act the same way.

We present a list of the variables that were found to be significant for both periods and the results from the regressions for the period from 1989:12 to 2007:02. In the table that follows, the numbers in the parenthesis are the t-statistics and the numbers in brackets next to the variables are the time lags for each variable.

1) Δbrl{2}: the change of the brazilian real currency spot rate with two lags

2) Δipus{2}: the change of US industrial production with two lags

3) Δcpi_us{3}: the change of US Consumer Price Index For All Urban Consumers with three lags

4) Δpcecore{1}: the change of Personal Consumption Expenditures price index less Food & Energy with one lag

5) Δppicore{3}: the change of the Producer Price Index: Finished Goods Less Food & Energy with three lags

6) Δgoldbln{3}: the change of Gold Bullion LBM U$/Troy Ounce with three lags

7) Δgoldhar{3}: the change of Gold, Handy & Harman Base $/Troy Oz with three lags

8) Δncucash{3}: the change of Copper Cathode C/LB with three lags

9) Δbuilding_permits{2}: the change of New Private Housing Units Authorized by Building Permit with two lags

10) Δcpicore{1}: the change of Consumer Price index for All Urban Consumers less Food & Energy with one lags

11) Δconsumption{2}: the change of Personal Consumption Expenditures with two lags

| Variable | Δbrl{2} | Δipus{2} | Δcpi_us{3} | Δpcecore{1} |
|---|---|---|---|---|
| Constant | 0,14587 | 2,28737 | 0,98773 | -0,36224 |
| | (0,42903) | (6,04068) | (1,84852) | (-0,59289) |
| β | 0,14716 | -1,81567 | 3,50139 | 11,22852 |
| | (5,23614) | (-2,75465) | (2,14728) | (4,36244) |
| R^2 | 0,128468 | 0,030898 | 0,019005 | 0,074041 |

| Variable | Δppicore{3} | Δgoldbln{3} | Δgoldhar{3} | Δncucash{3} |
|---|---|---|---|---|
| Constant | 1,41059 | 1,77673 | 1,77432 | 1,76722 |
| | (3,43491) | (5,04916) | (5,04706) | (5,03464) |
| β | 3,02471 | 0,22784 | 0,23347 | 0,13363 |
| | (2,0544) | (2,51877) | (2,60758) | (2,76753) |
| R^2 | 0,017424 | 0,026396 | 0,028237 | 0,031694 |

| Variable | Δbuilding_permits{2} | Δcpicore{1} | Δconsumption{2} | |
|---|---|---|---|---|
| Constant | 6,87582 | -1,04663 | 2,44369 | |
| | 4,1747 | -1,35716 | 5,89947 | |
| β | -0,0000033 | 12,20817 | -2,20123 | |
| | -3,11436 | 4,1939 | -2,56608 | |
| R^2 | 0,039157 | 0,068817 | 0,026922 | |

**C) Out of sample forecasts**

What we want is to predict for every month which one of the two markets is going to outperform the other. And the way to succeed in that is to control the predictive ability of the variables we found in the previous section, in an out of sample basis. The reason for this approach is that an investor who wants to predict which market will perform better in the period **t** has available information for the period **t-1, t-2, t-3** etc.

The model we use to test the out of sample predictability of a variable is a **binary probit** model. It creates probability forecasts that actually indicate which market is expected to perform better in the next investing period. The use of such a model is preferred because our aim is to find successfully the sign of the relative performance of the two markets and eventually if the MSCI Emerging Markets Index will outperform the S&P 500 or the opposite.

**D) Binary-Probit model**

In this part we will explain the procedures followed by a binary probit model. Primarily it analyzes the effect one or more independent variables X have on a non observable variable Y.

The non observable variable Y is defined by the following regression:

$$Y = \beta X_i + u_i$$

Y can be observed only through a dummy variable which equals 1 (Y = 1) when Y ≥ 0 and equals 0 (Y = 0) when Y < 0 . In our case, Y ≥ 0, means that MSCI EM will outperform S&P 500 and as a result Y=1. On the contrary, when Y<0, S&P 500 will outperform MSCI and in that case Y=0.

Following this rule we create the time series of the dummy variable Y. The next step is to set the in sample period from 1989:12 to 2000:01 and estimate the following regression:

$$Y_t = c + \beta X_{(t-n)} \quad \text{where,}$$

$Y$ = the dummy variable we created and

$X_{(t-n)}$ = the variable we use each time, with 1, 2 or 3 lags

Based on the coefficients c, β of the above regression and the price the variable X takes for each period, starting from 2000:01, we take the first out of sample probability forecast, $p_{t+1}$, that the dummy variable Y=1 and as a result in the period 2000:02 MSCI EM will outperform S&P 500 or that Y=0 and the opposite stands. Then we increase the in sample period by one month, which now spans from 1989:12 to 2000:02, and re-estimate the above regression. We follow the same procedure to take a forecast for the month 2000:03 and continue this process until 2007:02.

The binary probit model gives us 85 forecasts for the period from 2000:02 to 2007:02. The forecasts can result into two different situations. If the probability we receive $p_{t+n}$ > 0,5 then we expect MSCI EM to outperform S&P 500 and achieve a greater return. Otherwise, if the probability $p_{t+n}$ < 0,5 then we expect S&P 500 to outperform MSCI EM and achieve a greater return.

**E) Model Construction**

After we complete our forecasts for the whole time period we are interested, we want to build the best possible model for our long/short portfolio of the two indexes we track, the MSCI EM index and the S&P 500 index.

We use each variable that we previously found to be significant, alone or in sets of two, three or up to four variables together and find the hit ratio of every possible set of variables. Hit ratio is the percentage of correct forecasts that are made by every set of variables. A correct forecast is made when our forecast for the period t+n is $p_{t+n}$ > 0,5 and during this period the MSCI EM index outperforms S&P 500. Also correct forecast is made when $p_{t+n}$ < 0, 5 and during this period the S&P 500 index outperforms MSCI EM. On the other hand when our forecast is $p_{t+n}$ > 0, 5 and during this period the S&P 500 index outperforms MSCI EM we have a wrong forecast and the same applies when $p_{t+n}$ < 0, 5 and during this period the MSCI EM index outperforms S&P 500.

When we complete our tests of the various combinations of variables we choose our model which, in the case of the two indexes examined here, is:

$$Y = c + \beta_1 \Delta brl\{2\} + \beta_2 \Delta goldhar\{3\} + \varepsilon$$

About the two variables we eventually use in our model we must report that both of them are positively correlated with the returns in the emerging markets and when the Brazilian real spot rate or the price of the gold increases the emerging markets seem to perform better than the S&P 500. The β coefficient is in both cases positive and statistically significant at the 5% level.

# 4) RESULTS

The forecasts we have made with the use of the binary probit model help us create an investing strategy. It is consisted by the following rules:

I) If the probability that we receive for each period is greater than 0.5, $p_{t+n} > 0.5$, then we go long the MSCI EM index and we go short the S&P 500 index.

II) If the probability that we receive for each period is smaller than 0.5, $p_{t+n} < 0.5$, then we go long the S&P 500 index and we go short the MSCI EM index.

