

# PORTFOLIOS OF HEDGE FUNDS

## WHAT INVESTORS REALLY INVEST IN

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### ABSTRACT

Using monthly return data over the period June 1994 – May 2001 we investigate the performance of randomly selected baskets of hedge funds ranging in size from 1 to 20 funds. The analysis shows that increasing the number of funds can be expected to lead not only to a lower standard deviation but also, and less attractive, to lower skewness and increased correlation with the stock market. Most of the change occurs for relatively small portfolios. Holding more than 15 funds changes little. The population average appears to be a good approximation for the average basket of 15 or more funds. With 15 funds, however, there is still a substantial degree of variation in performance between baskets, which dissolves only slowly when the number of funds is increased. Survivorship bias is largely independent of portfolio size and thus cannot be diversified away. Finally, our efficiency test indicates that one only needs to combine a small number of funds to obtain a substantially more efficient risk-return profile than that offered by the average individual hedge fund.

## **I. INTRODUCTION**

Thanks to substantial marketing and media hype, hedge funds have recently become the favourites of many retail as well as institutional investors. Recently, two of the largest pension funds in the world, CalPERS and ABP, both announced plans to invest several billions of dollars in this asset class. The decision to include hedge funds in the asset allocation is typically based on a comparison of portfolios with and without hedge funds, where the hedge fund component is represented by a publicly available hedge fund index. Such an approach is not without dangers though. As shown in Brooks and Kat (2001), there can be considerable heterogeneity between indices that aim to reflect the same type of strategy as different indices tend to cover different parts of the hedge fund universe. In addition, some hedge fund indices contain more survivorship bias than others. As a result, investors' perception of hedge fund performance and value-added heavily depends on the index studied. Another potential problem lies in the fact that investors will not actually invest in the hedge fund index that is used in the analysis but in a basket containing a much smaller number of funds. This is either done directly or, which appears to be the more popular approach nowadays, through a so-called fund of funds structure. Since the index is calculated over a much larger number of funds than contained in the basket, the index may not be a good proxy for the basket. If this misrepresentation is significant, this can have serious consequences for the outcome of the investment process, with the investor expecting one thing but ending up with something markedly different.

In this paper we investigate how the performance of relatively small baskets of hedge funds deviates from that of the population. Using data over the period June 1994 – May 2001, we study baskets of hedge funds that are randomly selected from a large sample of funds, explicitly accounting for fund closures. From the monthly returns on portfolios ranging in size from 1 to 20 funds we calculate six different sample statistics: the mean, standard deviation, skewness, kurtosis, correlation with the S&P 500, and the correlation with the Salomon Brothers Government Bond Index. In addition, we apply the dynamic trading based efficiency test developed earlier in Amin and Kat (2001a) to investigate how the risk-return efficiency of the latter portfolios changes as the number of funds increases.

We are aware of two other studies of hedge fund diversification that follow a methodology similar to ours. Henker (1998) studied portfolios of hedge funds over the period 1992-1997. Peskin, et al. (2000) studied hedge fund portfolios over 1990-2000. Both these studies are not without problems, however. Neither of them looks at skewness, kurtosis or at the correlation between hedge fund portfolio returns and equity and bond returns. In addition, Henker's sample of funds is extremely small and his results are not free of survivorship bias.

The paper proceeds as follows. In the next section we discuss the data we will use. In section III we discuss the methodology followed and our main results. In section IV we turn to the matter of survivorship bias, while in section V we investigate the risk-return efficiency of the portfolios studied. Section VI concludes.

## **II. THE DATA**

The data in this study were obtained from Tremont TASS, which is one of the best known and largest hedge fund databases currently available. The database at our disposal contains monthly net of fee returns on a total of 2183 hedge funds and funds of funds from June 1994 up to and including May 2001. We had to eliminate 171 funds due to incomplete and ambiguous data. We also eliminated the funds of funds from the sample. Per May 2001 this left us with 1195 live and 526 dead funds. As shown in Amin and Kat (2001b), concentrating on live funds only will on average overestimate the mean return on individual funds by around 2% as well as introduce a significant downward bias in estimates of the standard deviation. Not taking dead funds into account also causes an upward bias in the skewness and a downward bias in the kurtosis estimates of individual fund returns. To incorporate this in our analysis we decided not to work with the raw return series of the 264 funds that survived the period 1994-2001. Instead, we created 455 7-year monthly return series by, starting off with the 455 funds that were alive in June 1994, replacing every fund that closed down during the sample period by a fund randomly selected from the set of funds following the same type of strategy and alive at the time of closure. For simplicity, we will still refer to the data series thus obtained as 'fund returns'.

