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On performance persistence in emerging markets: Empirical evidence from Asia-Pacific

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ABSTRACT

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The purpose of this study is to investigate the performance persistence of international mutual funds, employing a data sample which includes 2,168 European mutual funds investing in Asia-Pacific region; Japan excluded. Also, a number of performance measures is tested and compared, and especially, this study tries to find out whether iterative Bayesian procedure can be used to provide more accurate predictions on future performance. Finally, this study examines whether the cross-section of mutual fund returns can be explained with simple accounting variables and market risk.

To exclude the effect of the Asian currency crisis in 1997, the studied time period includes years from 1999 to 2007. The overall results showed significant performance persistence for repeating winners when performance was tested with contingency tables. Also the annualized alpha spreads between the top and bottom portfolios were more than ten percent at their highest. Nevertheless, the results do not confirm the improved prediction accuracy of the Bayesian alphas.

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Tämän tutkielman tavoitteena on tutkia kansainvälisten rahastojen tuottojen pysyvyyttä otoksella, joka sisältää 2168 eurooppalaista rahastoa, jotka sijoittavat Aasia-Tyynellemeren alueelle (Japani poislukien). Tutkielma vertailee myös erilaisten menestysmittareiden tuloksia, ja erityisesti tavoitteena on tutkia Bayesialaisten alfojen ennustuskykyä. Lopuksi, tämä tutkielma pyrkii selvittämään missä määrin yksinkertaiset kirjanpitoarvot sekä markkkinariski selittävät eroja rahastojen tuotoissa.

Vuoden 1997 Aasian valuuttakriisin vaikutusten eliminoimiseksi, tutkittava ajanjakso on rajattu vuodesta 1999 vuoteen 2007. Tulosten mukaan menestyksen jatkuvuus on kaiken kaikkiaan ollut tutkitulla ajanjaksolla merkitsevää, ja parhaimman sekä huonoimman portfolion vuotuinen riskikorjattujen tuottojen erotus on kuuden vuoden ajanjaksolla ollut jopa yli kymmenen prosenttia. Tulokset eivät kuitenkaan puolla Bayesian alfojen tarkempaa ennustuskykyä

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Table of Contents

1. Introduction 1
1.1. Performance persistence and market efficiency 2
1.2. Limitations and the structure of the thesis 3
2. Performance persistence; literature review... 4
2.1. The seminal papers from 1960s 4
2.2. Performance persistence; studies from 1970s on 7
2.3. Multi-index models.. 10
2.4. Downside risk -based performance measures 14
3. Performance measures 17
3.1. Raw returns 17
3.2. Sharpe ratio 18
3.3. Treynor measure 21
3.4. Downside Treynor ratio 23
3.5. Jensen measure 24
3.6. Multi-index model 26
4. Empirical analysis... 28
4.1. Full sample; Asia-Pacific.. 31
4.1.1. Contingency analysis; the methodology 32
4.1.2 Contingency analysis; empirical results 33
4.1.3. Stacked time series regressions 37
4.2. Country-specific performance persistence 42
4.2.1. Iterative Bayesian framework.. 43
4.2.2. Three-year selection period 45
4.2.3. One-year selection period 48
4.3. Long/short investment strategy 51
4.3.1. Theoretical background 51
4.3.2. Market neutral long/short investment strategy 52
4.4. Factors explaining the returns.. 55
5. Concluding remarks... 61
References: 65
Appendix A: Calculations; one-month risk-free rate of return, Jarque-Bera value and Spearman’s rank correlation coefficient

1. Introduction

The growth in the Asian equity markets has been enormous during the last few decades, and excluding Japan and Australia, the U.S. dollar denominated Asia's capitalization has risen almost tenfold since 1990 (Purfield et al., 2006). In the most recent years, China and India have experienced almost double-digit GDP growth (IMF, 2008). The fast development of the Asian markets has in turn increased the investors' interest for the Asia-Pacific, and along, the investment banks have increased investment opportunities for this market area.

Though the variety of performance persistence studies is vast, the studies focusing in the emerging markets have mainly concentrated in validating the risk measures. Thus, the purpose for this study is to extend the performance persistence analysis to the emerging markets, specifically to Asia-Pacific; Japan excluded. To my knowledge, this is the first study with the specified target area. The other objective for this study is to test Bayesian shrinkage procedure, and to examine its selective ability against some, more traditional performance measures. This study will also introduce a downside risk -based performance measure, downside Treynor, and compare its selective ability to other performance metrics. Specifically, this study tries to find the answers for the following questions:

Q1 Are the international fund markets in Asia-Pacific area (Japan excluded) efficient or is it possible to systematically pick up the future winner funds?

Q2 How do the different methodological choices affect the performance persistence results?

Q3 To what extent do the style factors explain future returns?

1.1. Performance persistence and market efficiency

The Sharpe (1964)-Lintner (1965)-Mossin (1966) Capital Asset Pricing Model (CAPM) and the Markowitz (1952; 1959) portfolio theory[1] provided the framework for performance evaluation in the following decades. These theoretical frameworks enabled the researchers to take different risk profiles and portfolio efficiency into account when the relative performance is measured. Most of the common performance measures employed today were developed in the 1960s based on the CAPM and the modern portfolio theory.

Past performance is almost a fundamental when funds are marketed for investors. Hence, a justified question is whether the past performance persists or not. If the past returns could be used to predict the future returns, the markets would be inefficient, and so far the studies have suggested that markets are in general efficient (at least the risk-adjusted returns in a weak form). Malkiel (1988) described the market efficiency in a following manner:

> *"Taken to it's logical extreme, it means that a blindfolded monkey throwing darts at a newspaper's financial pages could select a portfolio that would do just as well as one carefully selected by the experts. Now, financial analysts in pinstripes do not like being compared with bare-assed apes."* (Malkiel, 1988)

Although this study will not take a stand on the market efficiency per se, the different forms of efficiency have to be shortly covered. The efficient market hypothesis in its strongest form states that all publicly and privately available information is already incorporated in stock prices. Thus, the excess returns resulting from active portfolio management would be purely random. According to the semi-strong form of efficiency, all the publicly

[1] Markowitz (1959) extended his earlier article to a monograph and presented methods for constructing efficient portfolios (that is, minimizing the expected volatility and maximizing the expected return).

available information is already in the share prices. In other words, only insider trading offers persistent excess returns. Finally, the weak form rules out the technical analysis based on historical prices. However, this form of efficiency would leave some room for active management based on the fundamental and economic analysis. (Grinold and Kahn, 2000; 481)

1.2. Limitations and the structure of the thesis

This study examines performance persistence of European open-end mutual funds whose objective is to invest in Asia-Pacific; Japan excluded. The fund categories do not completely exclude investments in other markets, and also the fund categories might have changed over time. The data suffers from survivorship bias, and includes only the funds which existed in the beginning of the year 2008. This could exaggerate the results from the contingency analyses. However, the survivorship bias has an opposite effect on the results from the stacked return time series tests, and therefore, the true alpha spreads between top and bottom portfolios are higher than reported hereafter.

The rest of this study is organized as follows. Section 2 will provide literature review starting from the seminal papers from the 1960s. Section 3 introduces performance measures used in this study (the iterative Bayesian procedure is introduced in 4.2.1). Section 4 includes the empirical part of this study, and finally, Section 5 concludes.

2. Performance persistence; literature review

The literature offers a great variety of articles focusing on the performance persistence. In general, the studies have shown that although the past performance can not predict future winners, the negative performance is much more predictable. The following review will try to present the variety of the research methods and the results of the overall performance persistence studies published since the 1960s.

This section is divided into four parts and each part introduces studies in chronological order. The first part glances through the early studies from the 1960s. The second part of this section reviews the results and the methods from the performance persistence studies from 1970s on. The third part introduces studies with multi-index models, and finally, the fourth part focuses on the studies with downside risk measures.

2.1. The seminal papers from 1960s

In their seminal papers; Treynor, Sharpe and Jensen created the basis for the risk-adjusted fund performance evaluation. Consequently, these papers presented performance measures, which even today, are the most widely used performance measures in fund evaluation (all of these performance measures are discussed in more details in Section 3).

In 1965, Treynor presented the first performance measure which could be used to compare funds with different risk profiles. The short empirical part of his study provided evidence on stationarity[2] of returns. In two

[2] Stationarity meant that the market sensitivity of a fund remained relatively constant through time, and therefore, beta coefficient was a proper measure of risk.

subsequent five-year periods, the returns fell on the characteristic line[3] even though the returns were volatile in a short-term. (Treynor, 1965)

Sharpe (1966) carried out more profound empirical analyses using reward-to-variability ratio[4], which supported the performance persistence during a period from 1954 to 1963. Sharpe used prior ten-year period as a selection period and found a positive correlation coefficient between the subsequent periods. The Treynor index, however, gave substantially more accurate predictions (the performance was measured with the reward-to-variability ratio). According to Sharpe (1966), the Treynor index does not capture the level of diversification of a fund, *"… and for this it is an inferior measure of past performance, but for this reason it might be a better measure for predicting future performance"*. (Sharpe, 1966)

The overall results showed some signs of performance persistence, and on average, mutual fund managers selected stocks at least as well as the benchmark index, Dow-Jones Industrials Average. However, after the costs were deducted, mutual funds fell short from the Dow-Jones portfolio. (Sharpe, 1966)

The performance measures developed by Treynor and Sharpe could provide risk-adjusted rankings for funds (that is, based on the results, you could say that fund A is better than fund B). However, these measures could not quantify the difference between funds. Jensen (1968) created an absolute measure of performance which could also account for risk. The empirical results confirmed the results from Sharpe (1966, op cit.). On average, mutual funds could not even earn their brokerage fees on risk-adjusted basis (115 funds in 1955-1964).

Jensen also acknowledged the effect of non-stationarity of the risk measure, the fact that the mutual fund manager might easily change the

[3] Characteristic line, or security market line, as well as the derivation of the Treynor ratio are discussed in more details in section 3.2.
[4] Reward-to-variability ratio, also known as the Sharpe ratio. More from Sharpe ratio in 3.3.

portfolio risk (decrease or increase the volatility). Therefore, the author pointed out that the performance measure, alpha, measures only the manager's forecasting ability, and hence, does not account for the level of diversification nor the changes in investment policies (investment manager with superior information should change the investment policy according to market trends and hold only winning stocks in the portfolio). (Jensen, 1968)

In his following study, however, Jensen (1969) came to a conclusion that the risk coefficients were on average stationary through time[5] (with a wider empirical analysis than Treynor (1965, op cit.)). Jensen also extended the empirical analysis from the previous study, and during the period from 1955 to 1964, using observations gross of expenses, 50.2 percent of the 115 funds were able to deliver positive alpha. The consistency in portfolio returns, however, was purely random.

After deducting all management expenses and brokerage commissions, the average annual performance measure, alpha, was -8.9 percent in the period from 1955 to 1964. However, after all the expenses were added back and the cash balances were assumed to earn the risk-free rate of return, the average performance measure was +.0009 which indicated that funds held neutral portfolios before the expenses were deducted. Thereby, the results suggested strong form market efficiency; even the brightest, most well paid analysts could not beat the market on risk-adjusted basis:

> *"These analysts work in the markets every day and have wide-ranging contacts and associations, and are unable to forecast accurately enough to forecast returns to recover their research and transaction costs."* (Jensen, 1969)

[5] Jensen also noted that the risk of a portfolio could be held strictly stationary through time only if the proportions of stocks were continuously adjusted to original fractions.

On the contrary, Jensen found out that inferior performance might persist even for decades. One plausible explanation for this could be the fact that mutual funds have stochastic[6] cash flows, and therefore, they can not have 100 percent of assets invested. However, the empirical evidence indicated that the large negative performance measures were not due to a chance. (Jensen, 1969)

2.2. Performance persistence; studies from 1970s on

Through the following decades, researchers have extensively utilized, tested and developed the performance measures invented by Treynor, Sharpe and Jensen[7]. Especially, during the last two decades the number of performance studies has increased exponentially, thanks to the developed data bases and the improved calculation capacity. Hence, it is neither appropriate nor possible to go through all the relevant studies written so far. The following will present only a fraction of all the relevant studies.

Carlson (1970) utilized, in the first part of his study, the Sharpe ratio as a proxy for risk, and concluded that ranking different kind of mutual funds simultaneously (common equity funds, balanced funds and income funds) leads only to spurious results. Another part of this study questioned the appropriateness of the generally used benchmark indexes. Employing regression analysis, Carlson found out that the widely used S&P index could explain only 81 percent of the variability of annual returns while the common stock fund index explained 87 percent of the variability. The drop in the residual variance was even more significant, from 64 percent to 37 percent for regressions with S&P index and common stock fund index as benchmarks, respectively. The overall results for common equity funds did not support consistent performance persistence, although the mean return

[6] Read, random.
[7] These performance measures are introduced in Chapter 3.

and risk in the first decade served as good predictors for the subsequent decade (the rank correlation coefficients were statistically significant at one-percent level, 1948-1967). (Carlson, 1970)

In the following decades, the selection and holding periods shortened from five to ten years, to one to three years, and the data frequency used in the analyses shortened from annual observations to monthly or weekly observations. Discovered performance persistence depended mainly on the selected observation period and the performance metrics employed. E.g., Malkiel (1995) found out that during the period from 1971 to 1979 (with a survivorship bias free data), winners in the previous year tended to repeat (65%). However, in the subsequent period (1980 to 1991) the proportion of repeating winners dropped to 51 percent.

Malkiel also pointed out that the mutual fund complexes tend to bury unsuccessful funds by merging them into more successful funds, because selling a fund with a poor track record is extremely difficult. Hence, only the successful funds tend to survive. In the period from 1982 to 1991, ignoring the survivorship bias would have improved the average annual fund returns by 140 basis points. The author also noted another source of bias (which is closely related to survivorship bias). A number of mutual fund management complexes have a custom to start a number of "incubator" funds, and after a while, start actively marketing only for the most successful ones, dropping out the rest. (Malkiel, 1995)

Some of the persistence studies have focused on the performance persistence of successful fund managers. Porter and Trifts (1998) studied if the superior performance of experienced fund managers in a five-year period predicted the performance in the following five-year period.