Here, we present the results of our investing strategy for the out of sample period we examine, where we apply our forecasts, which spans from 2000:02 to 2007:02. We also compare our strategy with a simple strategy of buy-hold of the MSCI EM index.

Furthermore, we compare our strategy with a strategy of buy-hold of an equally mixed portfolio of the MSCI EM index and the S&P 500 index. In this case, we alter our strategy and take only long positions. Specifically we go long the MSCI EM index when $p_{t+n} > 0.5$, and go long the S&P 500 index when $p_{t+n} <$ 0.5. We do not take short positions in that case, in order to achieve an investing strategy of a similar risk profile as that of the mixed buy-hold portfolio and see how our strategy works in a less risky investment setting.

Finally, we present the results an investor would have by choosing and passively tracking the S&P 500 index for the same period.

| | | Mean Return (Annualized) | Standar Deviation (Annualized) | Information Ratio | Total Return |
|---|---|---|---|---|---|
| I | Long/Short MSCI EM/S&P 500 Portfolio | 16,25% | 17,76 | 0,92 | 115,09% |
| | Buy-Hold MSCI EM Portfolio | 8,56% | 18,17 | 0,47 | 60,62% |
| II | Long MSCI EM/S&P 500 Portfolio | 8.71% | 15,07 | 0.57 | 61.76% |
| | Buy-Hold Mixed MSCI EM/S&P 500 Portfolio | 4,34% | 15,14 | 0,29 | 30,75% |
| | Buy-Hold S&P 500 | 0,12% | 14,20 | 0,01 | 0,88% |

By examining the results we could draw a few conclusions. First, the return of both our strategies is almost twice that of the one achieved in the benchmarks we examine. What is more important is the fact that such a return is acquired even though our tactical strategies have lower annualized risk. Furthermore, both strategies have a much better information ratio (excess return per unit of risk) and it is almost double that of the respective benchmark we examine here.

Strategy I, which is more aggressive and risky since it involves taking short positions, has an annualized return almost 8% higher than that of the passive strategy something much more impressive if we take into consideration the fact that the annualized risk of the buy-hold strategy is 0,41 units higher. It has impressively better information ratio than the passive approach and in terms of total return our investing strategy outperforms the passive one by almost 50% in a period of seven years.

Strategy II, where we take only long positions, is more suitable for investors who desire an investing profile with lower risk. Here, we outperform the benchmark strategy by 4,37% annually, and the annualized risk in this situation is slightly lower for the active approach we engage. The total return of this strategy for the period we examine reaches 61,76% and the buy-hold strategy is outperformed by 31,01%. The information ratio equals 0,57 and is almost twice that of the passive strategy.

We must also mention that the decision to follow a passive buy-hold strategy of the S&P 500 index for the seven year period under examination would have no result since the index performs almost equally to zero and this happens while the investors take on a significant amount of risk.

Next we present some more statistics about our strategies concerning the best and worst returns throughout the whole period.

| | | Minimun Return | Maximum Return | Fractile 5% |
|---|---|---|---|---|
| I | **Long/Short MSCI EM/S&P 500 Portfolio** | -9,48% | 18,39% | -6,70% |
| | **Buy-Hold MSCI EM Portfolio** | -14,58% | 12,76% | -8,24% |
| II | **Long MSCI EM/S&P 500 Portfolio** | -9,59% | 9,95% | -7,71% |
| | **Buy-Hold Mixed MSCI EM/S&P 500 Portfolio** | -11,55% | 8,39% | -7,61% |
| | **Buy-Hold S&P 500** | -11,65% | 9,23% | -8,08% |

Both strategies have provided higher maximum return for the investor and at the same time the minimum return is not as low as that of the buy-hold strategies. The S&P 500 index as a buy-hold strategy does not seem to perform well in this category of statistics also.

In strategy I, our portfolio has a negative minimum return but it is 5,1% higher compared to the benchmark. The maximum return of the tactical strategy is 18,39% and 5,63% higher than that of the passive strategy. Furthermore, the 5% fractile statistics shows us that 5% of our observations represent returns lower than -6,70%

while for the buy-hold portfolio this number is decreased by 1,54%. These results indicate that the tactical approach we have used as an investment alternative can provide downside protection, that is protect against volatile downside movements of the financial markets while at the same time it offers upside potential a fact indicated by the significantly higher maximum return attained.

Strategy II performs a little worse in the category of the 5% fractile but the minimum return observed is almost 2% higher than the benchmark and simultaneously the maximum return is 1,66% greater than the mixed passive strategy of the two indexes. Still we can say this strategy also offers the privileges of strategy I, downside protection and upside potential but to a lesser degree.

The next aspect that we want to exhibit is the predictive accuracy of our strategy, the correct and wrong forecasts and the corresponding hit ratio, and analyze what results had each category of forecasts. We discuss two strategies but their difference regards our choice of investment and this does not affect the hit ratio so for both strategies the same results apply concerning the predictive success. What changes, are the results of the forecasts.

| | | **Correct Forecast** | | **Wrong Forecast** | | **Hit Ratio** |
|---|---|---|---|---|---|---|
| | | **Overweight** | **Underweight** | **Overweight** | **Underweight** | |
| | ***Observations*** | 39 | 21 | 10 | 15 | 60/85 |
| **I** | **Long/Short MSCI EM/S&P 500 Portfolio** | | | | | 70,59% |
| | ***Total Return*** | 99,76% | 69,05% | -19,19% | -34,52% | |
| | ***Observations*** | 39 | 21 | 10 | 15 | 60/85 |
| **II** | **Long MSCI EM/S&P 500 Portfolio** | | | | | 70,59% |
| | ***Total Return*** | 65,39% | 4,38% | -10,91% | 2,89% | |

The out of sample period lasts 85 months. The correct forecast for 54 months is to overweight and the correct forecast for the rest 31 months is to underweight. Overweight means that MSCI EM is going to perform better than the S&P 500 and we should follow a strategy that will overweight this market relative to the S&P 500. Underweight means that the S&P 500 will outperform MSCI EM and we should act appropriately and overweight this index relative to MSCI EM. Overall our model made a total of 49 predictions indicating overweight as the correct strategy and 36 predictions indicating we should underweight. The model seems to be quite accurate achieving a very satisfying hit ratio of 70,59%.