Implicitly we assume that in case of fund closure investors are able to roll from one fund into the other at the reported end-of-month net asset values and at zero additional costs. This may underestimate the true costs of fund closure to the investor for two reasons. First, when a fund closes shop its investors will have to look for a replacement. This search takes time and is not without costs. Second, investors may get out of the old and into the new fund at values that are less favourable than the end-of-month net asset values contained in the database. Unfortunately, it is impossible to incorporate this into the analysis without further information.

### **III. METHODOLOGY AND RESULTS**

From the above 455 funds we created 500 different portfolios of equal size  $N$ ,  $N=1,2,\dots,20$ , by random sampling without replacement. One could of course argue that investors will not select portfolios by random sampling. Although this is certainly true, this does not mean that in many cases random sampling is not a fair approximation of the actual fund selection process. So far, there is no reliable evidence that some investors (including fund of funds managers) are consistently able to select future out-performers nor of the existence of specific patterns or anomalies. When corrected for possible biases, there is no significant persistence in hedge fund performance nor is there any significant difference in performance between older and younger funds, large and small funds, etc. In addition, older funds are often (more or less) closed for new investments. Investors that are relatively new to hedge fund investing are therefore often forced to invest in funds with little or no track record. If so, selecting funds based on (the statistical properties of) their track record is not an option. The fund prospectus and due diligence interviews with the manager may provide some information, but in most cases this information will only be sketchy at best.

We calculated the monthly returns on every portfolio assuming equal weighting of all funds. From the monthly returns thus obtained we calculated the mean, standard deviation, skewness, kurtosis, correlation with the S&P 500, and the correlation with

the Salomon Brothers Government Bond Index. For portfolio sizes ranging from 1 to 20, the 5<sup>th</sup>, 10<sup>th</sup>, etc. percentiles of the resulting frequency distributions are shown in figure 1-6. The horizontal line in every graph depicts the population value, i.e. the value of the relevant sample statistic for an equally-weighted portfolio containing all 455 funds.

<< Insert Figure 1 >>

From figure 1 we see that, whatever the size of the portfolio, the frequency distribution of the sample means is symmetric and that the median is more or less equal to the population mean of 0.95%. Since every portfolio return is a linear combination of the returns on the component funds, the latter finding is of course not very surprising. The variation around the median is much higher for small portfolios than it is for larger portfolios. For individual funds the difference between the 75% and 25% percentile is 86% of the median and the difference between the 90% and 10% percentile 179%. For portfolios containing 10 funds the 75-25% percentile difference is 36% and the 90-10% percentile difference is 68% of the median value. For larger portfolios the drop in the level of variation slows down significantly. For portfolios containing 20 funds for example the difference between the above percentiles is still equal to 24% and 46% of the median.

<< Insert Figure 2 >>

Figure 2 shows that the frequency distributions of the standard deviations are positively skewed. As the number of funds increases the median drops quickly towards the population value of 2.16%, but at a strongly decreasing rate. For individual funds the median is 4.83%. For portfolios of 5 funds it is 3.03%, for portfolios of 10 funds 2.74% and for portfolios of 20 funds the median is 2.44%. A similar result for common stock portfolios was first reported by Evans and Archer (1968). Whitmore (1970), however, has made it clear that the observed drop in portfolio standard deviation is a purely technical matter, i.e. it can be fully explained by the mathematics of portfolio variance itself. Again, the variation around the median is much higher for small

portfolios than for larger portfolios. For individual funds the difference between the 75% and the 25% percentile is 202% of the median, while the difference between the 90% and 10% percentile is 362%. For portfolios of 10 funds on the other hand these numbers are 45% and 86% respectively. For portfolios containing more than 10 funds the degree of variation drops much slower. For portfolios containing 20 funds the difference between the 75% and 25% percentile is 33% and between the 90% and 10% percentile is 61% of the median.