For the first five-year period (1986-1990), 43 out of the 93 managers averaged above the median compared to all managers in the same investment category. The average MPR (mean annual performance rank) for these managers was 60.3 percent (significantly greater than 50%). However, for the following period (1991-1995), the average MPR for the successful managers in the previous period fell to 51.1 percent, and also the number of managers averaging above the median fell from 43 to 23. (Porter and Trifts, 1998)

Loviscek and Jordan (2000) studied whether individual investor could profit by investing in the top holdings of Morningstar's five-star rated funds. Five-star rating is the company's highest rating and it is awarded to only about 2 percent of the approximately 2,000 mutual funds it evaluates[8]. The study was conducted by constructing portfolios of top-five holdings from the five-star rated funds, for the years from 1989 to 1993. The performance of these portfolios was tested against the S&P 500 by using one-year to five-year buy-and-hold strategies from 1990 to 1998.

Best results were received from the one-year holding period. Four times out of five, the constructed portfolio outperformed the S&P 500 on risk-adjusted basis. Also the overall results were promising: in 17 out of 25 pairwise comparisons, portfolios outperformed the S&P 500. However, Loviscek and Jordan concluded that the results are probably not convincing enough for individual investors to adopt this stock selection strategy. (Loviscek and Jordan, 2000)

Sandvall (2000) examined short-term persistence of Finnish mutual funds during a 30-month period from 1995 to 1998. Using a six-month selection period and a six-month holding period, Sandvall found out that, on average, there was a short-term momentum in mutual fund returns. The annualized spread between the past winners (30%) and the past losers (30%) was 3.28 percent for stock funds, and this was statistically significant at ten percent level. (Sandvall, 2000)

[8] According to Loviscek and Jordan (2000). Nowadays, within each Morningstar category, top 10 percent of mutual funds are awarded with five-star rating (Morningstar 2008a).

Droms and Walker (2001) studied international mutual funds, and by employing contingency tables, found statistically significant short-term persistence (for one year and after that the persistence faded away). Another test compared the spread between top ten funds and bottom ten funds. The average winners during the 20-year period earned annually 2.70 percent more than average losers[9]. The spread, however, was not statistically significant, due to high degree of variability of differences between winners and losers across the studied time period (1978-1996). (Droms and Walker, 2001)

2.3. Multi-index models

New era in the performance persistence studies began in the early 1990s. The development of the information technology, improved data bases and the increased calculation capacity enabled more complex statistical models in fund analysis. The simple linear linkage between the market return and stock return was set under a serious consideration.

Fama and French (1992) noticed that the relation between the market risk (beta coefficient) and the average stock return was weak in the period from 1963 to 1990. During this period, the average returns from the top and bottom beta portfolios were practically the same (1.20% and 1.18% respectively)[10]. On the other hand, there was a robust negative relation between size and average return, and a significant positive relation between the book-to-market equity and average return. Although the beta coefficient had no impact on the expected returns by itself, it had a positive relation when the size variable was taken into account. (Fama and French, 1992)

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[9] 10 top performing funds from the previous year (raw returns) were included in the top portfolio and the loser portfolio was constructed based on corresponding worst performing funds.
[10] The results from Malkiel (1995) confirmed the weak linkage between the betas and average returns from 1971 to 1991 (r-square for beta coefficient was 0.00).

In 1996, Fama and French studied further the consistencies in past returns, which were not explained by the CAPM. The results showed that the anomalies[11] disappeared by employing a three-factor model, which included the market risk, the difference between the return from small cap stocks and large cap stocks (SMB) and the difference between the return from high book-to-market equity stocks and low book-to-market equity stocks (HML). Besides explaining the cross-section of fund returns, the results also showed that the average absolute pricing errors (alphas) diminished. For the traditional CAPM, alphas were three to five times larger than for the three-factor model. However, the model could not explain the persistence in short-term returns, and the time-series regressions also indicated a consistent pattern in risk-adjusted returns. During a period from 1963 to 1993, the highest risk-adjusted returns were received from portfolios which consisted of either small-cap value stocks or large-cap growth stocks. (Fama and French, 1996)

Elton et al. (1996) found out that by using risk-adjusted returns, the past performance could predict the future performance in a short run and in a longer run. The authors ranked funds into ten deciles with a four-index model which included the market index, size index, value index and the bond index. The funds for the three-year holding periods were selected using the three-year alpha and funds for the one-year holding period were selected by adding the monthly residuals during the last selection year to the overall three-year alpha. The alpha for the holding period was calculated as the overall alpha plus the average monthly residual during the holding period.

The results showed statistically significant rank correlation coefficients at one-percent level for portfolios selected with the risk-adjusted returns, while the portfolios ranked with total returns were significant only at ten percent level. More interesting on this study, however, was that by

[11] Anomalies here refer to patterns in average returns that CAPM does not explain.

employing the modern portfolio techniques[12] to create efficient portfolios out of funds, led to a statistically significant improvement in the top decile portfolios. (Elton et al., 1996)

Carhart (1997) included a momentum strategy to the three-factor model suggested by Fama and French (1996, op cit.). The momentum index was created by buying the previous years winners (top 30%) and selling the previous years losers (bottom 30%). The results from the regression analyses showed that the average four-factor alphas for the top portfolios were only marginally (and statistically insignificantly) greater than zero. However, the spread between the top and bottom funds remained statistically significant. The most persistent negative performance was detected for the bottom decile portfolio, and even the spread between the bottom portfolio and the second lowest portfolio was statistically significant. (Carhart, 1997)

> *"Good performance is associated with low expense ratios and the rank correlation coefficient suggests that expense ratios provide somewhat better predictions than the Treynor Index."* (Sharpe, 1966, op cit.)

Sharpe had already found out the explanatory power of expense ratios in 1966. Jensen (1969, op cit.) on the other hand, had acknowledged that the positive alpha might well be due to lower expenses. Although the linkage is not necessary linear between expense ratios and returns, these findings would suggest that rational investors selecting funds would include expense ratios in the decision making process. Harless and Peterson (1998) studied whether investors make choices based on the past performance (easy to compare, but the predictive validity is low) or based on expense ratios (small differences, but the predictive validity is high).

[12] The efficient portfolios were formed utilizing the Treynor-Black (1973) appraisal ratio, which had further developed into a following form: $X_i = \frac{(\alpha_i / \sigma_{\epsilon}^2)}{\sum_i (\alpha_i / \sigma_{\epsilon}^2)}$ where the X_i is the optimal weight, α_i is the fund alpha and σ_{ϵ}^2 is the variance of the error term in the four-factor model.

The results were not that surprising. Investors generally ignored the risk and expenses; the unadjusted returns had a higher positive effect to net sales than the risk-adjusted returns, and also the expense ratios had a positive effect on the net sales and total assets[13]. In addition, besides the fact that investors ignored the risk and expenses, they tended to make adjustments to fund holdings extremely slowly, allowing poorly performing mutual funds to persist. (Harless and Peterson, 1998)

A study by Detzel and Weigand (1998) decomposed the source of persistence into fund characteristics. The objective was to give for the investors a better understanding of which information is the most relevant when choosing a fund. Findings from this study suggested that investors should also consider other factors besides the past performance. (These factors included the funds size and style characteristics, and current market trends.)

The results showed that a remarkable proportion of performance persistence could be explained by the characteristics of the stocks held by a fund. The risk and expense ratios explained 15 percent of the cross-section of returns, and after the size of the stocks held by a fund and investment styles (B/M, E/M and CF/M) were incorporated, the adjusted R^2 rose to 42 percent. Adjusting the annual returns with the above mentioned variables, the average year-by-year returns became serially uncorrelated. (Detzel and Weigand, 1998)

Results from Prather et al. (2004) are consistent with the findings from Detzel and Weigand. After adjusting the fund performance with the investment objectives, the specific factors affecting to the fund performance were; P/E, CF/B, expense ratio, market capitalization and the number of funds under management. Instead, the lagged performance

[13] Positive coefficients could indicate that the funds with higher expense ratios were more popular and larger than the funds with lower expense ratios.

measure had a negative coefficient, which indicated a reversal pattern in past performance. (Prather et al., 2004)

Babalos et al. (2007) compared the ex post verification problem of the performance persistence. The study included funds from the Greek market during the years from 1998 to 2004, and the results suggested strong performance persistence when single-index models or the Sharpe ratio were utilized. However, employing multi-index models reversed the results, and only a weak persistence was discovered before the year 2001. The most appropriate performance measure according to the authors was the augmented Carhart measure which, in addition to original Carhart measure, included the yield from the bond index. (Babalos et al., 2007)

Pätäri and Tolvanen (2008) studied performance persistence among hedge funds. The performance persistence was examined with stacked return time series, constructed for top and bottom quartile portfolios. The employed performance measures included: Sharpe Ratio, 9-factor alphas and corresponding Bayesian 9-factor alphas. The authors concluded that the performance persistence varies strongly among fund styles and depends on the selected performance metrics. The cross-sectional regression tests showed that the most sensitive in detecting performance was the Sharpe ratio. (Pätäri and Tolvanen, 2008)

2.4. Downside risk -based performance measures

The academics and practitioners have for long debated about the appropriateness of the mean-variance risk measure derived from the CAPM. The CAPM model relies on the assumption that investors have mean-variance preferences[14] and returns are normally distributed. On the contrary, the empirical studies have shown that the returns generally are not symmetrical and have fat tails (Galagedera, 2007; 4). The basis of the critics for the mean-variance CAPM has been that, in general, investors do not advocate the upside volatility. From the investor's point of view, when the markets are rising, it is good to have more volatile stocks in the portfolio, and the risk of a portfolio should rather be related to portfolios reactions for the downside market movements.

Hwang and Pedersen (2004) studied if the downside risk measures could be used to capture the risk of asset returns in emerging markets. The authors tested the appropriateness of the mean-variance CAPM with two asymmetric risk measures, LPM-CAPM[15] and ARM[16]. The S&P 500 index[17] was used as a benchmark index and a three-month US treasury bill as the risk-free rate of return. The results showed that the CAPM is as suitable for emerging markets as for the FTSE Small Cap equities. Also the number of equities benefiting from downside risk measures was not significant, and the CAPM model explained at least as much as the LPM-CAPM and the ARM in approximately 80 percent of cases. The asymmetric measures were most useful in explaining the returns in some African countries.

The South Asian and the East Asian markets, however, showed signs of maturing, and 85 percent of the returns did not reject the normality hypothesis at ten percent level. For the second sub-period (1998-2002), after the data from the Asian currency crisis had been removed, the CAPM

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[14] The investor finds the risk of an asset to be its standard deviation from its expected return. The mean-variance models also assume that both the upside and downside movements are equally risky.
[15]The LPM-CAPM (the Lower Partial Moment CAPM) is equivalent to CAPM, but the volatility (or beta) is calculated with the values lower than the target return, which in this study was the risk-free rate of return.
[16] The ARM (a general Asymmetric Response Model) is an asymmetric risk measure free of equilibrium assumptions.
[17] Hwang and Pedersen (2004, op cit.) tried to convince the incorporation of the S&P 500 index as a benchmark index by "selecting the American investor's perspective". However, everyone knows that using 500 largest US corporations as a global benchmark will only lead to spurious results.

was chosen for approximately 94 percent of stocks in the East Asia. Also the non-normality dropped further after the Asian currency crisis data was removed, and in the East Asian countries, more than 70 percent of stock returns were normally distributed at five percent level. (Hwang and Pedersen, 2004)

Estrada (2007) compared the explanatory power of the CAPM beta and the downside beta in the developed markets and in the emerging markets. The main conclusion was that the downside beta provided a more trustworthy measure of risk than the beta coefficient from the traditional CAPM model. Estrada also pointed out that the downside beta is more useful, the more skewed the returns are.

Estrada used in his model the MSCI All Country World Index as the benchmark index (which is a far more proper benchmark than the S&P 500 index used by Hwang and Pedersen (2004, op cit.)) and the downside beta was estimated by using the observations when the market returns were below the average. The results showed that the downside betas could explain substantially larger portion of the variability in mean returns. For emerging markets sample the explanatory power of the mean-variance beta and the downside beta were 0.36 and 0.55, respectively. In the developing markets sample, however, none of the risk measures could significantly explain the cross-section of returns. (Estrada, 2007)

3. Performance measures

The modern portfolio theory in the 1950s and the CAPM model in the mid 1960s had a major role in creation of performance measures, which could account for different risk profiles between assets. In the 1960s, three performance measures (Treynor ratio, Sharpe ratio and Jensen alpha) were developed, and although these measures have been criticized many times during the past few decades, these measures are still the most commonly used measures for fund performance evaluation (after raw returns).

The performance measures employed in this study include; the raw returns, the Sharpe ratio, the Jensen measure, the Treynor ratio and its augmented version, downside Treynor, and a three-index model suggested by Fama and French (1996, op cit.). The selection ability of the shrunk estimates from the three-factor model alpha is also tested. The iterative Bayesian shrinkage procedure will be introduced in 4.2.1.

3.1. Raw returns

The raw return is the most common performance measure, and therefore, also the calculation has to be briefly covered. The methods for calculating raw returns may vary significantly, and since the data used in this study is from the Morningstar database, their method is introduced.

Morningstar calculates the total returns by dividing the change of fund's net asset value (the capital gains and dividends are assumed to be reinvested) by the initial net asset value. The net asset values have been adjusted with management fees and all the other automatically deducted costs. Hence, the total returns have not been adjusted with load fees. The calculation can be presented in a following manner: (Morningstar, 2008a)

$$R_i = \frac{NAV_t - Exp + D - NAV_{t-1}}{NAV_{t-1}} \qquad (1)$$

R_i = Total return for fund i

NAV_t = Net asset value of the fund at time t

Exp = Automatically deducted costs for the fund

D = Received dividends and interest payments

NAV_{t-1} = Net asset value of the fund at time t-1

3.2. Sharpe ratio

To derive the Sharpe measure, we need to first remind ourselves about the Markowitz portfolio theory, and especially the efficient frontier. In short, the efficient frontier shows the highest possible expected return for a portfolio for a given amount of risk. Figure 1, shows the efficient frontier in a return volatility space. The concave line presents all the efficient possibilities investor can choose from (that is, an investor can not create combinations from stocks that would have a higher expected return with the same amount of risk). Both funds, A and B, lie on the efficient frontier, and therefore, the choice between these funds relies only on investor's risk preferences. The fund manager's job is to offer portfolios which lie on the efficient frontier.