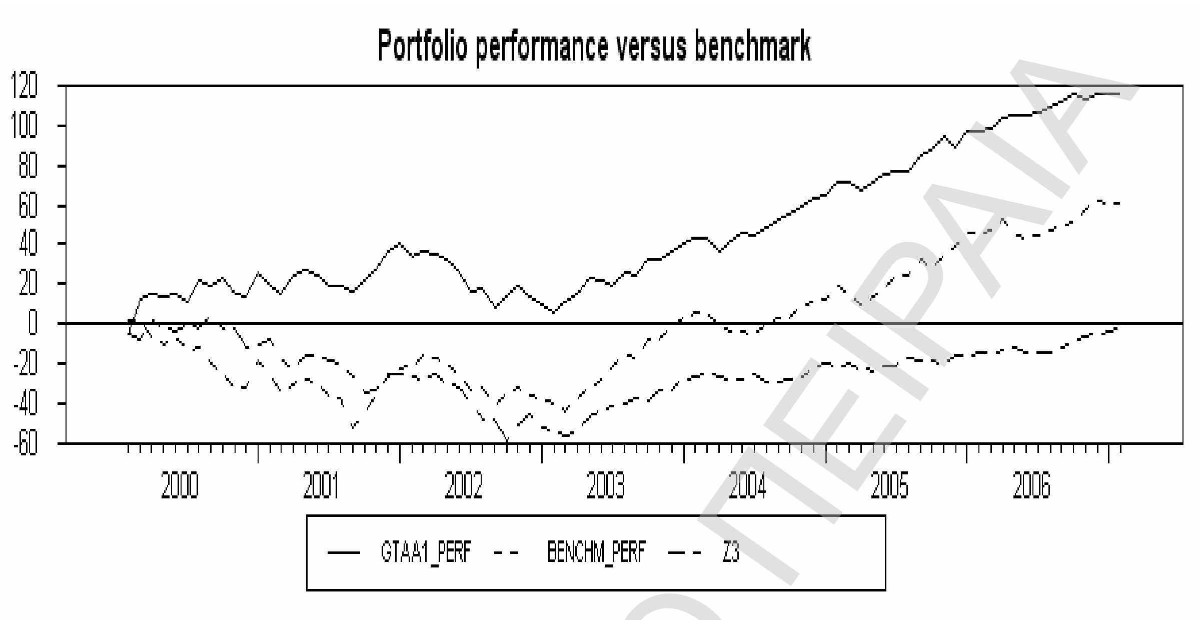
From the 54 periods where overweight would be the correct forecast we predicted 39 of them correctly setting a hit ratio of 39/54 = 72%. On the other hand we predicted with success 21 out of 31 periods during which we the proper forecast would be to underweight MSCI EM with a corresponding hit ratio of 21/31 = 67%. Therefore, it is obvious that we had somehow better predictions during the periods when MSCI EM outperformed the S&P 500.

In the first strategy employed, the correct overweight predictions earned us a profit of 99,76% while the wrong underweight predictions seem to affect the performance of the strategy followed quite negatively resulting in a return of -34,52%. From the 49 overweight forecasts we gained about 80% while the 36 forecasts to underweight gained us almost 35%.

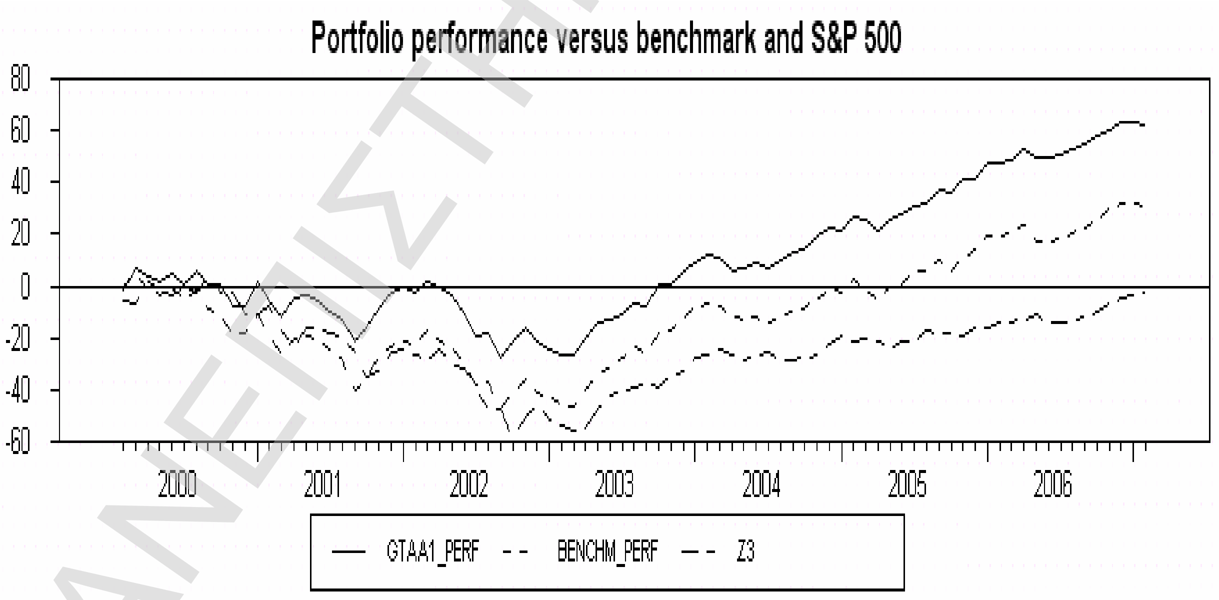
In the second strategy the correct overweight signals brought in 65,39% while the wrong signals in this category resulted in the reduction of the performance by 10,91%. The 21 periods we predicted correctly as underweight periods, resulted in 4,38% gains and surprisingly the 15 periods we made bad forecasts and decided to underweight led also to gains of 2,89%. During this strategy the decision to underweight means to go long the S&P 500 index. These two last results show that during the 36 months we chose to go long, correctly or not, in that index it had mostly positive results but of quite small magnitude.

Next we present graphs of the total performance of our strategies, the passive buy-hold strategies and the S&P 500.

*Graph of long/short portfolio strategy total performance*




*Graph of long only portfolio strategy total performance*




A general conclusion from both graphs is that out strategy is well over the benchmark we have used in each case and it outperforms the S&P 500, represented by the time series z3, even more impressively.

In the first strategy where we invest in a more aggressive way and take short positions in the two markets we see that during the period from 2000 till the beginning of 2003 when the markets perform negatively our strategy seems to overcome this general tendency of the markets and gives positive returns. This does not happen in the second strategy which follows the market but it has much smaller losses during that period.

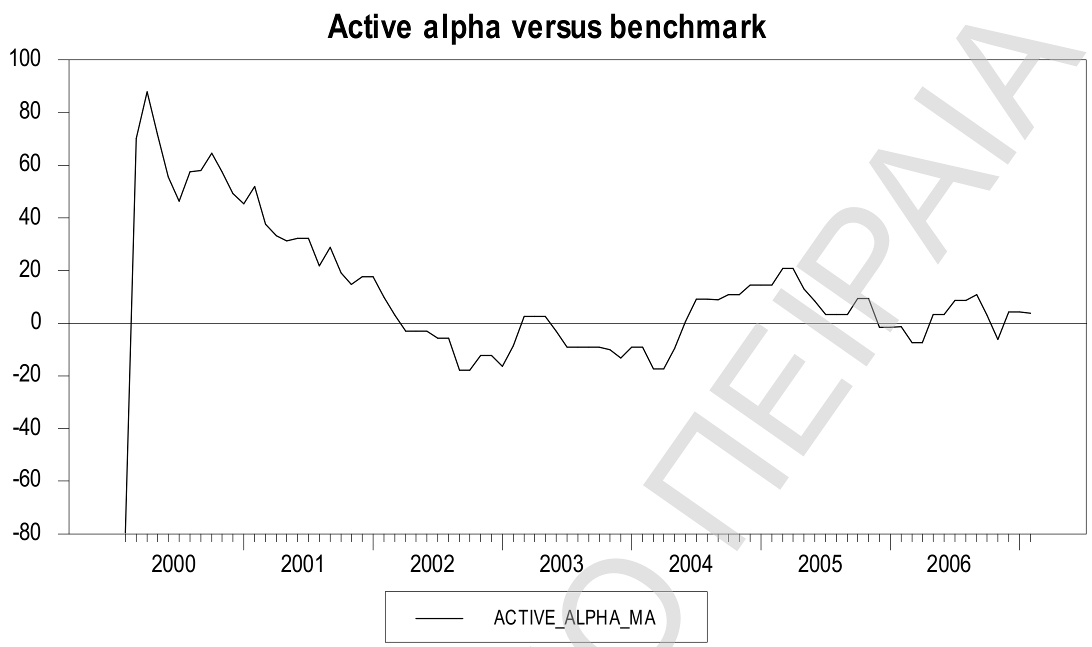
During the remaining period from the beginning of 2003 until 2007:02 we see that the markets, both the emerging and the developed ones as represented by MSCI EM and S&P 500 respectively, follow an increasing course.