<< Insert Figure 3 >>

Figure 3 shows the frequency distributions of the observed skewness statistics. The graph has several interesting features. First, especially for smaller portfolios the frequency distributions are negatively skewed. Second, starting from a value of  $-0.12$ , the median skewness drops towards the population skewness of  $-0.59$  when the number of funds in portfolio is increased. For portfolios of 10 funds the median skewness is  $-0.38$  while for portfolios of 20 funds it is  $-0.48$ . A similar finding has been reported for common stock portfolios in Simkowitz and Beedles (1978). Contrary to what we saw before for the standard deviation, the observed drop in portfolio skewness is a truly empirical observation. It cannot simply be explained by the mathematics of portfolio skewness itself. Third, when the number of funds in portfolio increases the variation around the median declines but the drop is slower than for the mean and standard deviation. For individual funds the difference between the 90% and 10% percentile is 533% of the median. For portfolios of 10 funds the difference is 300%, while for portfolios containing 20 funds it is 250%. The difference between the 75% and 25% percentile shows similar behaviour. For individual funds the difference between the 75% and 25% percentile is 226% of the median. For portfolios of 10 and 20 funds these numbers are 142% and 119% respectively.

<< Insert Figure 4 >>

In figure 4 we see that the frequency distributions of the observed kurtosis statistics exhibit high positive skewness. Irrespective of the size of the portfolio, the median is more or less equal to the population kurtosis of 5.94. As with the previous statistics, the variation around the median declines as the number of funds increases. However, it does so in a very particular way. The higher percentiles grow much closer to the median when the number of funds increases, but the lower percentiles do not. The largest drop of the higher percentiles occurs for portfolios containing between 1 and 10 funds. After that there is little change. For individual funds the difference between the 75% and 25% percentile is 73% and the difference between the 90% and 10% percentile is 188% of the median. For portfolios containing 10 funds the 75-25% percentile difference is 51% and the 90-10% percentile difference is 93%. For portfolios containing 20 funds the difference between the above percentiles is 39% and 78% of the median, which is not too different from what we found for portfolios of 10 funds.

<< Insert Figure 5 >>

The frequency distributions of the correlation with the S&P 500 are depicted in figure 5. All distributions are negatively skewed, irrespective of the number of funds. Starting at a value of 0.34 for individual funds, the median rises quickly towards the population value of 0.67 when the portfolio size increases. With 10 funds in portfolio the median correlation is already up to 0.58, but with 20 funds it is only slightly higher at 0.62. The variation around the median declines with the number of funds in the usual way. For individual funds the difference between the 75% and the 25% percentile is 44% of the median, while the difference between the 90% and 10% percentile is 87%. For portfolios of 10 funds these numbers are 24% and 51% respectively. For portfolios containing more than 10 funds the degree of variation again drops slower, especially when measured from the medium percentiles. For portfolios containing 20 funds the difference between the 75% and 25% percentile is 17% and between the 90% and 10% percentile is 33% of the median.

<< Insert Figure 6 >>

Finally, figure 6 shows the frequency distributions of the correlation with the Salomon Brothers Government Bond Index. Contrary to the correlations with the S&P 500, the frequency distributions are fairly symmetric. Starting from a value of  $-0.05$ , the median approaches the population value of  $-0.09$  quite quickly. With 10 funds the median is  $-0.07$ , while with 20 funds it is  $-0.08$ . Similar to what we found for skewness, the decline in variation around the median is slower than usual. For individual funds the difference between the 75% and 25% percentile is 186% of the median. For portfolios of 10 funds the difference is 124%, while for portfolios containing 20 funds it is still 98%. The difference between the 90% and 10% percentile shows similar behaviour. For individual funds the difference is 363% of the median. For portfolios of 10 and 20 funds these numbers are 223% and 179% respectively.

In sum, figure 1-6 provide us with a number of interesting observations. First, for the mean and kurtosis the median value tends to be more or less equal to the population value, irrespective of the size of the portfolio. For the other statistics the median value quickly approaches the population value as the number of funds in the portfolio is increased. Adding more funds will tend to decrease the standard deviation and skewness of the portfolio return, while at the same time raising its correlation with the stock market. Second, although for all sample statistics the variation around the median declines substantially when the number of funds increases, the process is slower for skewness and the correlation with bonds than it is for the mean, standard deviation, kurtosis and correlation with the S&P 500. For larger portfolios the decline slows down considerably when the number of funds increases. Third, only the frequency distributions of the mean and the correlation with bonds are symmetric. The distributions of the standard deviation and kurtosis are positively skewed, while the distributions of skewness and the correlation with the S&P 500 are negatively skewed. In other words, when randomly selecting a portfolio of hedge funds there is an increased probability of finding a relatively high standard deviation and kurtosis, low skewness and low correlation with the S&P 500.