> *"The tasks of the mutual fund include security analysis, portfolio analysis, and the selection of a portfolio in the desired risk class."* (Sharpe, 1966)

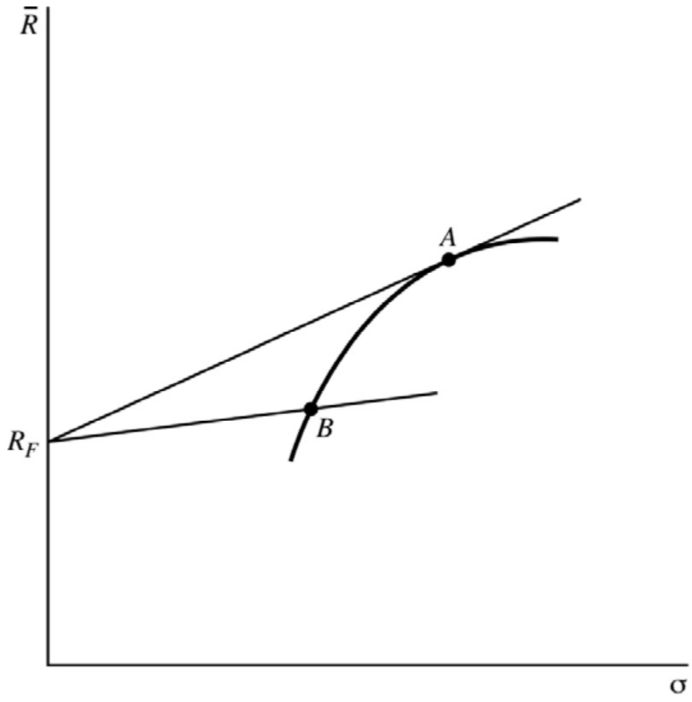

Figure 1: Portfolio selection from the efficient frontier (Elton et al., 2003; 626).

Figure 1 shows that although both funds, A and B, are efficient, it is possible to rank these portfolios in presence of a risk-free asset. The best portfolio available is the tangency portfolio A, and the line $R_F A$ represents all the available return-standard deviation possibilities investor can choose from by selecting different proportions invested in the risk-free asset and in the fund A. Now, for example, instead of investing in the portfolio B, investor could receive higher return with an equal volatility by selecting a point from the line $R_F A$ and investing part of her wealth in the portfolio A and the rest in the risk-free asset.

At first sight, it seems a bit difficult and time-consuming to rank funds in return-standard deviation space. Luckily, this same portfolio, and equivalent portfolio rankings can be done in a much easier way. The Sharpe measure finds the same, the best possible portfolio, simply by dividing the funds excess return by its standard deviation. The Sharpe ratio (or reward-to-variability ratio) can be presented as follows:

$$S_i = \frac{R_i - R_f}{\sigma_i} \quad (2)$$

S_i = Sharpe ratio for fund *i*

R_i = Return for fund *i*

R_f = Risk-free rate of return

σ_i = standard deviation for fund *i*

Figure 2 shows more accurately how the mechanism behind the formula above works. The Sharpe ratio chooses the fund that has the steepest slope with the risk-free rate of return. From the figure, it is also easy to see how sensitive the ranking is for the choice of risk-free asset. Fund B would be ranked first if the risk-free rate of return was lower, and a higher risk-free rate of return would alter the ranking order for funds B and C.

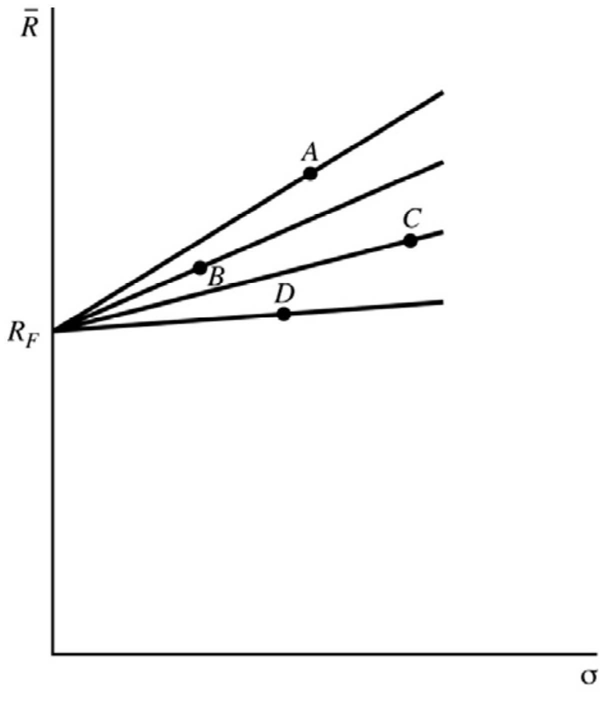

Figure 2: Possible investment combinations with a risk-free asset and risky portfolios (Elton et al. 2003; 627).

3.3. Treynor measure

Treynor (1965, op cit.) was first to suggest a performance measure which could also adjust for different levels of risk. The Treynor ratio ranks funds by dividing the fund's excess return by its systematic risk. Although the previously presented Sharpe ratio measured funds excess return to its total risk, standard deviation, the connection between these two performance measures can easily be seen by comparing Figure 2 on the previous page and Figure 3 below.

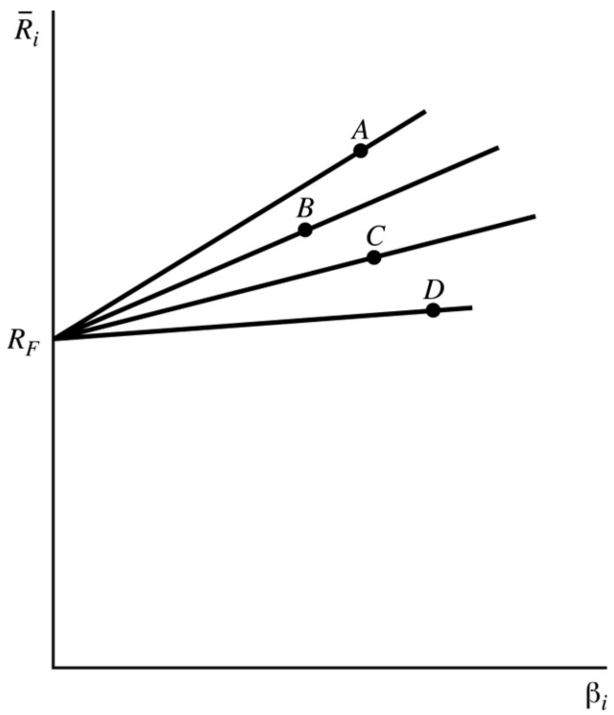

Figure 3: The mechanism behind the Treynor ratio (Elton et al. 2003; 633)

The only difference between these two figures is the changed risk measure. However, the interpretations are the same; the fund with the highest slope will dominate all the other funds. The risk parameter for the Treynor ratio was derived from the characteristic line[18]. Treynor had noticed that the fund returns fell to a linear line in respect to market return

[18] Treynor called the security market line, "the characteristic line", and the slope of the line (the risk or the beta coefficient) was referred "volatility".

even though the returns were volatile during the observation period (1954-1963). This market sensitivity can be estimated with a following formula:

$$\beta_i = \frac{Cov(R_i, R_m)}{VAR(R_m)} \tag{3}$$

β_i = Beta coefficient (or the market sensitivity) for fund *i*

$Cov(R_i, R_m)$ = Covariance between the fund *i* return and the market return

$VAR(R_m)$ = Variance of the market return

Utilizing the beta coefficient derived above, the Treynor ratio is written as follows:

$$T_i = \frac{R_i - R_f}{\beta_i} \tag{4}$$

T_i = Treynor ratio for fund *i*

R_i = Return for fund *i*

R_f = Risk-free rate of return

β_i = Beta coefficient for fund *i*

Sharpe (1966, op cit.), criticized the Treynor measure[19] for its inability to take different levels of diversification into account. However, Treynor had already pointed out that the risk beside the market risk is a response for the particular stocks that fund holds and if the fund is properly diversified, this risk will tend to average out (Treynor, 1965; 66).

[19] Treynor ratio, also known as the reward-to-volatility ratio.

3.4. Downside Treynor ratio

The academics have for long debated about the appropriateness of the mean-variance risk measures. During the last few decades, several articles have presented various downside risk measures, which could be used to improve the mean-variance CAPM. The most common downside risk -based model has been the Lower Partial Model (LPM), which proxies the risk of an asset to be its deviations below the prespecified target rate of return. According to Harlow and Rao (1989), the market participants find the risk as the downside deviations below the average market returns.

The semi-variance approach presented here, utilizes the monthly observations below the median market return from a 36-month period. Thereby, the estimated beta coefficients are estimated from 18 monthly observations. The downside Treynor is estimated with a following formula:

$$DT_i = \frac{R_i - R_f}{\beta_{iD}} \quad (5)$$

DT_i = Downside Treynor ratio

R_i = Return for fund i

R_f = Risk-free rate of return

β_{iD} = Beta coefficient from the observations below the median market return

The downside Treynor ratio from this formula should detect the convexity from the fund returns, and thereby, reward the convex security market lines and downgrade the concave ones. Figure 4 shows how the convexity in returns will affect on the beta estimates. Slope from the line A presents an estimation with the mean-variance model and slope from the line B presents an estimation from the downside deviations. The estimated beta coefficient from the downside deviations (the line B) is a more trustworthy measure of risk, if the investor is averse to the fund's reactions for the below median market movements. If the investor is not averse to the upside volatility, the beta coefficient from the line A will exaggerate the fund's risk. The downside Treynor employs the beta coefficient from the line B, and therefore, the estimated performance measure will have substantially higher value than the Treynor ratio estimated with a beta coefficient from the line A.

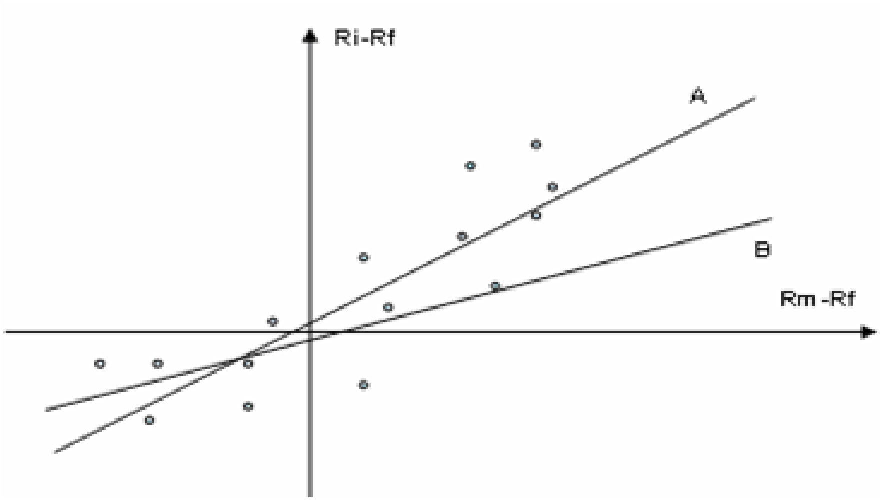

Figure 4: The line A represents the security market line from all of the observations and the line B presents the security market line estimated from the downside market deviations.

3.5. Jensen measure

The performance measures presented earlier do not quantify the value added, and thereby, can only be used for ranking funds. Jensen (1968, op cit.) utilized the security market line and developed a performance measure, which calculates the differential return between the realized returns and returns which are expected by the CAPM.

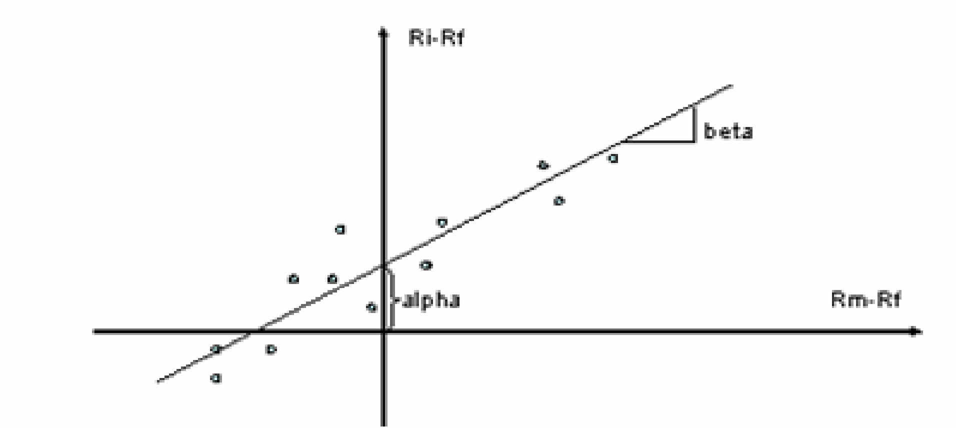

Figure 5: The derivation of the Jensen measure (alpha).

The mechanics for deriving the Jensen measure (alpha) can be seen from Figure 5. The returns for fund *i* and for the market returns are represented as excess returns (that is, the risk-free rate of return has been deducted from the returns), and therefore, the expected security market line will cross the y-axis through the origin. The difference from the expected cut-point is the Jensen measure. This differential return also quantifies the value added. E.g., if the point estimates present monthly observations, the alpha presented in the Figure 5 shows the monthly excess return for the fund *i*. The Jensen measure can be estimated with the following formula:

$$R_i - R_f = \alpha_i + \beta_i (R_m - R_f) + \varepsilon_i \qquad (6)$$

α_i = Intercept of the regression model, the Jensen measure for fund *i*

R_i = Return for fund *i*

R_m = Market return

R_f = Risk-free rate of return

β_i = Beta coefficient for fund *i*

ε_i = Error term for fund *i*, which has an expected value of zero

Jensen (1969, op cit.) acknowledged the critics by Sharpe (1966, op cit.), and the fact that the beta coefficient is an appropriate risk measure only if the portfolio is sufficiently diversified. However, Jensen came to a conclusion that if the fund manager had superior information about the future, she should hold a less diversified portfolio. Therefore, the alpha measures only the fund manager's ability to pick stocks, not the efficient diversification.