The first strategy continues to deliver positive returns and as we proceed through time it outperforms the benchmark and the S&P 500 even more. The second strategy seems to follow the behaviour of the world markets for that period of time too, but it also continues to outperform the markets and increases the gap between its performance and the one the benchmark or the S&P 500 achieves.

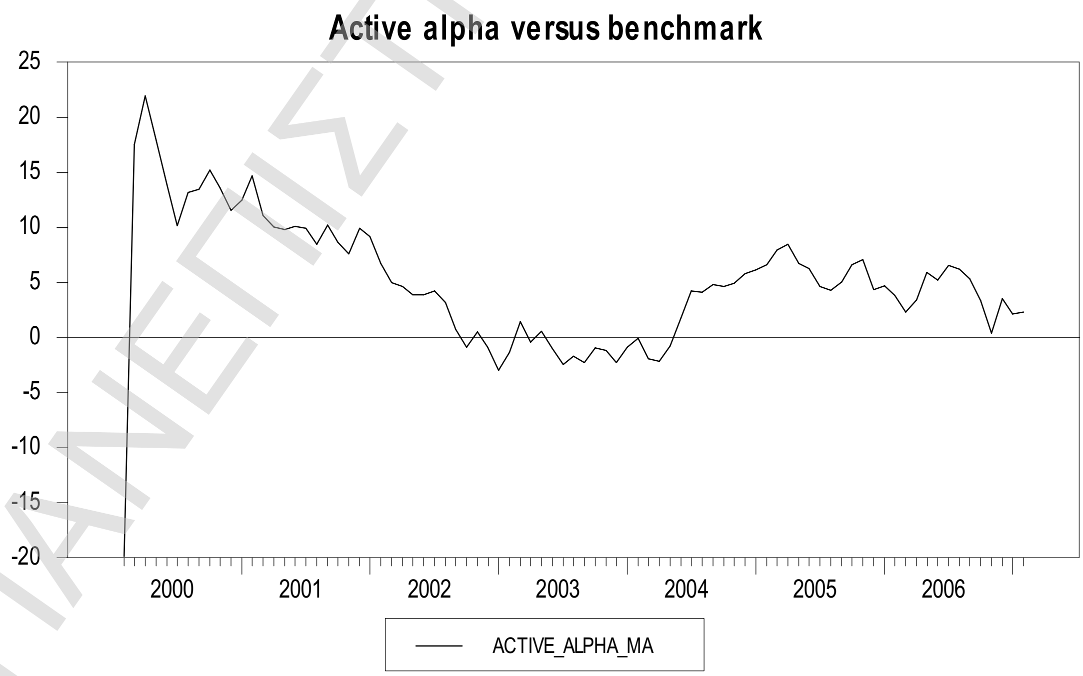
As a conclusion we can say that when we follow a tactical strategy which involves taking both long and short positions we outperform the markets during the whole period we examine but what is more important is that during difficult times for the investors when the markets perform badly our strategy continues to deliver significant profits. When we follow a more preservative strategy and take only long positions in the two markets examined we actually follow the markets but the tactical approach we use helps us either abate the negative results or enhance our profits when the markets perform well overall.

Next we present the excess returns our strategies achieved during the seven year period examined in the present study relative to the benchmark we have used which is the MSCI EM index in the first strategy and an equally mixed portfolio of the MSCI EM index and the S& P 500 index in the second strategy. To find the excess returns we created a time series called active alpha which is the difference between the return of our strategy and the return of the respective benchmark. Then we compute the 12-month rolling window average. The graphs for the two cases are the following:

*Graph of long/short portfolio strategy active alpha*




*Graph of long only portfolio strategy active alpha*



First we must note that the peaks at the beginning of the periods are a result of the fact that we have the first observations and the averages are computed by one or two observations.

Both strategies behave the same way. If we break the period we examine into two sub-periods – the first from 2000 till the beginning of 2003 when the markets perform poorly and the second from 2003 till the beginning of 2007 - we will see that when the markets have negative returns our strategies perform way much better for most of the time and they only seem to be inferior to the benchmarks towards the end of the markets' negative period.

During the next four years the markets bring positive results. The first strategy performs better most of the time but there are certain periods when the markets perform a little better. The second strategy, after a period during which the alpha it delivers is slightly negative, has permanently a positive alpha until the end of the term we examine.

The most important aspect is that our strategy performs better during difficult times when the markets are declining and during these periods it delivers great alpha returns. And when the markets are following an increasing course again the strategies still provide positive alpha for most of the time but in a smaller scale.

A last point we must examine is how the **transaction costs** affect the performance of our strategies. We can implement those strategies easily with the use of Futures or ETF's. In the present study we examine how the use of ETF's affects an investor. Next we present some information about the long and short ETF's for both markets. First we see information for long ETF's provided by iShares.

**iShares long S&P 500 ETF**

| | |
|---|---|
| Total Expense Ratio | 0,09% |
| Net Assets | $ 16,41 billion |
| Price to earnings | 19,02 |
| Price to book | 3,74 |
| No of Holdings | 502 |
| Beta vs. S&P 500 | 1 |

**iShares long MSCI EM ETF**

| | |
|---|---|
| Total Expense Ratio | 0,74% |
| | |
| Net Assets | $ 23,85 billion |
| Price to earnings | 18,2 |
| Price to book | 3,83 |
| No of Holdings | 361 |
| Beta vs. S&P 500 | 1,3 |

The Total Expense Ratio (TER) for the short ETF's for both markets equals 0,95% and it is higher than the TER related to the long products. The Total Expense Ratio (TER) indicates the annual running costs of a fund. It includes the management fee, fund administration, custody and other costs (e.g. costs for the auditor, regulatory and license fees). The TER does not include any initial subscription or sales charges that might be payable.