When deciding whether or not to invest in hedge funds many investors use one of the available hedge fund indices to determine whether the addition of hedge funds to their portfolio will improve its risk-return characteristics. These indices are typically

calculated as simple equally-weighted population averages. In the above we have seen that the population average is a good approximation for the average basket of 15 or more hedge funds. The emphasis is on ‘average’, however. Figure 1-6 clearly show that with 15 funds there is still a substantial degree of variation in performance between baskets. In other words, despite the fact that the behaviour of the average basket of 15 or more funds can be expected to be similar to that of the population, the basket that the investor holds may behave significantly different. Increasing the number of funds in portfolio does not provide an easy answer to this problem as the remaining variation only dissolves slowly. Obviously, investors should incorporate this uncertainty into their portfolio decision-making procedure. Doing so will effectively make hedge funds a riskier asset class, which may well lead to a reduction in many investors’ hedge fund allocations.<sup>1</sup>

<< Insert Table 1 and 2 >>

When thinking about the observed variation in the various sample statistics, one is inclined to assume that the latter are uncorrelated. A priori, there is no reason why this should be the case, however. We therefore calculated the correlation coefficients between all six statistics for portfolios of 1, 5, 10, 15, and 20 funds. The results can be found in table 1. Although somewhat higher for larger portfolios, the correlation between most statistics does not appear to be very high. The most noteworthy exceptions are the correlations between (1) standard deviation and correlation with the S&P 500, (2) skewness and kurtosis, and (3) skewness and correlation with the S&P 500. One explanation for this is that different types of hedge fund strategies offer significantly different risk-return profiles.<sup>2</sup> As our portfolios are constructed by random sampling, we are likely to obtain a number of portfolios that are dominated by one or two particular strategies, especially when the portfolios are small. If these strategies have different statistical properties, with one strategy for example combining low skewness with high correlation with the S&P 500 and another strategy exhibiting the reverse, this will be reflected in the correlation coefficients that we calculated. Table 2 shows the average mean, standard deviation, skewness, kurtosis and correlation with the S&P 500 for funds following six different types of strategies. The table shows that there is quite some variation between the different

strategies. The average long/short equity fund for example combines a relatively high mean and standard deviation with little skewness and a fair amount of correlation with the S&P 500. The profile of the average relative value fund on the other hand is completely opposite, combining a relatively low mean and standard deviation with high negative skewness and low correlation with the S&P 500.

What do our results imply for the number of funds to hold? In figure 1-6 we have seen that increasing the number of funds will tend to reduce standard deviation, reduce skewness and increase the correlation with the stock market. There is a limit to this though, as it only takes about 15 funds for the median values to closely approach the population values. In addition, it only takes around 15 funds to very substantially reduce the variability around the median. Holding more than 15 funds changes little, i.e. the most relevant range of choice lies between 1 and 15 funds. Within this range it is difficult to make general recommendations without further details on investors' utility functions.<sup>3</sup> If an investor's highest priority was to avoid negative skewness and keep correlation with the equity market to a minimum, then he should invest in a single fund. This leaves a lot of uncertainty though. If an investor wanted more certainty, he should diversify. However, this means accepting a reduction in skewness and a rise in correlation with the stock market, which will severely limit the basket's usefulness as a portfolio diversifier. Most investors nowadays seem to choose for the latter alternative and invest in a basket of hedge funds, either directly or through a fund of funds. Apart from the strong reduction in uncertainty, a second reason to do so is the fact that, as shown in Amin and Kat (2001b), nowadays almost 15% of the funds alive at the beginning of the year close before the end of the year. When a fund closes, its investors will have to look for a replacement. This search is costly, takes time, and may lead to a fund that charges substantial entry fees and/or higher management and/or incentive fees than the old fund.