3.6. Multi-index model

Fama and French (1992, op cit.) showed that the market risk could not explain the variability in the cross-section of returns. Instead, the market equity (size factor) and the book equity-to-market equity (style factor) explained statistically significantly the cross-sections of realized returns. After the incorporation of the size factor, including the market risk improved the explanatory power of the model. The following formula follows the one suggested by Fama and French (1996, op cit.):

$$R_i - R_f = \alpha_i + \beta_{iM}(R_m - R_f) + \beta_{iSMB} SMB + \beta_{iHML} HML + \varepsilon_i \quad (7)$$

α_i = Intercept of the regression model, the performance measure for fund *i*

R_i = Return for fund *i*

R_m = Market return

R_f = Risk-free rate of return

β_{ij} = Fund *i*'s sensitivity to factor *j* (*j* = M, SMB and HML)

SMB = Differential return of small cap stocks and large cap stocks

HML = Differential return of value stocks and growth stocks

ε_i = Error term for fund *i*, which has an expected value of zero

The presented formula decomposes the fund's excess returns into market returns, the returns from buying small cap stocks and selling large cap stocks, and the returns from buying high book-to-market equity stocks and selling low book-to-market equity stocks (Babalos et al. 2007, op cit.). Thereby, the constant from this regression model should provide a more accurate performance measure, which also takes different investment styles into account.

The multi-index model has also been used in 4.4., where funds percentage returns[20] have been explained with accounting variables and the market risk. Thereby, the following formula will present the multi-index model in a generic form:

$$R_i = \alpha_i + \sum_{k=1}^{K} \beta_{ik} F_k + \varepsilon_i \tag{8}$$

α_i = Constant in the regression model

R_i = Return for fund *i*

β_{ik} = Factor loading of fund *i* to factor *k*

F_k = Return for factor *k*

ε_i = Error term

[20] Also the regression models presented in 4.3., utilize percentage returns. All the other regression models presented in this study employ logarithmic excess returns.

4. Empirical analysis

The fund data for this thesis is from the Morningstar database, and the overall data includes 2,168 European open-end mutual funds which objective is to invest in the Asia-Pacific (Japan excluded). The fund is defined in this category if over 75 percent of stocks held by the fund have been invested in Asia-Pacific, and less than ten percent of stocks have been invested in Japan (Morningstar, 2008a). The FTSE AW APAC; Japan excluded -index is used as a proxy for benchmark index for the full sample analysis, and since all the returns are on monthly basis and in euros, the risk-free rate of return is the one-month euribor[21]. The benchmark indexes for the country-specific analyses have been retrieved from DataStream database. These indexes include; the MSCI country-specific index and the style indexes (growth, value, small cap and large cap) for China, India and Taiwan. These indexes are dollar denominated, and therefore, total return time series have been translated into euros before further calculations.

The data suffers from the survivorship bias, and therefore, some of the persistence found among the "winners" might be due to this fact. However, according to the literature, if the performance persistence exists, it is mainly due to repeating "losers"[22]. Therefore, intuitively the survivorship bias should have an opposite effect on the overall results reported from hereafter. Also, the data includes time series for all investment classes and for all currencies. Employing several time series for one fund could have caused an unwanted correlation between the fund returns, and therefore, only one fund per FundId was retained. The exclusions were made by following criteria:

[21] Appendix A shows the calculation method used to converting the annualized monthly risk-free rate of return to monthly logarithmic risk-free rate of return.
[22] E.g., see Jensen (1969, op cit.) or Porter and Trifts (1998, op cit.).

1. Longest track record (the primary purpose of the fund)
2. Currency (euro over dollar, and dollar over the rest)
3. Accrued over income
4. Investment class (starting from A)

Also funds with an incomplete return time series were excluded, and after these exclusions, the number of funds was reduced to 994. Finally, a large number of Malaysian funds (83) were excluded, because these funds had a vast number of missing values in 2006 and 2007. The final number of funds included for further analyses became 911. Table 1 presents statistics from the sample.

Table 1: Statistics from the sample, 1999-2007 (annualized).

	Year								
	1999	2000	2001	2002	2003	2004	2005	2006	2007
Number of funds	416	471	531	573	623	677	746	827	911
Low	2 %	-65 %	-37 %	-58 %	-19 %	-30 %	-8 %	-54 %	-34 %
High	551 %	56 %	83 %	42 %	201 %	78 %	160 %	138 %	137 %
Median	**88 %**	**-28 %**	**2 %**	**-23 %**	**21 %**	**5 %**	**37 %**	**18 %**	**23 %**
Std. deviation	0.44	0.17	0.20	0.11	0.23	0.09	0.19	0.18	0.19
Avg. deviation	0.29	0.13	0.15	0.08	0.15	0.07	0.13	0.12	0.14
FTSE APAC	**73 %**	**-19 %**	**2 %**	**-21 %**	**23 %**	**15 %**	**40 %**	**19 %**	**26 %**

The number of (survived) funds has steadily increased from 416 in 1999 to 911 in 2007. The standard deviation of the annual returns was in its highest level in 1999, and thereafter, the variability of annual returns has remained quite stable. On average, the median European mutual fund investing in the Asia-Pacific (Japan excluded) has reached to an average annual return of 11.3 percent while the average annualized return from the benchmark index has been 14.3 percent. Thereby, the median fund has earned on average three percents (annually) less than the passive benchmark index (with survivorship bias!!).

The reason for the selected time period is to exclude the data during the Asian currency crisis in 1997. Calculating market sensitivities during this time period could have led to unreliable results (e.g., some Indian funds would have received seemingly low beta coefficients, approximately 0.3, from a 36-month selection period from 1997 to 1999). Also, as Hwang and Pedersen (2004, op cit.) found out in their study, removing the currency crisis data from the sample improved significantly the normality of the returns. In this study, 80 percent of logarithmic return distributions do not reject the normality hypothesis[23].

Though excluding the data before the year 1999 unquestionably improved the normality of returns, the variation of the returns from year-to-year still remained relatively high as can be seen from Table 1. In 1999 the stock market was still recovering from the severe impact of the currency crisis and during the following years, the burst of the dot-com bubble increased the uncertainty. In 2003, however, the investors received back their confidence on the growth in the Asia-Pacific. Figure 6 shows the development of the benchmark index from 1999 to 2007.

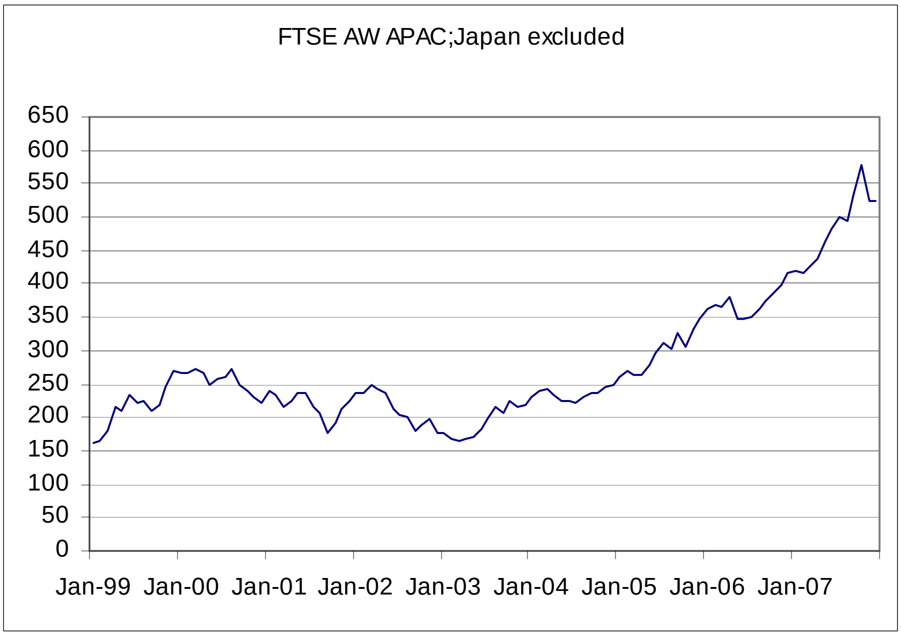

Figure 6: The development of the benchmark index from 1999 to 2007.

As can be seen from the Figure 6, the market trend has changed twice during the past nine-year period, and the length for the previous bull and bear market has been approximately the same. Therefore, the expected

[23] The normality of returns was examined with Jarque-Bera test. The formula is described in Appendix A.

probability for detecting performance persistence during the selected time period is not very high (or the performance of a fund should persist regardless of the market trend).

The first part of this section concentrates on detecting performance persistence employing the full fund sample and a single benchmark index. Contingency tables have been used to determine whether past winners repeat or not, and the methods and the presentation format follow the working paper of Babalos et al. (2007, op cit.) with a small distinction. Instead of using one-year selection and holding periods, three-year selection and holding periods are used. The reason for this is the use of monthly return observations instead of weekly observations. Finally, the difference between investing in the top decile portfolio and the bottom decile portfolio quantifies the difference of risk-adjusted performance by selecting winners instead of losers.

The second part of this section narrows up the investment objective to single countries, and also the single-index model is changed to a three-factor model, suggested by Fama and French (1996, op cit.). Also the Bayesian shrinkage procedure is introduced and the predictive accuracy of these estimates is tested. The stacked returns time series introduced in 4.1.3 is used to estimate the statistical significance of the results. The third part of this section presents results from market neutral long/short investment strategy, and finally, the fourth part of this section follows the study by Detzel & Weigand (1998, op cit.) and tries to find out whether simple accounting variables can explain the cross-section of fund returns.

4.1. Full sample; Asia-Pacific

In the first part of our empirical analysis we employ the full sample (911 funds) and try to find out whether performance persistence can be detected in a large scale. First, a contingency analysis employs simple performance measures and determines whether an investor can utilize the information provided by these measures. Second, stacked return time series quantifies the risk-adjusted returns received by selling the worst performing decile and buying the best performing decile.

4.1.1. Contingency analysis; the methodology

The following contingency analysis presents corresponding contingency tables which Babalos et al. (2007, op cit.) utilized in their study. However, the multi-index models have been excluded, and the compared performance measures include; raw returns, Jensen measure, Sharpe ratio, Treynor ratio and downside Treynor ratio.

The deployed non-parametric tests are the Z-test by Malkiel (1995, op cit.), the cross-product ratio test by Brown and Goetzmann (1995) and the chi-square test by Kahn and Rudd (1995)[24]. The null hypothesis for all these tests is that the performance persistence does not exist. The formulas are introduced in a form that were also presented by Babalos et al. (2007, op cit.).

In the test by Malkiel (1995, op cit), the past winner (W) has an equal probability to be a winner (W) or a loser (L) in the subsequent period. The test statistic follows a standard normal distribution and is calculated as follows:

$$M = \frac{(WW - (WW + WL) * 0.5)}{\sqrt{(WW + WL) * 0.5 * 0.5}} \qquad (9)$$

[24] Kahn and Rudd (1995) studied a sample of 150 equity funds, and found no evidence of persistence in the time-period from 1988 to 1993. Brown and Goetzmann (1995) found relative performance persistence from the period of 1976 to 1988. Malkiel (1995, op cit.) found performance persistence in 1971 to 1979, but the persistence faded away in the subsequent period (1980 to 1991).

In the cross-product ratio (CPR) by Brown and Goetzmann (1995) the number of funds changing category in the next period equals the number of funds remaining in the same category. The CPR values greater than unity indicate persistence and values smaller than unity indicate reversal.

$$CPR = \frac{WW * LL}{WL * LW} \tag{10}$$

The statistical significance is determined with a following Z-test.

$$z = \frac{\ln CPR}{\sqrt{\frac{1}{WW} + \frac{1}{LL} + \frac{1}{WL} + \frac{1}{LW}}} \tag{11}$$

Finally, the chi-square test by Kahn and Rudd (1995) compares whether the observed frequencies and the expected frequencies (N/4) differs statistically significantly. The chi-square statistic follows a chi-square distribution with one degree of freedom.

$$\chi^2 = \frac{(WW - N/4)^2}{N/4} + \frac{(WL - N/4)^2}{N/4} + \frac{(LW - N/4)^2}{N/4} + \frac{(LL - N/4)^2}{N/4} \tag{12}$$

4.1.2 Contingency analysis; empirical results

The first performance measure used is the raw returns. Table 2 shows that the performance persistence has been strong throughout the time period and the overall results show that on average the winners have high probability (58%) of remaining winners in the subsequent period[25]. The only period when the performance persistence among the winners was not

[25] The cut-point in the subsequent period is calculated from the all available funds in that particular period. Therefore, the winner in the selection period also has to beat the funds which have emerged during the selection period, to become a winner in the subsequent period.

statistically significant (Malkiel's Z-test), was the period from 01/03 to 04/06 even though 55 percent of the past winners did repeat.

Table 2: **Raw returns**
Contingency table; a three-year selection period and a three-year holding period

	Number of					%	Malkiel		B&G	K&R
	Funds	WW	WL	LW	LL	**Repeat W**	Z-test	CPR	Z-stat	chi²
99-01/02-04	416	120	88	79	129	**0.58**	2.22*	2.23	4.00**	16.94**
00-02/03-05	471	137	98	102	134	**0.58**	2.54**	1.84	3.26**	10.81**
01-03/04-06	532	145	121	116	150	**0.55**	1.47	1.55	2.51**	6.51*
02-04/05-07	573	175	111	93	194	**0.61**	3.78**	3.29	6.80**	49.90**
Total	1992	577	418	390	607	**0.58**	5.04**	2.15	8.38**	72.66**

(*) statistically significant at 5% level (**) significant at 1% level

The results are quite similar to the results from the Greek markets by Babalos et al. (2007, op cit.). The largest distinction is that even during the market trend change, the proportion of repeating winners remained well over 50 percent (55%) while in the Greek market, only 41 percent of the past winners repeated (with one-year selection and one-year holding periods). One reason for the existence of repeating winners might be that when returns are compared without adjusting for risk, the most volatile and aggressive mutual funds tend to benefit the most from the positive market trend. This does not, however, explain the repeating winners (although insignificant) in the period from 01/03 to 04/06 (see Figure 6 on page 30). Another source of persistence might be the survivorship bias. It is very likely that especially during the period from 2001 to 2003 a notable number of funds might have been ceased to exist. Nevertheless, this does not explain the even higher proportion of repeating losers (61% overall[26]).

The following performance measure, the Sharpe ratio, takes the total risk of a fund into account and should therefore provide more trustworthy results of performance persistence. Table 3 shows the mixed results

[26] It should be noted that the row "total" shows serially correlated values; the subsequent periods have two uniform years with previous three year period.

compared to the previous table. In the first and the last comparison periods, the proportion of repeating winners increased, but during the middle periods, the proportion of repeating winners fell below the average and in the period from 01/03 to 04/06, the reversal was even statistically significant. The overall results, however, suggest that although the performance persistence existed only in two sub-periods out of four, the performance persistence was statistically significant at one percent level during the entire sample period. One plausible explanation for the detected performance persistence could be that the different investment styles have generated unequal returns with same volatility. The most plausible explanation, however, is the differences in volatilities and returns in different economies in Asia-Pacific.