The way we compute the transaction costs involved in our investment is the following. For our long/short portfolio when we are long the MSCI EM index and short the S&P 500 index we sum the TER of the two respective ETF's and compute the annual TER of our investment. Then we divide the annual TER by 12 to find the monthly TER since the frequency we make forecasts and invest accordingly is monthly. For every month we remain in the same situation, long the MSCI EM and short the S&P 500, we subtract the monthly TER. When our forecast suggests we must go long the S&P 500 and short the MSCI EM we follow the same procedure and use the suitable ETF's this time. The monthly TER for the first case when we go long the MSCI EM index equals 0,140%. The monthly TER when we are long the S&P 500 equals 0,087% and is lower because of the very low TER the S&P 500 long ETF has. In the second strategy when we go only long our two indexes the transaction costs are computed the same way but they do not involve the TER of the short ETF's and as a result are much lower. The monthly TER for the situation of long position in the MSCI EM equals 0,062% and for the long position in the S&P 500 equals 0,0075%.

Now we must see the performance of our strategies after the transaction costs are calculated and included in the results.

| | | Tactical Switches | Transaction Costs | Total Return | Total Return after T-costs |
|---|---|---|---|---|---|
| I | **Long/Short MSCI EM/S&P 500 Portfolio** | 47 | 9,90% | 115,09% | 105,18% |
| | **Buy-Hold MSCI EM Portfolio** | | | 60,62% | 60,62% |
| II | **Long MSCI EM/S&P 500 Portfolio** | 47 | 3,30% | 61,76% | 58,46% |
| | **Buy-Hold Mixed MSCI EM/S&P 500 Portfolio** | | | 30,75% | 30,75% |
| | **Buy-Hold S&P 500** | | | 0,01 | 0,88% |

The tactical switches show how many times we have changed our positions in order to follow the forecast we have made. The transaction costs are an important part of a tactical investing approach and we see that they decrease the profits we have made in each case and especially in the first case where we take short positions. But still after we have subtracted the transaction costs we can see that both strategies perform well and outperform the benchmarks and the S&P 500 by a great amount.

# 4) CONCLUSIONS

We tried to implement a Global Tactical Asset Allocation strategy between two indexes, the S&P 500 and the MSCI Emerging Markets index. Various economic variables were incorporated in this study and we used their predictive ability to make forecasts about which of the two markets examined is expected to perform better each month.

Two different strategies were used the one more aggressive where we took long/short positions in the indexes according to our predictions and a second where we used a less risky investing profile and took only long positions in one market while we stayed out of the other market again following our forecasts. We created forecasts and implemented our strategies for the period from 2000:01 to 2007:02.

Both strategies outperformed their benchmarks which were passive buy-hold strategies and this happened even though our strategies were less risky. What is more important though is the fact that the long/short strategy performs quite well in periods of negative market conditions and when the market is moving upwards it still outperforms the benchmark for the biggest part of the period examined. Our second strategy seems to follow the market but at all times it offers either fewer losses or more gains than the market. Furthermore, when we took into account the factor of the transaction costs, which plays a very important role in investments that have a tactical approach, the strategies still performed well over their respective benchmarks and the S&P 500.

The predictive abilities of our model were very satisfying since it provided a hit ratio of 70,59% predicting correctly for 60 out of 85 months which index will outperform the other. The forecasts made were slightly better for the periods during which the MSCI EM index outperformed the S&P 500.

Another important advantage of our strategies is that they seem to offer to an investor downside protection since the negative returns are not as great as those of the markets and at the same time they have upside potential, achieving maximum returns that are by far bigger than what the benchmark and the S&P 500 exhibit. We also examined the excess returns of the strategies through the use of an alpha time series and the results enhanced our conviction that the strategies perform better during times that the markets are declining something that happens from 2000 till the beginning of

2003 and when the markets are performing well from 2003 to 2007 the strategies still bring in positive alpha but in a smaller scale.

Our strategies can be easily implemented using Futures of Exchange Traded Funds. In this study we have used ETF's because they cover a far broader range of indices than futures and help us track the desired indexes.

The results of the present study lean towards the investors who believe a more active approach should be used when someone wants to follow an investment strategy. Passive strategies can create profits for an investor but the decision to give more attention to an investment and deal with it on a tactical basis seems to be much more profitable and suitable in order to gain maximum benefits from it.

## APPENDIX

Here we present a full list of the series we used throughout the present study.

**Dow Jones Wilshire Style Indexes**

| Series | Ticker | Description | Start |
|---|---|---|---|
| DWST | DWST Index (Bloomberg) | Dow Jones Wilshire US Small-Cap Total Return Index (stocks ranks 751-2500) | 06/78 |
| DWSGT | DWSGT Index (Bloomberg) | Dow Jones Wilshire US Small-Cap Growth Total Return Index (stocks ranks 751-2500) | 06/78 |
| DWSVT | DWSVT Index (Bloomberg) | Dow Jones Wilshire US Small-Cap Value Total Return Index (stocks ranks 751-2500) | 06/78 |
| DWLT | DWLT Index (Bloomberg) | Dow Jones Wilshire US Large-Cap Total Return Index (750 largest) | 06/78 |
| DWLGT | DWLGT Index (Bloomberg) | Dow Jones Wilshire US Large-Cap Growth Total Return Index (750 largest) | 06/78 |
| DWLVT | DWLVT Index (Bloomberg) | Dow Jones Wilshire US Large-Cap Value Total Return Index (stocks ranks 751-2500) | 06/78 |
| SVX | SVX Index (Bloomberg) | S&P 500/Citigroup Value Index | 12/74 |
| SGX | SGX Index (Bloomberg) | S&P 500/Citigroup Growth Index | 12/74 |

**Industrial production series**

| Series | Ticker | Description | Start |
|---|---|---|---|
| IPUS | IP Index (Bloomberg)+ INDPRO (Fed of St. Louis) | USA Industrial Production 2002=100 SA | 01/21 |
| IPEA | EUITEMU Index (Bloomberg) | Eurozone Industrial Production Excluding Construction SA | 01/85 |
| IPFR | FPIPI Index (Bloomberg) | France Industrial Production SA 2000=100 | 01/90 |
| IPGE | GRIPI Index (Bloomberg) | Germany Industrial Production SA | 01/78 |
| IPUK | UKIPI Index (Bloomberg) | UK Industrial Production SA | 01/60 |
| IPJP | JNIP Index (Bloomberg) | Japan Industrial Production SA | 01/78 |
| IPGR | GKIPI Index (Bloomberg) | Greece Industrial Production | 01/00 |
| IPGROE | oecd:grc_printo01_ixobsam (ECOWIN) | Greece, Industry, Production of total industry excluding construction, SA | 01/62 |
| IPGREUR | EUITGR Index (Bloomberg) | Eurostat IP Industry ex construction SA | 01/80 |