Although the statistics calculated in this study are used for descriptive purposes only, in more formal terms they can also be interpreted as estimators for the corresponding distributional parameters. Taking the latter point of view, the observed variation around the median stems from two different sources. First, because many funds follow

distinctly different strategies their returns can be expected to follow different distributions as well. Table 2 gives an indication of the differences between the main strategies. It should be noted, however, that there is also substantial variation within the various classes themselves. Second, as we only have 86 monthly returns to work with we are confronted with estimation error. Even if all funds had identically distributed returns we would expect to find variation in the parameter estimates. Because hedge fund return distributions vary substantially between funds and can be highly complex, it is difficult to formally distinguish between these two sources of variation. Due to diversification effects, however, parameter estimates for larger portfolios can be expected to contain less estimation error than estimates for small portfolios.

#### **IV. SURVIVORSHIP BIAS**

Hedge fund data vendors do not provide their subscribers with data on dead funds. As a result, investors are forced to use only surviving funds in their analysis. With dead funds explicitly incorporated in the above, we can easily obtain an estimate of the bias that is introduced by only looking at surviving funds by repeating the above analysis using only the 264 funds that survived the period 1994-2001 and then compare the results with those obtained earlier. The difference is the survivorship bias.<sup>4</sup> Table 3-8 show for every sample statistic that we calculated the difference between the 5<sup>th</sup>, 10<sup>th</sup>, 25<sup>th</sup>, 50<sup>th</sup>, 75<sup>th</sup>, 90<sup>th</sup> and 95<sup>th</sup> percentile of the survivor portfolios and the portfolios containing live as well as dead funds used in the previous section. For brevity we concentrate on portfolios of 1-10 funds.

<< Insert Table 3-8 >>

From table 3 we see that excluding dead funds has a significant effect on the means. Irrespective of the size of the portfolio, all percentiles increase. Due to the exclusion of dead funds the median mean return increases by 0.16% on average (or 1.92% per annum), which is in line with earlier estimates reported in the literature.<sup>5</sup> Table 4 shows that excluding dead funds leads to a significant reduction in the observed standard deviations. For very small portfolios the effect seems stronger than for larger portfolios,

but not by much. On average the median monthly standard deviation drops by 0.24%. From table 5 we see that the exclusion of dead funds causes a rise in overall skewness and that the low percentiles rise a lot more than the high percentiles. The number of funds has little impact again. The results for kurtosis in table 6 are exactly opposite. Overall, the exclusion of dead funds causes kurtosis to drop, with the higher percentiles dropping a lot more than the lower percentiles. In addition, for small portfolios the effect is stronger than for larger portfolios. Finally, table 7 and 8 show that excluding dead funds has little impact on correlation. Both the correlation with the S&P 500 and the correlation with the bond index rise only slightly. In sum, there are two important conclusions to be drawn. First, survivorship bias is a serious problem in hedge fund data. Excluding dead funds will lead one to significantly overestimate mean and skewness and underestimate standard deviation and kurtosis. Second, survivorship bias is largely independent of portfolio size, meaning that the problem cannot be diversified away.

## **V. THE EFFICIENCY TEST**

In Amin and Kat (2001a) we introduced a dynamic trading based efficiency test to investigate whether hedge funds offer investors value for money in terms of risk and return.<sup>6</sup> We found that the majority of individual funds do not offer a superior risk-return profile. However, we also found that hedge fund indices offer a significantly better deal than the average individual hedge fund. To investigate how quickly efficiency improves when we move from individual funds to portfolios the most straightforward approach would be to apply the efficiency test to the portfolios studied in the previous sections. However, with only 86 data points available the efficiency test cannot be expected to be very accurate. We therefore revisited the Zurich Capital Market (previously MAR/Hedge) data used earlier in Amin and Kat (2001a). Starting with the 54 funds that were alive in May 1990, we repeated the portfolio construction procedure used before to produce 10 years of monthly portfolio return data. Subsequently, we ran the efficiency test on the data thus obtained. The results are graphically depicted in figure 7.