Table 3: **Sharpe ratio**

Contingency table; a three-year selection period and a three-year holding period

	Number of					%	Malkiel		B&G	
	Funds	WW	WL	LW	LL	**Repeat W**	Z-test	CPR	Z-stat	chi^2
99-01/02-04	416	123	85	76	132	**0.59**	2.63**	2.51	4.57**	22.02**
00-02/03-05	471	112	123	125	111	**0.48**	-0.72	0.81	-1.15	1.35
01-03/04-06	532	121	145	144	122	**0.45**	-1.47	0.71	-1.99*	3.98*
02-04/05-07	573	184	102	82	205	**0.64**	4.85**	4.51	8.38**	76.28**
Total	1992	540	455	427	570	**0.54**	2.69**	1.58	5.10**	27.79**

(*) statistically significant at 5% level (**) significant at 1% level

Table 4 presents the results from the next performance measure, the Jensen alpha. Compared with the raw returns, the most significant change is in the period from 01/03 to 04/06 when the proportion of repeating winners, ranked with the Jensen alpha, fell below the average (48%). When the results are compared with the Sharpe ratio, the most notable difference can be found from the period from 00/02 to 03/05, where the repeating winners remained below the average (48%) when the ranking and evaluation was made with the Sharpe ratio, while the ranking with the Jensen alpha showed statistically significant repeating winners (57%). One plausible explanation for this difference could be that the Asia-Pacific area, Japan excluded, includes several separate economies, and hence, the market returns from these areas do not react simultaneously and at the same scale for the overall market movements.

Table 4: **Jensen alpha**
Contingency table; a three-year selection period and a three-year holding period

	Number of					%	Malkiel		B&G	
	Funds	WW	WL	LW	LL	**Repeat W**	Z-test	CPR	Z-stat	chi²
99-01/02-04	416	120	88	79	129	**0.58**	2.22*	2.23	4.00**	16.94**
00-02/03-05	471	134	101	96	140	**0.57**	2.15*	1.93	3.53**	12.85**
01-03/04-06	532	127	139	124	142	**0.48**	-0.74	1.05	0.26	1.76
02-04/05-07	573	180	106	89	198	**0.63**	4.38**	3.78	7.52**	60.58**
Total	1992	561	434	388	609	**0.56**	4.03**	2.03	7.76**	65.23**

(*) statistically significant at 5% level (**) significant at 1% level

Like the Jensen measure, also the Treynor ratio measures the performance of a fund by adjusting the fund's excess returns with its market risk. However, the Treynor ratio takes account the dispersion of the returns around the security market line, and hence, is more related to actual returns the investor receives. The results shown in the Table 5, however, do not significantly differ from the results received by using the Jensen measure. The proportion of repeating winners in the third period rises to 50 percent and the total proportion of repeating losers reaches the highest of all measures, over 61 percent.

Table 5: **Treynor ratio**
Contingency table; a three-year selection period and a three-year holding period

	Number of					%	Malkiel		B&G	
	Funds	WW	WL	LW	LL	**Repeat W**	Z-test	CPR	Z-stat	chi²
99-01/02-04	416	121	87	79	129	**0.58**	2.36**	2.27	4.09**	17.58**
00-02/03-05	471	130	105	101	135	**0.55**	1.63	1.65	2.71**	7.56**
01-03/04-06	532	133	133	119	147	**0.50**	0.00	1.24	1.22	2.95
02-04/05-07	573	182	104	87	200	**0.64**	4.61**	4.02	7.83**	65.81**
Total	1992	566	429	386	611	**0.57**	4.34**	2.09	8.07**	69.67**

(*) statistically significant at 5% level (**) significant at 1% level

The results from the final measure, the downside Treynor ratio, are shown in Table 6. In the third period, from 01/03 to 04/06, the performance persistence is reversed again, and the reversal among winners is statistically significant at five percent level. On the other hand, in the other three periods, ranking funds with the downside Treynor leads to a stable persistence among winners in the subsequent periods, and the proportion of repeating winners is approximately 60 percent.

Table 6: Downside Treynor ratio
Contingency table; a three-year selection period and a three-year holding period

	Number of					%	Malkiel		B&G	
	Funds	WW	WL	LW	LL	**Repeat W**	Z-test	CPR	Z-stat	chi²
99-01/02-04	416	124	84	76	132	**0.60**	2.77**	2.56	4.67**	22.77**
00-02/03-05	471	139	96	96	140	**0.59**	2.81**	2.11	3.99**	16.07**
01-03/04-06	532	118	148	137	129	**0.44**	-1.84*	0.75	-1.65*	3.62
02-04/05-07	573	169	117	96	191	**0.59**	3.07**	2.87	6.08**	40.94**
Total	1992	550	445	405	592	**0.55**	3.33**	1.81	6.52**	46.18**

(*) statistically significant at 5% level (**) significant at 1% level

These results for persistent winners can not be considered absolutely reliable due the survivorship bias. However, the survivorship bias makes the strong persistence among the losers even more reliable. Also, using a single-index model in a wide market area could have caused the observed performance persistence. Nevertheless, the following stacked return time series tries to increase the reliability of the results.

4.1.3. Stacked time series regressions

To test more accurately, how much it benefits to invest in the top decile portfolio rather than in the bottom decile portfolio, stacked return time series are constructed for the top and bottom deciles. The idea is to create an annually adjusted portfolio for winners and losers, based on the previous three-year selection period. The resulting time series for top and bottom portfolios will have 72 monthly observations (2002 to 2007), and these time series are regressed on the benchmark index. Consequently, the statistical significance of the difference of the constants from these regression models (the Jensen alphas) is evaluated[27].

Table 7: The difference of investing in the top and bottom portfolios (2002-07).

Ranking on	Portfolio	LN Alpha (monthly)	s.e.	Annualized difference	Welch's t-value	sig.
Panel A: 2002-2007						
Raw return	Top decile	0.0033	0.0031	**7.83 %**	1.28	0.204
	Bottom decile	*-0.0030*	0.0038			
Jensen alpha	Top decile	0.0043	0.0031	**10.34 %**	1.52	0.131
	Bottom decile	*-0.0039*	0.0044			
Sharpe ratio	Top decile	0.0029	0.0028	**8.35 %**	1.45	0.148
	Bottom decile	*-0.0038*	0.0036			
Treynor ratio	Top decile	0.0044	0.0031	**9.43 %**	1.55	0.122
	Bottom decile	*-0.0031*	0.0037			
Downside Treynor	Top decile	0.0001	0.0034	**2.00 %**	0.33	0.742
	Bottom decile	*-0.0016*	0.0037			
Panel B: 2002-2004						
Raw return	Top decile	0.0021	0.0032	**6.58 %**	1.03	0.306
	Bottom decile	*-0.0032*	0.0041			
Jensen alpha	Top decile	0.0021	0.0032	**5.12 %**	0.80	0.425
	Bottom decile	*-0.0020*	0.0041			
Sharpe ratio	Top decile	0.0020	0.0032	**5.73 %**	1.03	0.306
	Bottom decile	*-0.0027*	0.0032			
Treynor ratio	Top decile	0.0022	0.0033	**5.61 %**	0.93	0.354
	Bottom decile	*-0.0024*	0.0036			
Downside Treynor	Top decile	-0.0001	0.0040	**1.72 %**	0.30	0.768
	Bottom decile	*-0.0015*	0.0038			
Panel C: 2005-2007						
Raw return	Top decile	0.0051	0.0059	**7.50 %**	0.67	0.505
	Bottom decile	*-0.0010*	0.0068			
Jensen alpha	Top decile	0.0071	0.0057	**14.88 %**	1.13	0.261
	Bottom decile	*-0.0045*	0.0085			
Sharpe ratio	Top decile	0.0049	0.0050	**10.20 %**	0.94	0.350
	Bottom decile	*-0.0032*	0.0070			
Treynor ratio	Top decile	0.0069	0.0056	**11.89 %**	1.04	0.301
	Bottom decile	*-0.0025*	0.0070			
Downside Treynor	Top decile	*0.0014*	0.0065	**1.23 %**	0.10	0.914
	Bottom decile	*0.0004*	0.0068			

[27] The survivorship bias has an opposite effect on the observed results than, for example, for the results for repeating winners at 4.1.2. The presumption here is that the worst performing funds are those that in general cease to exist, and therefore, the spread between top and bottom funds deteriorates.

Table 7 presents the results and statistical significances of alpha spreads from these regression models[28]. The annual difference by using simple performance measures for fund selection shows that by investing in the top portfolios would generate on average substantially higher risk-adjusted returns compared to the returns of the bottom portfolios. Portfolios with the widest alpha spreads were selected with the Jensen alpha (the average annual alpha spread was over 10%). Even the average annual alpha spread from portfolios selected by raw returns was more than seven percent.

The created downside risk -based performance measure, however, seemed to select funds randomly, and the constructed top portfolios could only marginally outperform the bottom portfolios. The change is dramatic compared to the results from contingency tables, where the winners outperformed significantly the losers three out four times. Thus, it seems that downside risk -based performance measures can only be used to predict downside measures, and therefore, based on the observed results it is not possible to determine which of the performance measures is the correct one, the semi-variance performance measure or one of the variance based performance measures.

Nevertheless, even the highest observed difference could not reach the statistical significance even at ten percent level. The reason for this can be found from standard errors, which are remarkably high during the whole sample period. Closest for statistical significance is the alpha spread from portfolios based on the Treynor ratio with a t-value of 1.55 (significant at 12% level). The alpha spreads based on the Jensen alpha and the Sharpe ratio criteria are also close to statistical significance.

[28] The regression analysis was made with a statistical program, SPSS, and the method was linear regression (equation 6) where the dependent variables were the constructed portfolios and the independent variable was the benchmark index, FTSE AW APAC; Japan excluded. On average, the regression models had adjusted r-squares of 68%, 84% and 50% for the full sample, the first period and the second period, respectively.

To increase the reliability of the results, Panel B and Panel C show the results for two sub-periods, from 2002 to 2004 and from 2005 to 2007. Although the annualized alpha spreads vary strongly, none of the risk-adjusted annualized differences falls below five percent (except for the portfolios selected with the downside measure). The most extreme variability can be seen from the risk-adjusted excess returns from portfolios selected with the Jensen measure. For the depreciating stock markets, the Jensen measure selected portfolios with second worst alpha spreads and the average annual difference fell from ten percent (full sample) to five percent. The change in the subsequent period is naturally as extreme, and in the appreciating stock markets, the average annual alpha spread between portfolios selected by the Jensen measure is as high as 15 percent.

More interesting, however, is the strong performance of raw returns in the whole sample period. Selecting winners based on raw returns generated high risk-adjusted returns (although insignificant) throughout the six-year period, and in the depreciating stock markets, the highest alpha spread was received from portfolios selected based on raw returns. Nevertheless, the top portfolios selected with either the Jensen measure or the Treynor ratio earned annually, on average, 1.3 percent higher risk-adjusted returns.

The overall results so far indicate that the investor should in general select the best performing fund instead of the worst performing fund[29]. The extremely poor performance of the downside measure, on the other hand, needs to be analysed a bit further. The observed results indicated that the downside risk -based performance measures could not be used to predict the future winners in a mean-variance framework. However, the Morningstar informs on its website, that although the Morningstar rating accounts for all variations, the weight on the downside variations is higher

[29] Due the survivorship bias, it is plausible that a large part of the worst performing funds has ceased to exist, and therefore, also the insignificance of the results could be a result from the survivorship bias.

(Morningstar, 2008b). Therefore, an additional selection method needs to be included.

The balanced performance measure employs both the downside beta and the mean-variance beta (presented in 3.3 and 3.4) with prespecified weights. The formula can be written as follows:

$$R_i - R_f = \alpha_i + (20\% * \beta_{iD} + 80\% * \beta_i)(R_m - R_f) + \varepsilon_i \qquad (13)$$

Thereby, the excess return for the fund *i* is the constant plus balanced beta times the excess return of the market rate of return. The constant is calculated to be an average residual[30] during a 36-month period. Table 8 presents the results for portfolios selected with the balanced alpha.

Table 8: The difference of investing in the top and bottom portfolios selected with a balanced alpha (20%*downside beta+80%*mean-variance beta).

Ranking on	Portfolio	LN Alpha (monthly)	s.e.	Annualized difference	Welch's t-value	sig.
Panel A: 2002-2007						
Balanced alpha	Top decile	0,0048	0,0030	**11.21%**	1.70*	0.092
	Bottom decile	*-0,0040*	0,0043			
Panel B: 2002-2004						
Balanced alpha	Top decile	0,0042	0,0030	**8.25%**	1.33	0.189
	Bottom decile	*-0,0024*	0,0040			
Panel C: 2005-2007						
Balanced alpha	Top decile	*0,0061*	0,0056	**12.79%**	1.02	0.312
	Bottom decile	*-0,0039*	0,0081			

(*) denotes statistical significance at 10% level

The overall annualized alpha spread increased almost a percentage compared to portfolios selected with an ordinary Jensen measure. Also the variability of returns slightly decreased, and therefore, the average monthly alpha spread reached statistical significance at ten percent level. In the first sub-period, the improvement in the alpha spread is even more remarkable. Compared to the results from the Jensen measure, selecting portfolios with a balanced alpha improved the average annualized alpha spreads more than three percents. In the bull markets (2005-2007),

[30] Elton et al. (1996, op cit.) calculated the three-year holding period alphas with a similar method.

however, emphasizing downside deviations slightly worsened the annual difference. The presented results suggest that in uncertainty, it is beneficial to be risk averse and overweight downside deviations even though pure downside risk measures can not be used to predict returns in the mean-variance framework.

4.2. Country-specific performance persistence

The previous analyses showed remarkable differences in risk-adjusted returns by investing either in the top portfolios or in the bottom portfolios. The Asia-Pacific is, however, a large market area, which includes several independent economies. This could also explain by and large, the observed high standard errors. To further test the reliability, the sample is divided by the funds geographical investment objectives. The selection is done by using the Morningstar fund classification, and these three sub-samples; China equity, Taiwan equity and India equity, had 76, 150 and 73 funds, respectively, at the end of the year 2007. Figure 7 shows the development of the total return indexes in the selected economies.