**Leading Indicators**

| Series | Ticker | Description | Start |
|---|---|---|---|
| ISM PMI | NAPMPMI Index (Bloomberg) | ISM Manufacturing | 01/60 |
| PMIMF_PR | NAPMPROD Index (Bloomberg) | ISM Manufacturing - Production | 01/60 |
| PMIMF_NORD | NAPMNEWO Index (Bloomberg) | ISM Manufacturing – New Orders | 01/60 |
| PMIMF_ORD | NAPMBACK Index (Bloomberg) | ISM Manufacturing – Backlog Orders | 01/93 |
| PMIMF_INV | NAPMINV Index (Bloomberg) | ISM Manufacturing – Inventories | 01/60 |
| PMIMF_EMP | NAPMEMPL Index (Bloomberg) | ISM Manufacturing – Employment | 01/60 |
| PMIS | NAPMNMAN Index (Bloomberg) | ISM Non-Manufacturing (business activity) | 07/97 |
| PMIS_NORD | NAPMNNO Index (Bloomberg) | ISM Services – New Orders | 07/97 |
| PMIS_ORD | NAPMNBO Index (Bloomberg) | ISM Services – Backlog Orders | 07/97 |
| PMIS_INVCH | NAPMNIC Index (Bloomberg) | ISM Services – Inventory Change | 07/97 |
| PMIS_INVS | NAPMNIS Index (Bloomberg) | ISM Services – Inventory Sentiment | 07/97 |
| PMIS_EMP | NAPMNEMP Index (Bloomberg) | ISM Services – Employment | 07/97 |
| UM_CSENT | uom:ics (ECOWIN) | United States, University of Michigan, Consumer Sentiment Index, USD | 01/78 |
| CB_CCONF | ew:usa05005 (ECOWIN) | United States, Consumer Surveys, Conference Board, Consumer confidence, SA, USD | 02/67 |
| PMIMF_EA | ew:emu04500 (ECOWIN) | Euro Zone, Business Surveys, PMI, Manufacturing Sector, Total, SA | 06/97 |
| PMISE_EA | ew:emu04600 (ECOWIN) | Euro Zone, Business Surveys, PMI, Services Sector, Total business activity, SA | 07/98 |
| IFOEXP_GE | ew:deu04010002 (ECOWIN) | IFO, Germany, Business Surveys, Business expectations index, business sector, SA, Index | 01/91 |
| R10Y_US | H15T10Y Index (Bloomberg) | 10-Year Treasury Constant Maturity Rate | 01/59 |
| FFUNDS | FEDL01 Index (Bloomberg) | Effective Federal Funds Rate | 01/60 |
| R10Y_GE | ew:deu14020 (ECOWIN) | Germany, Government Benchmarks, 10 year, Yield, End of Period, EUR | 01/57 |
| EURUSD | ew:usa19101 (ECOWIN) | United States, Spot Rates, EUR/USD, Close, USD | 07/74 |
| GSCOMM | GSCISPOT Index (Bloomberg) | Goldman Sachs - Commodity Index (Spot return) | 12/69 |
| OIL | USCRWTIC | Bloomberg West Texas Intermediate | 05/83 |

| | | | |
|---|---|---|---|
| | Index (Bloomberg) | (WTI) Cushing Crude Oil Spot Price | |
| unrate | UNRATE (Fed of St. Louis) | Civilian Unemployment Rate | 01/48 |
| duration | USDUMEDN Index (Bloomberg) | US Unemployment Duration Median SA | 01/60 |
| futures3M | EDH7 Comdty (Bloomberg) | Eurodollar Futures 3M | 03/9 |
| US0001M | US0001M Index (Bloomberg) | Libor 1month | 12/84 |
| BZCDI30D | BZCDI30D Index (Bloomberg) | Brazil 30 Day CD Interbank Deposit Certificate | 08/92 |
| OERUR004 | OERUR004 Index (Bloomberg) | OECD Russia Interest Rates 3 Month VIBOR | 01/97 |
| NCUCASH | NCUCASH Index (Datastream) | Copper Cathode C/LB | 02/71 |
| GOLDHAR | GOLDHAR Index (Datastream) | Gold, Handy & Harman Base $/Troy Oz | 02/79 |
| GOLDBLN | GOLDBLN Index (Datastream) | Gold Bullion LBM U$/Troy Ounce | 02/68 |
| PPICORE | PPICORE Index (Bloomberg) | Producer Price Index: Finished Goods Less Food & Energy | 01/74 |
| PCECORE | PCECORE Index (Bloomberg) | Personal consumption expenditures price index less Food & Energy | 01/59 |
| CPICORE | CPICORE Index (Bloomberg) | Consumer Price Index for All Urban Consumers: All Items Less Food & Energy | 01/57 |
| CONSUMPTION | PCE Index (Bloomberg) | Personal Consumption Expenditures | 01/59 |
| Building_Permits | Permit Index (Fed of St. Louis) | New Private Housing Units Authorized by Building Permit | 01/60 |

**Main indexes and main indexes' PE series**

| Series | Ticker | Description | Start |
|---|---|---|---|
| SP500 & SP500PE | SPX Index (Bloomberg) | US Standard and Poor's 500 Index | 01/59 PE: 04/86 |
| CAC40 & CAC40PE | CAC Index (Bloomberg) | France CAC 40 Index | 07/87 PE: 06/01 |
| DAX & DAXPE | DAX Index (Bloomberg) | Germany DAX Index | 10/59 PE: 05/97 |
| FTSE100 & FTSE100PE | UKX Index (Bloomberg) | UK FTSE 100 Index | 01/84 PE: 05/93 |
| NIKKEI225 & NIKKEI225PE | NKY Index (Bloomberg) | Japan Nikkei 225 | 01/70 PE: 04/00 |
| DJSTOXX50 & DJSTOXX50PE | SX5P Index (Bloomberg) | Europe DJ Stoxx 50 | 12/86 PE: 05/01 |
| ASE & ASEPE | ASE Index (Bloomberg) | Greece ASE Index | 01/87 PE: 11/95 |
| FTSE20 & FTSE20PE | FTASE Index (Bloomberg) | Greece FTSE-20 | 04/98 PE: 04/99 |
| TPX | TPX Index (Bloomberg) | Japan TOPIX INDEX | 01/59 |
| HS | HSI Index (Bloomberg) | Hong Kong HANG SENG INDEX | 11/69 |
| HSCEI | HSCEI Index (Bloomberg) | HSCEI-Hang Seng China Index | 07/93 |
| ASX200 | AS51 Index (Bloomberg) | Australia S&P/ASX 200 INDEX | 05/92 |
| KLCI | KLCI Index (Bloomberg) | Malaysia Kuala Lumpur Comp Index | 01/77 |
| STI | STI Index (Bloomberg) | Singapore Straits Times Index | 01/85 |
| IBOV | IBOV Index (Bloomberg) | Brazil Bovespa Stock Index | 01/90 |
| MEXBOL | MEXBOL Index (Bloomberg) | Mexico Bolsa Index | 07/85 |
| SBTSY10 | SBTSY10 Index (Bloomberg) | Citigroup Salomon US 10yr Treasury Benchmark Index | 01/80 |

**MSCI (Morgan Stanley Capital International) series**

| Series | Ticker (Bloomberg) | Description | Start |
|---|---|---|---|
| growth_ea | MGLDEMU Index (Bloomberg) | MSCI EMU Growth | 12/87 |
| growth_pac | MGLAP Index (Bloomberg) | MSCI Pacific Growth | 12/96 |
| growth_pacf | MGLAPF Index (Bloomberg) | MSCI Pacific Free Growth | 12/96 |
| growth_pacxjp | MGLAPXJ Index (Bloomberg) | MSCI Pacific x Japan Growth | 12/96 |
| growth_pacfxjp | MGLAPFXJ Index | MSCI Pacific Free x Japan Growth | 12/96 |

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|---|---|---|---|
| | (Bloomberg) | | |
| growth_euxuk | MGLDE15X Index (Bloomberg) | MSCI Europe x UK Growth | 01/98 |
| small_ea | MXEMSC Index (Bloomberg) | MSCI EMU Small Cap | 01/95 |
| small_pac | MCLAP Index (Bloomberg) | MSCI Pacific Small Cap | 01/98 |
| small_euxuk | MCLDE15X Index (Bloomberg) | MSCI Europe x UK Small Cap | 01/98 |
| small_pacxjp | MCLAPXJ Index (Bloomberg) | MSCI Pacific x JN Small Cap | 12/96 |
| small_us | MCLDUS Index (Bloomberg) | MSCI USA Small Cap | 01/98 |
| value_ea | MVLDEMU Index (Bloomberg) | MSCI Euro area Value | 12/87 |
| value_pac | MVLAP Index (Bloomberg) | MSCI Pacific Value | 12/96 |
| value_pacf | MVLAPF Index (Bloomberg) | MSCI Pacific Free Value | 12/96 |
| value_pacxjp | MVLAPXJ Index (Bloomberg) | MSCI Pacific x Japan Value | 12/96 |
| value_pacfxjp | MVLAPFXJ Index (Bloomberg) | MSCI Pacific Free x Japan Value | 12/96 |
| value_euxuk | MVLDE15X Index (Bloomberg) | MSCI Europe x UK Value | 01/98 |
| ms_ea | MSDLEMU Index (Bloomberg) | MSCI EMU Developed Countries | 12/87 |
| ms_us | MSDLUS Index (Bloomberg) | MSCI USA Developed Countries | 12/69 |
| ms_pac | MSDLP Index (Bloomberg) | MSCI Pacific Developed Countries | 12/87 |
| ms_pacf | MSDLPF Index (Bloomberg) | MSCI Pacific free Developed Countries | 12/87 |
| ms_pacfxjp | MSDLPFXJ Index (Bloomberg) | MSCI Pac Free x Japan Developed Countries | 12/87 |
| ms_euxuk | MSDLE15X Index (Bloomberg) | MSCI Europe x UK Developed Countries | 12/87 |
| djstoxx600 | SXXP Index (Bloomberg) | Europe DJ Stoxx 600 | 12/86 |
| russell2000 | RTY Index (Bloomberg) | US Russell 2000 Index | 12/78 |
| ms_emfree | MSELEGF Index (Bloomberg) | MSCI EM Free | 12/87 |
| ms_latam | MSELEGFL Index (Bloomberg) | MSCI Latin America | 12/87 |
| ms_emasia | MSELEGFA Index (Bloomberg) | MSCI EM Asia | 12/87 |
| ms_china | MSELTCF Index (Bloomberg) | MSCI China | 12/92 |
| value_us | DJUSVA Index (Bloomberg) | Dow Jones US Value Index | 01/92 |
| growth_us | DJUSGR Index (Bloomberg) | Dow Jones US Growth Index | 01/92 |

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|---|---|---|---|
| ms_brazil | MSELTBR Index (Bloomberg) | MSCI EM Brazil | 12/87 |
| ms_mexico | MSELTMXF Index (Bloomberg) | MSCI EM Mexico | 12/87 |
| ms_taiwan | TAMSCI Index (Bloomberg) | MSCI EM Taiwan | 12/87 |
| ms_korea | MXKR Index (Bloomberg) | MSCI EM Korea | 12/87 |
| ms_india | MXIN Index (Bloomberg) | MSCI EM India | 12/92 |
| ms_australia | MSDLAS Index (Bloomberg) | MSCI Australia Developed Countries | 12/69 |
| ms_hkong | MSDLHK Index (Bloomberg) | MSCI Hong Kong Developed Countries | 12/87 |
| ms_russia | MSELTRUS Index (Bloomberg) | MSCI EM Russia | 01/97 |

**USD indices**

| **Series** | **Ticker** | **Description** | **Start** |
|---|---|---|---|
| FTSE100USD | UKX Index (Bloomberg) | FTSE 100 in USD | 01/84 |
| NIKKEI225USD | NKY Index (Bloomberg) | Nikkei 225 in USD | 01/71 |
| DJSTOXX50USD | SX5P Index (Bloomberg) | DJ STOXX 50 in USD | 12/88 |
| DJSTOXX600USD | SXXP Index (Bloomberg) | DJ STOXX 600 in USD | 12/88 |
| ASEUSD | ASE Index (Bloomberg) | ASE in USD | 01/87 |
| FTSE20USD | FTASE Index (Bloomberg) | FTSE-20 in USD | 04/98 |
| HSUSD | HSI Index (Bloomberg) | Hong Kong HANG SENG INDEX in USD | 04/74 |
| HSCEIUSD | HSCEI Index (Bloomberg) | HSCEI-Hang Seng China Index in USD | 07/93 |
| ASX200USD | AS51 Index (Bloomberg) | Australia S&P/ASX 200 INDEX in USD | 05/92 |
| IBOVUSD | IBOV Index (Bloomberg) | Brazil Bovespa Stock Index in USD | 01/92 |
| MEXBOLUSD | MEXBOL Index (Bloomberg) | Mexico Bolsa Index in USD | 01/78 |
| ms_russiaUSD | MXRU Index (Bloomberg) | MSCI EM Russia in USD | 01/95 |
| ms_indiaUSD | MXIN Index (Bloomberg) | MSCI EM India in USD | 12/92 |
| ms_koreaUSD | MXKR Index (Bloomberg) | MSCI EM Korea in USD | 12/87 |
| ms_taiwanUSD | TAMSCI Index (Bloomberg) | MSCI EM Taiwan in USD | 12/87 |
| ms_latamUSD | MXLA Index (Bloomberg) | MSCI Latin America in USD | 12/87 |
| ms_emasiaUSD | MXMS Index (Bloomberg) | MSCI EM Asia in USD | 12/87 |
| ms_worldfrUSD | MXWD Index | MSCI World Free, All countries in | 12/87 |

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|---|---|---|---|
| CPI_US | (Bloomberg) CPIAUCSL (Fed of St. Louis) | USD Consumer Price Index For All Urban Consumers: All Items | 01/47 |