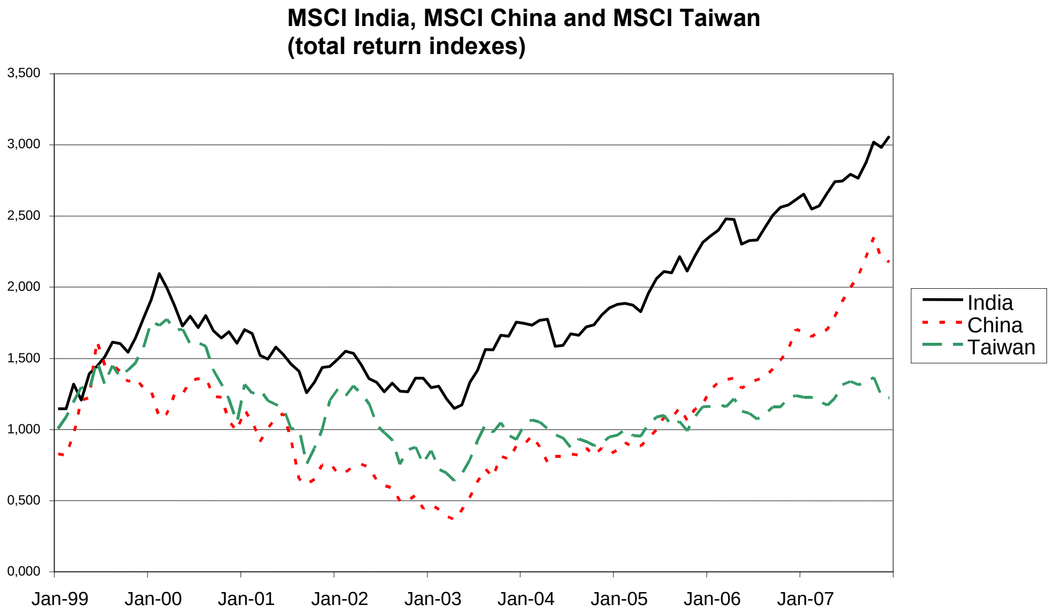

Figure 7: Cumulative logarithmic returns for benchmark indexes (1999-2007). The base value for all indexes in the beginning of the year 1999 is 1.00. The base currencies have been translated into euros before further calculations.

To evaluate more accurately the fund performance, a three-factor model by Fama and French (1996, op cit.) is employed. The factors for this model are market risk, value-minus-growth (HML) and small-minus-big stocks (SMB). The benchmark indexes for this part are from the DataStream database, and these indexes include the country-specific indexes presented in Figure 7, and the MSCI Growth, the MSCI Value, the MSCI Large Cap and the MSCI Small cap for China, India and Taiwan.

Following part presents the Bayesian shrinkage procedure and the consequent empirical part will examine whether these Bayesian estimates can help to separate skilful managers from lucky managers. The other performance measures used for selection are; the raw returns, the three-factor alpha and the Sharpe ratio. The three-factor alpha is used to evaluate the performance in the holding period. The results from the regression models might be biased because the funds can (and do) diversify the country-specific risk by investing across borders[31], and also the categories might have been changed through time (e.g., from Asia-Pacific equity fund to an India equity fund).

4.2.1. Iterative Bayesian framework

The basic idea behind the shrinkage procedure is to deploy the information revealed by the cross-section of funds instead of relying only to a number of passive indexes. Especially, if the observed funds have significant similarities, the pooled estimate could provide a more accurate benchmark than the unattached time series estimate. However, if the benchmark index provides more information and the pooled estimate is uninformative, a separate benchmark index should be used. (Huji and Verbeek, 2003)

[31] The fund is referred to as a country-specific fund if over 75% of its stocks have been invested to specified country. However, also “China-related companies” are treated as Chinese companies. (Morningstar, 2008a)

In general, both the cross-section of funds and the separate benchmark index contains some information, and hence, a weighted average would result to most reliable estimates of performance. The iterative empirical Bayesian procedure shrinks all the individual time series estimates towards the pooled estimates, and the degree of the shrinkage is determined by the reliability of the original estimates from the model (that is, less likely estimates are shrunk more towards the pooled estimate). (Huji and Verbeek, 2003)

The estimation process, presented by Huji and Verbeek (2003; 2007), begins by assuming that the priors follow normal distribution

$$\theta_i \sim N(\mu, \Sigma) \tag{14}$$

where θ_i denotes for alphas and factor sensitivities, μ denotes a (*k*+1) dimensional vector of cross-sectional means of alphas and *k* number of factor sensitivities, and Σ denotes a (*k*+1) by (*k*+1) covariance matrix of the prior estimates. Assuming the error terms independently and identically distributed, the posterior distribution of theta is normal with expectation

$$\boldsymbol{\theta}^*_i = \left(\frac{\mathbf{1}}{\boldsymbol{\sigma}_i^2} \mathbf{X}_i'\mathbf{X}_i + \boldsymbol{\Sigma}^{-1} \right)^{-1} \left(\frac{\mathbf{1}}{\boldsymbol{\sigma}_i^2} \mathbf{X}_i'\mathbf{X}_i\hat{\boldsymbol{\theta}}_i + \boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} \right) \tag{15}$$

where $\mathbf{X}_i'\mathbf{X}_i$ denotes a covariance matrix from *k*+1 factors where the additional factor is computed to unity, $\hat{\boldsymbol{\theta}}_i$ denotes for the OLS estimates, $\boldsymbol{\sigma}_i^2$ denotes the variance of the error terms and $\left(\frac{\mathbf{1}}{\boldsymbol{\sigma}_i^2} \mathbf{X}_i'\mathbf{X}_i + \boldsymbol{\Sigma}^{-1} \right)^{-1}$ denotes the corresponding covariance matrix. A recursive problem arises because to estimate the posterior parameter $\boldsymbol{\theta}_i^*$, we have to know μ, $\boldsymbol{\sigma}_i^2$ and Σ, and vice versa. Therefore, the following equations have been iteratively estimated, using the OLS estimates as the initial estimation of $\boldsymbol{\theta}_i^*$:

$$\mu^* = \frac{1}{N}\sum_{i=1}^{N}\theta_i^* \tag{16}$$

$$\sigma_i^{2*} = \frac{1}{T_i - k + 1}\left(y_i - X_i\theta_i^*\right)'\left(y_i - X_i\theta_i^*\right) \tag{17}$$

$$\Sigma^* = \frac{1}{N-1}\left[D + \sum_{i=1}^{N}\left(\theta_i^* - \mu\right)\left(\theta_i^* - \mu\right)'\right] \tag{18}$$

where N is the number of funds, T_i is the number of observations, k is the number of factors and D is the diagonal matrix to improve the convergence of the iterative process. After calculating the first estimates, the iteration process is repeated until the prespecified degree of convergence for the posteriors is reached. (Huji and Verbeek, 2003; 2007)

4.2.2. Three-year selection period

Both the selection and holding periods follow the methods presented in 4.1.3., and therefore, the first selection period is the three-year period from 1999 to 2001 and the first holding period is the year 2002. The top quartile portfolios and the bottom quartile portfolios[32] are constructed based on; the raw returns, the Sharpe ratio, the three-factor alpha and the Bayesian alpha. Thereafter, annually balanced stacked return time series are formed for the top and bottom portfolios, and finally these time series are

[32] The number of funds was too low for decile selection.

regressed with the benchmark indexes. Table 9 shows the results from these regression models[33].

Table 9: The risk-adjusted difference between top and bottom portfolio with three-year ranking and one-year holding period. Stacked return time-series from China, India and Taiwan (2002 to 2007).

Ranking on	Portfolio	LN Alpha (monthly)	s.e.	Annualized difference	Welch's t-value	sig.
Panel A: China						
Raw return	Top quartile	0.0001	0.0019	**4.80 %**	1.45	0.149
	Bottom quartile	*-0.0039*	*0.0019*			
Three-factor alpha	Top quartile	0.0002	0.0018	**4.63 %**	1.34	0.184
	Bottom quartile	*-0.0036*	*0.0022*			
Bayes	Top quartile	-0.0014	0.0020	**2.21 %**	0.64	0.521
	Bottom quartile	*-0.0032*	*0.0020*			
Sharpe ratio	Top quartile	0.0002	0.0019	**4.83 %**	1.47	0.143
	Bottom quartile	*-0.0037*	*0.0019*			
Panel B: India						
Raw return	Top quartile	-0.0005	0.0020	**3.21 %**	1.02	0.310
	Bottom quartile	*-0.0031*	*0.0017*			
Three-factor alpha	Top quartile	0,0010	0.0019	**5.05 %**	1.57	0.118
	Bottom quartile	*-0.0031*	*0.0018*			
Bayes	Top quartile	0.0007	0.0019	**3.43 %**	1.12	0.266
	Bottom quartile	*-0.0021*	*0.0016*			
Sharpe ratio	Top quartile	0.0015	0.0018	**3.50 %**	1.10	0.271
	Bottom quartile	*-0.0014*	*0.0019*			
Panel C: Taiwan						
Raw return	Top quartile	0.0044	0.0035	**0.99 %**	0.17	0.865
	Bottom quartile	*0.0036*	*0.0033*			
Three-factor alpha	Top quartile	0.0051	0.0035	**4.23 %**	0.74	0.458
	Bottom quartile	*0.0017*	*0.0030*			
Bayes	Top quartile	0.0046	0.0037	**4.69 %**	0.87	0.386
	Bottom quartile	*0.0008*	*0.0024*			
Sharpe ratio	Top quartile	0.0043	0.0034	**1.45 %**	0.26	0.797
	Bottom quartile	*0.0031*	*0.0032*			

The average adjusted r-square of the employed three-index model is significantly higher than that of the previous single-index model; approximately 92%, 96% and 85% for China, India and Taiwan, respectively. However, the results from the three-factor model also lowered the alphas, and the highest annualized alpha spreads are barely over five percent (the portfolios selected with the Jensen measure in

[33] These regression models follow the equation (6) and are made with statistical program SPSS (linear regression where the dependent variables are the stacked time series returns and the independent variables are the benchmark indexes).

India). The standard errors do not decrease any faster, and hence, the alpha spreads remain statistically insignificant. Closest to statistical significance is the alpha spread in India selected on the basis of the three-factor alpha (statistically significant at 12% level). Also the alpha spreads in China are close to statistical significance (except when the classification criterion for funds is the Bayesian alpha).

The estimated Bayesian alphas could not provide higher alpha spreads neither in China nor in India. On the contrary, selecting funds based on any other performance measure in China generated twice as high alpha spreads. In Taiwan, however, the portfolios selected with the Bayesian alpha generated the highest risk-adjusted returns while the differences between the top quartile portfolios and the bottom quartile portfolios, selected based on either raw returns or the Sharpe ratio, were only marginal.

There are several plausible explanations that could explain the observed inability of the Bayesian alphas to predict future winners. First, the number of funds was relatively low in samples of China equity funds and India equity funds, and when the sample size grew for Taiwan equity, the shrinkage procedure offered more trustworthy estimates. Second, the empirical three-factor model explained more than 90 percent of the portfolio returns in China and India, which did not leave that much to improve for the shrinkage procedure, and when the adjusted r-square fell to 84 percent in Taiwan, the cross-section of fund returns could offer more accurate predictions. Third, it is possible that the Bayesian shrinkage procedure should also be used to evaluate the performance of a portfolio in the holding period, and fourth, the best performance measure depends only on the selected sample and time period.

4.2.3. One-year selection period

The previous part gave rather inconsistent results, although a relatively good guide could be to choose the best performing fund instead of the worst performing fund. This part tries to increase the reliability by presenting the results from a 12-month selection period. Estimating the standard deviation for the Sharpe ratio and beta coefficients for the three-factor model could generate rather spurious results and the raw returns could provide most accurate predictors. However, as Huji and Verbeek (2007, op cit.) pointed out, the Bayesian shrinkage procedure could increase the reliability of the estimates with a small number observations.

Table 10: Results from one-year ranking and one-year holding period.

Ranking on	Portfolio	LN Alpha (monthly)	s.e.	Annualized difference	Welch's t-value	sig.
Panel A: China						
Raw return	Top quartile	0.0005	0.0021	**1.69 %**	0.48	0.632
	Bottom quartile	*-0.0008*	*0.0020*			
Three-factor alpha	Top quartile	0.0015	0.0023	**4.40 %**	1.32	0.188
	Bottom quartile	*-0.0020*	*0.0015*			
Bayes	Top quartile	-0.0003	0.0021	**3.86 %**	1.24	0.217
	Bottom quartile	*-0.0034*	*0.0014*			
Sharpe ratio	Top quartile	0.0003	0.0021	**1.38 %**	0.41	0.682
	Bottom quartile	*-0.0009*	*0.0018*			
Panel B: India						
Raw return	Top quartile	-0.0019	0.0019	**0.39 %**	0.13	0.895
	Bottom quartile	*-0.0022*	*0.0016*			
Three-factor alpha	Top quartile	0.0003	0.0018	**2.53 %**	0.86	0.389
	Bottom quartile	*-0.0018*	*0.0016*			
Bayes	Top quartile	0.0010	0.0015	**2.93 %**	1.20	0.231
	Bottom quartile	*-0.0014*	*0.0013*			
Sharpe ratio	Top quartile	-0.0015	0.0017	**0.54 %**	0.20	0.839
	Bottom quartile	*-0.0019*	*0.0014*			
Panel C: Taiwan						
Raw return	Top quartile	0.0043	0.0034	**1.16 %**	0.21	0.837
	Bottom quartile	*0.0033*	*0.0032*			
Three-factor alpha	Top quartile	0.0063	0.0037	**7.32 %**	1.22	0.223
	Bottom quartile	*0.0004*	*0.0031*			
Bayes	Top quartile	0.0046	0.0035	**4.76 %**	0.92	0.357
	Bottom quartile	*0.0008*	*0.0023*			
Sharpe ratio	Top quartile	0.0039	0.0032	**0.97 %**	0.18	0.857
	Bottom quartile	*0.0031*	*0.0031*			

Table 10 presents the results for corresponding regression models which were shown in Table 9, with a one-year selection period, ceteris paribus. Estimating the standard deviations with a sample of only 12 observations exacerbated remarkably the predictive ability of the Sharpe ratio, leading to only marginal differences between the top portfolios and the bottom portfolios. More surprising, however, is the lack of prediction power from the annual raw returns. The only two estimates which seem to have any prediction ability at all are the three-factor alpha and the Bayesian alpha. The relation between these two estimates is easy to understand, because the Bayesian shrinkage procedure starts with the sensitivities (betas) and constants (alphas) from the three-factor model. Therefore, the Bayesian estimate is only an improved estimate from the three-factor model and should provide more accurate estimates.

This improved accuracy, however, can not be found from the results. Only in the sample of India equity, the Bayesian portfolios generated a larger alpha spread than the portfolios selected with the three-factor model. In the Taiwan equity sample, the annual difference increased for both the Bayesian portfolios and the three-factor model, but the standard errors remained high, and therefore, even the annual spread from Jensen portfolios (7.3%) was statistically insignificant.

It seems that at least the first two considered explanations (on page 47) can be forgotten in the light of the results from the one-year selection periods. The portfolios selected with the Bayesian estimates offered a higher alpha spread only in the sample of India equity, which had the lowest number of funds and the empirical three-factor model had the highest explanatory power on portfolio returns (96%). The results do not either support the superiority of Bayesian estimates in shorter observation periods.

What can also be seen from the results is that, in Taiwan, investments in both the top portfolios and the bottom portfolios have generated large positive alphas, which would suggest that the managers for Taiwan equity funds in general possesses a superior information or stock-picking ability. Figure 7 on the page 42, however, offers a more plausible explanation. The fund managers in general offer well-diversified portfolios for investors, and therefore, reduce the country-specific risk (or simply search investment opportunities cross-borders) and this has paid off for Taiwan equity funds especially in 2006 and 2007. The cross-border investments could also explain the close to zero alphas for top portfolios in China equity funds and India equity funds. The growth has been strongest in these two economies especially during 2006 to 2007, and therefore, cross-border diversification has on average decreased the fund returns. The differences in cross-border diversifications could also explain not only the relatively high annual differences in risk-adjusted returns, but also the high standard errors and the statistical insignificance of the results.

Finally, Table 11 tries to find out if employing the three-factor alpha in the evaluation period could explain the fact that the portfolios selected with the three-factor alphas seem to outperform the portfolios selected with the Bayesian alphas. In the cross-sectional regression models the one-year alphas are regressed on lagged values.

Table 11: Cross-sectional regression models for three-factor alphas and Bayesian alphas with corresponding lagged values (results from SPSS)

Independent variables	**Dependent variables**					
Panel A: China		**3-factor**			**Bayes**	
	Adj. R^2	Beta	t-stat.	Adj. R^2	Beta	t-stat.
3-factor t-1	**3.45 %**	0.21	3.18***	0.77 %	0.06	1.73*
Bayes t-1	1.06 %	0.35	1.94*	**0.63 %**	0.14	1.62
Panel B: India						
	Adj. R^2	Beta	t-stat.	Adj. R^2	Beta	t-stat.
3-factor t-1	**3.67 %**	0.21	2.84***	0.93 %	0.05	1.65*
Bayes t-1	1.48 %	0.36	1.95*	**4.03 %**	0.21	2.97***
Panel C: Taiwan						
	Adj. R^2	Beta	t-stat.	Adj. R^2	Beta	t-stat.
3-factor t-1	**4.96 %**	0.22	6.42***	4.72 %	0.17	6.25***
Bayes t-1	4.72 %	0.29	6.26***	**6.85 %**	0.26	7.58***

(*) denotes significance at 10% level - (**) denotes significance at 5% level - (***) denotes significance at 1% level.

The results from the linear regressions indicate that the superiority of the three-factor alphas could well be caused by the fact that the three-factor model is also used in the evaluation period. Also, the results indicate that the Bayesian alphas predict more accurately the consecutive Bayesian alphas than the three-factor alphas predict the consecutive three-factor alphas. Only the results from the Chinese sample contradict this assumption. However, also the results from China sample support the idea that the best consistency is found between similar performance measures.

4.3. Long/short investment strategy

The observed results so far indicate that rational investors should choose past winners instead of past losers (although the alpha spread was statistically significant at ten percent level only for portfolios selected on the basis of balanced alpha). However, the tests conducted so far have concentrated only on risk-adjusted returns, and therefore, the following test will determine whether investors could earn real returns by buying the winners and selling the losers. The applied market neutral long/short investment strategy should not be reflected by the market movements. Nevertheless, it should not be confused to risk-free strategy. The risk in this strategy can be found from individual funds held long and sold short.

4.3.1. Theoretical background

Jacobs and Levy (1993) presented strategies, mechanics and plausible benefits from long/short equity investing. Moreover, three strategies were presented; market neutral, equitized, and hedge strategy. The market neutral strategy holds long and short portfolio in equal euro balance at all times, and therefore, has no effect on market movements. The spread between winners (long) and losers (short) is the profit made from this investment strategy. The equitized strategy, in addition to market neutral strategy, holds stock index futures equal to an amount of invested capital, and hence, in addition of the spread between winners and losers, profits (losses) from the equity market's rise (fall). Finally, the hedge strategy invests as well equal euro amounts for long and short. However, the market exposure varies on the basis of manager's market outlook.

Typically, 90 percent of the capital is used to buy winning stocks and to sell short losing stocks. The purchased stocks serve as collateral for the shorts and the remaining 10 percent of the capital is retained as a liquidity buffer to meet the daily marks to market on the short positions. The cash proceeds from the shorts and the liquidity buffer earn interest, which is used to pay a securities lending fee, brokerage fees, and the remaining is earned by the investor.

There are also practical benefits from long/short equity investing. First, instead of profiting only from winners, long/short strategies enable profits from the full performance spread between winners and losers. Second, all of the investors are looking for undervalued stocks and only a fraction of investors are searching for overvalued stocks (assumption; overvalued stocks are easier to find). Finally, security analysts issue much more buy recommendations than sell recommendations, probably because all customers are potential buyers and only current stock owners are potential sellers (except a small number of short-sellers). (Jacobs and Levy, 1993)

4.3.2. Market neutral long/short investment strategy

Table 12 shows the results the from market neutral long/short investment strategy. The method employed is much more simplified compared to the actual long/short investing. The total amount of capital is assumed to be invested and expenses are ignored. The annually rebalanced long and short portfolios are selected based on three-year selection periods (presented in Table 7 and in Table 9).

Table 12: Results from market neutral investment strategy. Monthly returns from long-short strategy are regressed on market index (FTSE AW APac; Japan excluded for full sample and country-specific MSCI-index for China, India and Taiwan)[34].

Ranking on		Constant (monthly)	Beta coefficient	Average annualized return
Panel A: Full sample				
Raw return	**Regression model**	**0.0070**	**-0.0420**	**7.22 %**
	T-statistic	*1.58*	*-0.46*	
Jensen alpha	**Regression model**	**0.0095**	**-0.1078**	**8.96 %**
	T-statistic	*1.82**	*-1.00*	
Balanced alpha	**Regression model**	**0,0094**	**-0.1074**	**9.06 %**
	T-statistic	*1.92**	*-1.10*	
Sharpe ratio	**Regression model**	**0.0073**	**-0.0557**	**7.51 %**
	T-statistic	*1.77**	*-0.65*	
Treynor ratio	**Regression model**	**0.0082**	**-0.0504**	**8.63 %**
	T-statistic	*1.88**	*-0.56*	
Downside Treynor	**Regression model**	**0.0017**	**-0.0773**	**0.23 %**
	T-statistic	*0.44*	*-0.97*	
Panel B: China				
Raw return	**Regression model**	**0.0045**	**0.1416**	**9.93 %**
	T-statistic	*1.64*	*3.66****	
3-factor alpha	**Regression model**	**0.0055**	**-0.1110**	**4.14 %**
	T-statistic	*1.93**	*-2.70****	
Bayesian alpha	**Regression model**	**0.0033**	**-0.1558**	**0.29 %**
	T-statistic	*1.04*	*-3.43****	
Sharpe ratio	**Regression model**	**0.0047**	**0.0025**	**6.09 %**
	T-statistic	*1.96**	*2.39****	
Panel C: Taiwan				
Raw return	**Regression model**	**0.0003**	**-0.0125**	**0.44 %**
	T-statistic	*0.16*	*-0.47*	
3-factor alpha	**Regression model**	**0.0018**	**-0.0035**	**2.22 %**
	T-statistic	*1.15*	*-0.15*	
Bayesian alpha	**Regression model**	**0.0028**	**0.0688**	**4.09 %**
	T-statistic	*0.96*	*1.52*	
Sharpe ratio	**Regression model**	**0.0008**	**-0.0119**	**1.06 %**
	T-statistic	*0.57*	*-0.54*	
Panel D: India				
Raw return	**Regression model**	**0.0054**	**0.0875**	**10.00 %**
	T-statistic	*1.89**	*2.30***	
3-factor alpha	**Regression model**	**0.0051**	**-0.0370**	**5.41 %**
	T-statistic	*1.99**	*-1.09*	
Bayesian alpha	**Regression model**	**0.0036**	**-0.0339**	**3.57 %**
	T-statistic	*1.49*	*-1.06*	
Sharpe ratio	**Regression model**	**0.0047**	**0.0817**	**8.71 %**
	T-statistic	*1.80**	*2.39***	

(*) denotes statistical significance at 10% confidence level - (**) denotes statistical significance at 5% confidence level - (***) denotes statistical significance at 1% confidence level.

[34] The percentage returns from market neutral long/short investment strategy are regressed on percentage returns from the market index. Also the regression models for China, India and Taiwan employ single-index models instead of three-factor models presented in Table 9.

The results show that in the Asia-Pacific; Japan excluded, by following a simple market neutral investment strategy, an investor would have earned on average an annual return of seven to nine percent (gross of expenses). Only portfolios selected on the basis of downside Treynor could not create additional value. Correlation between the returns from the long/short strategy and the market return was weak and statistically insignificant as should be for the applied investment strategy. Also the small negative beta coefficient makes sense, because the volatilities for bottom portfolios were on average higher than the volatilities for top portfolios.

The statistical significance for constants, however, was surprisingly low (statistically significant only at 10% level for long/short investment strategies based on; Jensen alpha, balanced alpha, Sharpe ratio and Treynor ratio). Figure 8 below shows a plausible reason for constants low significance. The proceeds from the market neutral long/short investment strategy are earned in two sub-periods (2002-03 and 2006-07). On the other hand, in the two-year period (2004-05) the returns from the long/short investment strategy have been slightly negative.

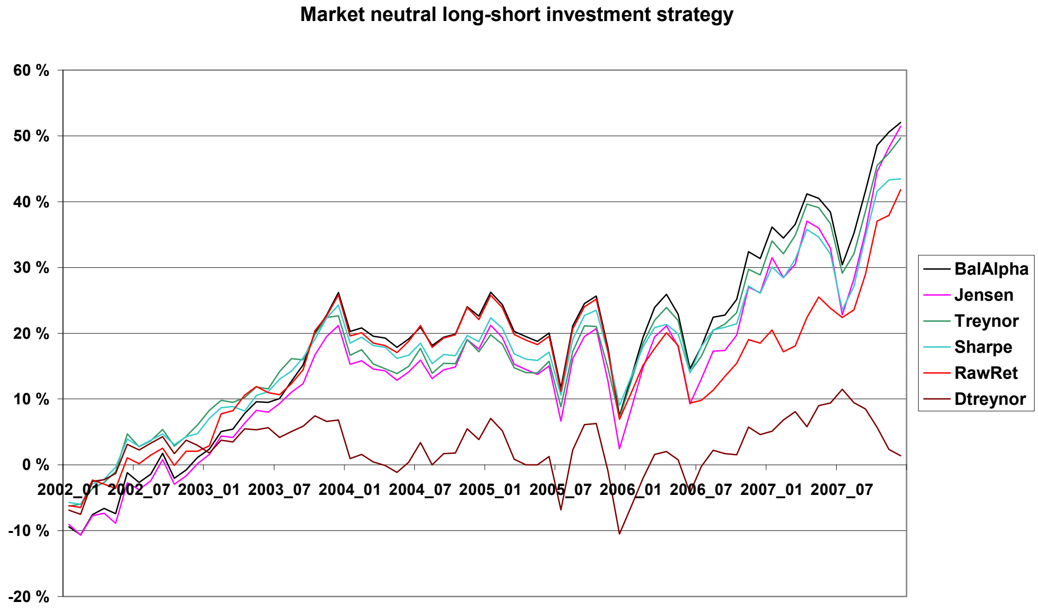

Figure 8: Cumulative logarithmic proceeds from annually rebalanced market neutral long/short investment strategy (holding periods 2002; 2007).

The country-specific results from Table 12 show rather ambivalent results. In China and in India, the highest returns from long/short strategies were earned for portfolios selected on the basis of raw returns (approximately 10% per annum). In Taiwan, however, the long/short strategy on the basis of raw returns generated only a marginal annual return. The portfolios selected on the basis of Bayesian alphas, on the other hand, shows a controversial return pattern, and in China and in India, where the average annual market return was over 30 percent (2002-2007), the market neutral long/short investment strategy generated only marginal returns. In Taiwan, however, the portfolios selected on the basis of Bayesian alpha created on average a higher return than the average market return (the average market return in Taiwan was less than three percent in 2002-2007).

The market sensitivities for country-specific regression models are close to zero as they should be for the applied investment strategy. The most reliable constants (highest t-values on average), on the other hand, were found from the regression models where the portfolios were selected on the basis of three-factor alpha. As a whole, however, the results suggest that an investor following a market neutral long/short investment strategy in Asia-Pacific; Japan excluded, should select funds from the entire market area. This way, an investor would have an opportunity to sell short funds which focus on economies with negative market outlooks and hold long for funds which focus on economies with positive market outlooks.

4.4. Factors explaining the returns

> *"Good performance is associated with low expense ratios and the rank correlation coefficient suggests that expense ratios provide somewhat better predictions than the Treynor Index."* (Sharpe, 1966)

Although the relation between the performance and expense ratio is not necessary that straightforward[35], several studies have shown remarkable negative relationships between expense ratios and returns[36]. Detzel and Weigand (1998, op cit.) also argued that simple accounting variables could explain the cross-section of fund returns. Therefore, the following analysis tries to find out, how well these variables can explain the cross-section of returns in the Asia-Pacific, from 2005 to 2007.