## FX series

| Series | Ticker | Description | Start |
|---|---|---|---|
| JPY | JPY Curncy (Bloomberg) | Japan USD/JPY spot rate | 01/71 |
| JPY1M | JPY1M Curncy (Bloomberg) | Japan USD/JPY 1m forward rate | 12/88 |
| EUR | EUR Curncy (Bloomberg) | EUR/USD spot rate | 12/98 |
| EUR1M | EUR1M Curncy (Bloomberg) | EUR/USD 1m forward rate | 12/98 |
| GBP | GBP Curncy (Bloomberg) | UK GBP/USD spot rate | 01/71 |
| GBP1M | GBP1M Curncy (Bloomberg) | UK GBP/USD 1m forward rate | 12/88 |
| AUD | AUD Curncy (Bloomberg) | Australia AUD/USD spot rate | 01/71 |
| AUD1M | AUD1M Curncy (Bloomberg) | Australia AUD/USD 1m forward rate | 12/83 |
| HKD | HKD Curncy (Bloomberg) | Hong Kong USD/HKD spot rate | 04/74 |
| HKD1M | HKD1M Curncy (Bloomberg) | Hong Kong USD/HKD 1m forward rate | 12/88 |
| NZD | NZD Curncy (Bloomberg) | New Zealand NZD/USD spot rate | 01/71 |
| NZD1M | NZD1M Curncy (Bloomberg) | New Zealand NZD/USD 1m forward rate | 12/88 |
| SGD | SGD Curncy (Bloomberg) | Singapore USD/SGD spot rate | 01/81 |
| SGD1M | SGD1M Curncy (Bloomberg) | Singapore USD/SGD 1m forward rate | 12/88 |
| INR | INR Curncy (Bloomberg) | India USD/INR spot rate | 01/73 |
| INR1M | IRN1M Curncy (Bloomberg) | India USD/INR 1m forward rate | 12/98 |
| KRW | KRW Curncy (Bloomberg) | Korea USD/KRW spot rate | 04/81 |
| KRW1M | KWN1M Curncy (Bloomberg) | Korea USD/KRW 1m forward rate | 12/88 |
| TWD | TWD Curncy (Bloomberg) | Taiwan USD/TWD spot rate | 10/83 |
| TWD1M | NTN1M Curncy (Bloomberg) | Taiwan USD/TWD 1m forward rate | 12/98 |
| THB | THB Curncy (Bloomberg) | Thailand USD/THB spot rate | 01/81 |
| THB1M | THB1M Curncy (Bloomberg) | Thailand USD/THB 1m forward rate | 12/95 |
| CNY | CNY Curncy (Bloomberg) | China USD/CNY spot rate | 01/81 |
| CNY1M | CCN1M Curncy (Bloomberg) | China USD/ CNY 1m forward rate | 12/98 |

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|---|---|---|---|
| BRL | BRL Curncy (Bloomberg) | Brazil USD/BRL spot rate | 01/92 |
| BRL1M | BRL Curncy (Bloomberg) | Brazil USD/BRL 1m forward rate | 07/00 |
| MXN | MXN Curncy (Bloomberg) | Mexico USD/MXN spot rate | 01/71 |
| MXN1M | MXN1M Curncy (Bloomberg) | Mexico USD/MXN 1m forward rate | 11/97 |
| RUB | RUB Curncy (Bloomberg) | Russia USD/RUB spot rate | 07/93 |
| RUB1M | RRN1M Curncy (Bloomberg) | Russia USD/ RUB 1m forward rate | 08/01 |
| BOJXEXN | BOJXEXN Index (Bloomberg) | Japan BOJ Effective Exchange Rates - Nominal | 01/71 |
| BOJXEXFR | BOJXEXFR Index (Bloomberg) | Japan BOJ Effective Exchange Rates – Real (monthly) | 01/71 |
| O12UK001 | O12UK001 Index (Bloomberg) | OECD Eurozone Currency Conversions Real Effective Exchange Rates | 01/71 |
| R10y_jp | ew:jpn14020 (ECOWIN) | Japan, Government Benchmarks, 10 year, Yield, End of Period, JPY | 10/66 |
| R10y_uk | ew:gbr14020 (ECOWIN) | United Kingdom, Government Benchmarks, 10 year, Yield, End of Period, GBP | 01/57 |
| OEJPK004 | OEJPK004 Index (Bloomberg) | OECD Japan Currency Conversions Real Effective Exchange Rates | 01/71 |
| OEUSK002 | OEUSK002 Index (Bloomberg) | OECD US Currency Conversions Real Effective Exchange Rates | 01/71 |
| OEGBK005 | OEGBK005 Index (Bloomberg) | OECD UK Currency Conversions Real Effective Exchange Rates | 01/71 |
| JBXRUSD | JBXRUSD Index (Bloomberg) | JP Morgan Real Broad Effective Exchange Rate USD | 01/71 |
| JBXRGBP | JBXRGBP Index (Bloomberg) | JP Morgan Real Broad Effective Exchange Rate BGP | 01/71 |

## REFERENCES


**Anson, Mark.,** "Strategic versus Tactical Asset Allocation" *The Journal of Portfolio Management*, Winter 2004, pp. 8-22

**Barry, Cristopher B., and Peavy III, John W., and Rodriguez, Mauricio,** "Performance Characteristics of Emerging Capital Markets" *Financial Analysts Journal,* January/February 1998, pp. 72-80

**Bekaert, Geert, and Harvey, Campbell R.,** "Emerging Markets Finance" *Journal of Empirical Finance,* 10, 2003, pp. 3-55

**Bekaert, Geert, and Erb, Claude B., and Harvey, Campbell R., and Viskanta, Tadas E.,** "Distributional Characteristics of Emerging Market Returns and Asset Allocation" *The Journal of Portfolio Management,* Winter 1998, pp. 102-116

**Bilson, Cristopher M., and Brailsford, Timothy J., and Hooper, Vincent J., "**Selecting Macroeconomic Variables as Explanatory Factors of Emerging Stock Market Returns" *Pacific-Basin Finance Journal,* 9, 2001, pp. 401-426

**Conover, Mitchell C., and Jensen, Gerald R., and Johnson, Robert R.,** "Emerging Markets: When are they Worth It?" *Financial Analysts Journal,* 2002, pp. 86-95

**Dahlquist, Magnus and Harvey, Campbell R.,** "Global Tactical Asset Allocation" (January 31, 2001)

**De Santis, Giorgio, and Imrohoroglu, Selahattin,** "Stock Returns and Volatility in Emerging Financial Markets" *Journal of International Money and Finance*, Vol. 16, No. 4, 1997, pp. 561-579

**Faber, Mebane T.,** "A quantitative approach to Tactical Asset Allocation" *The Journal of Wealth Management,* Spring 2007

**Flavin, T. J., and Wickens, M. R.,** "Macroeconomic influences on Optimal Asset Allocation" *Review of Financial Economics,* 12, 2003, pp. 207-231

**Harvey, Campbell R.,** "Predictable Risk and Returns in Emerging Markets" *Review of Financial Studies,* Vol. 8, No. 3, 1995, pp. 773–816.

**Ledesma Padilla, Juan Marcos and Zebad, Martin**, "Tactical Asset Allocation on Market Neutral Hedge Fund" (October 2004)

**MacBeth, James D., and Emanuel, David C.** "Tactical Asset Allocation: Pros and Cons" *Financial Analysts Journal,* November-December 1993, pp. 30-43

**Masters, Seth J.,** "The Problem with Emerging Markets Indexes" *The Journal of Portfolio Management* Winter 1998, pp. 93-100

**Nam, Joong-soo, and Branch, Ben,** Tactical Asset Allocation: Can it Work?" *The Journal of Financial Research,* Vol. XVII, No. 4, Winter 1994, pp. 465-479

**Rey, David,** "Tactical Asset Allocation: An Alternative Definition" *Working Paper, University of Basel/University of St. Gallen*

**Weigel, Eric J**., "The Performance of Tactical Asset Allocation" *Financial Analysts Journal,* September-October 1991, pp. 63-70