The number of mutual funds in the sample for this analysis is 117, 113 and 137 for the years 2005, 2006 and 2007, respectively. The conducted factor analysis showed a significant inconsistency in factor loadings during the overall three-year period, and therefore, the cross-sectional regressions follow the combinations suggested by Detzel and Weigand (1998, op cit.). The only difference is that the variables P/C and P/B have been replaced with a single variable, C/B, to reduce correlation between variables as suggested by Prather et al. (2004, op cit.).

The descriptive statistics for the employed fund sample is shown in the Table 13. Annual report net expense ratios from the fiscal year 2007 have been used as a proxy for all years, which could lead to spurious results. However, another possibility would have been to exclude expense ratios altogether because there was only a handful of observations for the individual years. The P/E -, P/B – and P/C –ratios and the average market capitalization are values from December at year *t*-1, and in the Morningstar database these ratios have been calculated with a trailing method[37]. Before further calculations, the average market capitalizations have also been translated into euros with month-end exchange rates, received from DataStream database. Four outlier funds were excluded

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[35] According to Huji and Verbeek (2007, op cit.), empirical studies show that after removing the worst performing funds, the relation between fund's expenses and performance seems to be more U-shaped rather than straight forward and e.g. Carlson (1970, op cit.) received a positive correlation coefficient for expense ratio during 1958-1967.
[36] E.g. see Sharpe (1966, op cit.), Carhart (1997, op cit.) and Prather et al. (2004, op cit.).
[37] Morningstar calculates price ratios from the month-end prices and the financial data and/or analysts' estimates (Morningstar, 2008c).

(one with a 0.25 beta coefficient, one with a 0.02 percent expense ratio and two with 12.5 percent expense ratios).

Table 13: Descriptive statistics for the data employed.

	Return	Beta	Expenses	Mkt Cap	P/B	P/C	P/E
Minimum	-4.7 %	0.53	0.20	64	0.80	3.47	6.05
Maximum	111.6 %	1.46	3.52	43 196	6.38	22.99	29.33
Median	26.6 %	1.06	1.84	7 493	2.61	9.68	16.06
Std Dev	12.9 %	0.15	0.51	4 510	0.77	2.60	3.02

The returns are annualized returns[38] for years 2005 to 2007, and the others are *t*-1 variables. The beta coefficients have been calculated from prior 36-month periods, and the benchmark index is FTSE AW APAC; Japan excluded. The expenses are the annual report net expense ratios (presented as hundred-fold) and the average market capitalizations are in millions of euros.

Table 14: Cross-sectional regression with unstandardized coefficients[39].

Model	Coefficient	Intercept	Beta	Exp	Size	C/B	P/E	Adj. r-square
Panel A: 2005 returns								
1	Regression	**0.11**	**0.25**	**0.02**				**0.104**
	t-statistic	*1.32*	*3.92****	*0.88*				
2	Regression	**0.29**	**0.25**	**0.02**	**-0.02**			**0.117**
	t-statistic	*2.11***	*3.96****	*0.72*	*-1.64*			
3	Regression	**0.25**	**0.18**	**-0.00**	**-0.01**	**0.92**	**-0.01**	**0.422**
	t-statistic	*1.94**	*3.30****	*-0.11*	*-1.07*	*5.29****	*-1.99***	
Panel B: 2006 returns								
1	Regression	**0.40**	**-0.19**	**0.03**				**0.028**
	t-statistic	*3.65****	*-2.08***	*0.95*				
2	Regression	**0.54**	**-0.19**	**0.03**	**-0.02**			**0.022**
	t-statistic	*2.12***	*-2.05***	*0.90*	*-0.62*			
3	Regression	**0.47**	**-0.20**	**0.02**	**-0.01**	**0.21**	**0.00**	**0.007**
	t-statistic	*1.58*	*-2.12***	*0.76*	*-0.52*	0.60	*0.13*	
Panel C: 2007 returns								
1	Regression	**0.08**	**0.16**	**0.03**				**0.040**
	t-statistic	*0.93*	*2.16***	*1.49*				
2	Regression	**0.39**	**0.16**	**0.02**	**-0.03**			**0.066**
	t-statistic	*2.36***	*2.22***	*1.12*	*-2.2***			
3	Regression	**0.23**	**0.05**	**-0.00**	**-0.04**	**0.26**	**0.02**	**0.274**
	t-statistic	*1.54*	*0.68*	*-0.11*	*-3.0****	1.08	*6.33****	

(*) denotes statistical significance at 10% level - (**) denotes statistical significance at 5% level - (***) denotes statistical significance at 1% level

[38] In Table 12, the returns are net of expenses. However, for further analyses, the net expenses have been added back.
[39] Detzel and Weigand (1998, op cit.) used standardized coefficients.

Table 14 presents the results from the cross-sectional regression models[40]. The first regression model, for the returns in year 2005, showed promising results. Adjusting the returns with the market risk and the expense ratio explained over ten percent of the cross-sectional returns, and incorporating the size factor improved marginally the model's explanatory power. Finally, completing the model with the final two factors (C/B and P/E) increased the explanatory power of the model to over 42 percent, which was also the explanatory power of the Detzel and Weigand (1998, op cit.) model.

In 2006, however, the regression models showed controversial results. The only statistically significant variable (besides the constant) was the negative beta coefficient. Also the explanatory power of the model fell close to zero and increasing the number of explanatory variables to the model seemed to only worsen the explanatory power. The explanation for such ambiguous results could be that the sensitivities for factors have varied strongly across the Asia-Pacific in 2006. The general variation can also be seen in Figure 7 on the page 42, where the MSCI China - and the MSCI India -indexes show much more rapid growth than the comparable MSCI Taiwan -index. In 2007, the explanatory power of the model rises again to 27 percent. The most profound reason for the high adjusted r-square seems to be, according to the model, highly significant P/E ratio.

The overall results show that the most statistically significant variable has been the beta coefficient, although at least two studies have shown that there is no connection between beta coefficients and realized returns[41]. However, the statistically significant negative coefficients in 2006 would indicate that funds with lower market risk (beta) have systemically outperformed the funds with higher market risk. The size factor was

[40] Statistical program SPSS was used, and the linear regression model follows equation (8); percentage return was dependent variable and beta coefficient, expense ratio, logarithmic market capitalization, P/E ratio and C/B ratio (*t*-1) were independent variables.
[41] Fama and French (1996) and Malkiel (1995).

statistically significant only in predicting the 2007 returns. However, the coefficients had negative sign in all years, indicating that the small cap stocks have outperformed the large cap stock companies during the observed three-year period. Finally, incorporating the expense ratios did not have the expected effect on explaining the cross-section of returns. In some degree, the results can be explained by falsely incorporating the annual report net expense ratios from year 2007. This, however, can not explain the inconsistency of signs in 2007.

Table 15: First-order serial correlation coefficients of adjusted mutual fund returns (residuals from the adjusted fund returns).

Model	Variables	Parameter	Value
Panel A: 2005-2006			
	Unadjusted returns	**ρ**	**-0.218**
		sig. (2-tailed)	*0.045**
4	Beta, Exp	**ρ**	**-0.120**
		sig. (2-tailed)	*0.272*
5	Beta, Exp, Size	**ρ**	**-0.159**
		sig. (2-tailed)	*0.145*
6	Beta, Exp, Size, P/E, C/B	**ρ**	**-0.152**
		sig. (2-tailed)	*0.165*
Panel B: 2006-2007			
	Unadjusted returns	**ρ**	**0.647**
		sig. (2-tailed)	*0.000***
4	Beta, Exp	**ρ**	**0.624**
		sig. (2-tailed)	*0.000***
5	Beta, Exp, Size	**ρ**	**0.606**
		sig. (2-tailed)	*0.000***
6	Beta, Exp, Size, P/E, C/B	**ρ**	**0.510**
		sig. (2-tailed)	*0.000***

(*) denotes statistical significance at 5% level - (**) denotes statistical significance at 1% level

Detzel and Weigand (1998, op cit.) noted that the persistence in returns disappeared after returns were adjusted with the coefficients and variables used in Table 14. Table 15 shows both the adjusted and unadjusted return correlations for consecutive years. The statistical test used, is the Spearman's rank correlation test[42] and the returns have been adjusted with sensitivities and constants from the regression models presented in

[42] The statistical program used was SPSS, and the formula is described in Appendix A.

Table 14. Hence, this test differs from the one presented by Detzel and Weigand (1998, op cit.) in a way that this test utilizes unstandardized coefficients with constants. The reason for this is that the following results present only correlations between two consecutive years instead of series of consecutive years.

In the first period, 2005 to 2006, the correlation of unadjusted returns barely reaches statistical significance (correlation was significant at five percent level). Adjusting the returns with the market risk and the expense ratio reduced the correlation, but further adjusting with the other variables, the correlation of the residuals increases again. Also the coefficients are negative in all four cases which indicate that if there has been correlation between returns, it has been negative. The following two-year period turns the results around. Incorporating additional variables does seem to slowly decrease the significance of the correlation, but the correlation still remained statistically significant at one percent level after the returns were adjusted with all variables. And again, the most plausible explanation for this lies in the differences between geographical investment objectives.

5. Concluding remarks

This study examined performance persistence in Asia-Pacific region; Japan excluded, and the studied time period included nine years (from 1999 to 2007). The full sample analyses included time series for 911 open-end mutual funds. First, contingency tables were employed to examine whether past winners repeat or not in the subsequent period. Second, stacked return time series quantified the performance spread for top and bottom decile portfolios. More accurate performance analyses were conducted with three sub-samples: China, India and Taiwan equity funds. Market neutral long/short investment strategies were employed to find out whether investors could benefit from the observed alpha spreads. Finally, cross-sectional regression analyses were conducted to find out if simple accounting variables and market risk could explain the future fund returns.

The choice for the benchmark index is extremely important when mutual fund performance is evaluated. The employed benchmark indexes might also partially explain the observed results. The first empirical part of this study showed that the persistence of the past winners was statistically significant in the Asia-Pacific during the years 1999 to 2007. On average, almost 60 percent of the winners in the prior three-year period turned out to be winners in the subsequent three-year period. However, the employed simple performance measures could not differentiate between separate investment styles (growth, value, small cap and large cap stocks), which most likely exaggerated the received results. According to the results from the contingency tables, total risk -based performance measure, the Sharpe ratio, seemed to be the most practical performance measure for the entire market area (Asia-Pacific; Japan excluded). By employing the Sharpe ratio, the past winners repeated only two out of four sub-periods examined.

The evidence of the inferior performance persistence was even stronger than the evidence of the superior performance persistence, and even the survivorship bias does not explain the persistence of repeating losers (in fact, the survivorship bias has an opposite effect). There was, however, one selection period (01/03) when the bottom decile portfolio outperformed (risk-adjusted) the top decile portfolio in the subsequent three-year holding period (04/06). Nevertheless, this was most likely due to a change in the market trend.

The annually rebalanced, stacked return time series showed that the average annual alpha spread between the top decile funds and the bottom decile funds was on average ten percent (when the portfolios were selected and evaluated with the Jensen measure), during the six-year period from 2002 to 2007. The sub-samples, on the other hand, indicated that the Jensen measure is the most appropriate performance measure for the bull markets, whereas the created balanced measure established portfolios which generated highest alpha spread for the bear markets. The balanced alpha had also the highest annual alpha spread for the full sample period (11.3%, which was also statistically significant at ten percent level).

Narrowing the fund’s investment objective to a single country and employing country- and style-specific benchmark indexes improved significantly the explanatory power of the models. However, the obtained alphas are not completely unbiased, because the funds in these single-country categories are international in nature, and hence, invest also cross-borders to diversify the country-specific risk. This could be the reason why the results showed positive alphas even for the bottom quartile portfolios in Taiwan and zero-alphas for the top quartile portfolios in China and India. This could also explain the insignificance of the results (although the highest annualized alpha spreads were five to seven percent).

The iterative Bayesian procedure could not be used consistently for forecasting the future winners. In general, the portfolios selected with the original three-factor alphas created a wider alpha spread than the portfolios selected with the Bayesian alphas. The results, however, indicated also that the reason for this was the ex post evaluation, which was made with the three-factor model. In two out of three samples (India and Taiwan), the cross-sectional regression models showed that the lagged Bayesian alphas had higher explanatory power on Bayesian alphas than corresponding lagged three-factor alphas on three-factor alphas. By employing the Bayesian estimates also for the holding period could, therefore, favour the Bayesian alphas.

The results from the employed market neutral long/short investment strategy indicated that from Asia-Pacific market area (Japan excluded) investors can find beneficial long/short investment strategies (although the results were presented gross of expenses). The most reliable results were received from the full sample where the market neutral long/short investment strategy generated an average annual return of seven to nine percent regardless the performance measure employed in the selection period (except the created downside Treynor). For country-specific market neutral investment strategies, on the other hand, the results indicated that the most profitable performance measure in the selection period seemed to depend mainly on the performance of market index. Moreover, the results indicated that the observed performance persistence might well be dependent on the economical diversity in the studied market area.

Mixed results from the cross-sectional regression analyses (in 4.4.) confirmed that the market area examined (the Asia-Pacific; Japan excluded) has too many individual economies, and therefore, a single model can not be used to explain the cross-section of returns (or at least the fit for the model varies between time periods). Simple accounting variables from prior year explained over 40 percent of cross-section of returns in 2005. For the following year, however, prior accounting variables had zero explanatory power, and for 2007 returns, the explanatory power rose again to 27 percent. The observed results do not either support the negative relation between expense ratios and realized returns.

The strongest evidence of persistence was found from repeating losers, which is consistent with the existing performance persistence literature. Also, the overall results from the full sample analyses and the single-country analyses indicated that it would be beneficial to use even the simplest performance measures before selecting a mutual fund (with historical price information). However, the following phrase from the SEC holds also for the presented results:

> *"…a fund's past performance is no guarantee of its future success."* (SEC, 2008)

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Appendix A: Calculations; one-month risk-free rate of return, Jarque-Bera value and Spearman's rank correlation coefficient

Logarithmic one-month risk-free rate of return:

$$R_f = \frac{\ln(1 + OneMonthEuribor)}{12}$$

Jarque-Bera value follows chi-square distribution with two degrees of freedom:

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4} \right)$$

n = the number of observations

S = the sample skewness

K = the sample kurtosis

The Spearman's rank correlation coefficient (ρ):

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

$d_i = x_i - y_i$ = the difference between ranks of two sets of data X_i Y_i

n = the number of observations

and the following test statistic follows the t-distribution with *n*-2 degrees of freedom:

$$t = \frac{\rho\sqrt{n-2}}{\sqrt{1-\rho^2}}$$