<< Insert Figure 7 >>

From figure 7 we see that the frequency distributions of the efficiency test results are negatively skewed. Starting at  $-5.33\%$  (which due to the negative skewness is slightly higher than the average of  $-5.95\%$  reported in Amin and Kat (2001a)) the median improves quickly when the number of funds increases. With 5 funds in portfolio the median is already up to  $-1.06\%$ , while with 20 funds it is only  $-0.31\%$ . The variation around the mean shows a strong decline when the number of funds is increased. For individual funds the difference between the 75% and 25% percentile is  $6.17\%$  and the difference between the 90% and 10% percentile is  $11.79\%$ . For portfolios containing 5 funds on the other hand the 75-25% percentile difference is  $2.28\%$  and the 90-10% percentile difference is  $5.13\%$ . For larger portfolios the drop in the level of variation slows down. For portfolios containing 10 funds the difference between the above percentiles is  $1.78\%$  and  $3.18\%$ . These results clearly indicate that it only takes a small number of funds to obtain a substantially more efficient risk-return profile, which is particularly good news for smaller investors.

## VI. CONCLUSION

Using monthly return data over the period June 1994 – May 2001, we investigated how the performance of relatively small randomly selected baskets of hedge funds deviates from that of the population. We also looked at survivorship bias and the efficiency of the risk-return profile offered. Our main conclusions are as follows:

1. **Expected diversification effects.** Increasing the number of funds in portfolio can be expected to lead not only to a lower standard deviation but also, and less welcome, to lower skewness and higher correlation with equity. Most of the change occurs for relatively small portfolios. One can expect to closely approach the population values with just 15 funds. Mean, kurtosis and correlation with bonds tend to be largely unaffected by a change in the number of funds.
2. **Variation in performance.** Individual hedge funds show extremely high variation in performance. When combined into portfolios the degree of variation drops strongly, although at a decreasing rate. For portfolios containing more than 15 funds the further decline in variation is only small.
3. **The optimal number of funds to hold.** A relatively high number of funds will reduce uncertainty but will at the same time decrease skewness and raise the correlation with equity. The relevant range of choice lies between 1 and 15 funds. Unless one holds a lot more, investing in more than 15 funds changes little.
4. **The index as proxy for a basket.** The population average is a good approximation for the average basket of 15 or more funds. With 15 funds, however, the investor is still confronted with a substantial degree of variation in performance between baskets. Investors should take this into account when making their asset allocation decisions.

5. **Survivorship bias.** Survivorship bias is largely independent of portfolio size, i.e. it cannot be diversified away. Excluding dead funds will lead one to significantly overestimate the mean and skewness and underestimate the standard deviation and kurtosis of portfolio returns.
  
6. **Risk-return efficiency.** From a risk-return perspective, individual hedge funds tend to be highly inefficient investment vehicles. However, one only needs to combine a small number of funds to obtain a substantially more efficient risk-return profile than offered by the average individual hedge fund.

The above is based on analysis of the monthly returns of randomly selected equally-weighted portfolios. It would be interesting to see whether and by how much these conclusions would change if we would drop one or more of these assumptions. Instead of monthly, we could look at quarterly or semi-annual returns for example. Apart from a lack of sufficient data, a priori there is little reason to expect this to yield significantly different results, however. Using value- instead of equally-weighted portfolios might have a bigger impact as this could create significant imbalances in portfolio weights. The most interesting variation is probably to repeat the analysis using stratified sampling, which would allow us to impose certain conditions on the composition of our portfolios with respect to the strategies, age, size, etc. of the component funds. We will save this for later though.

## FOOTNOTES

1. This is similar to the incorporation of parameter estimation risk. See for example Barry (1974) or Klein and Bawa (1976).
2. Around 40% of the funds in our sample are long/short equity funds, 10% are emerging market funds, 10% are global macro funds, 15% follow event driven strategies, and 15% invest on relative value.
3. Scott and Horvath (1980) show that under fairly weak assumptions concerning investors' utility functions, investors will typically desire high odd moments and low even moments, i.e. like mean and skewness but dislike standard deviation and kurtosis.
4. Recall that these estimates are based on the assumption that investors can swap funds at the reported net asset values without any additional costs.
5. See for example Amin and Kat (2001b), Fung and Hsieh (2000) or Brown, Goetzmann and Ibbotson (1999).
6. We will not go into the details of the procedure here. These can be found in the original paper.

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**Table 1: Correlation Between Sample Statistics**

Correlation between	N=1	N=5	N=10	N=15	N=20
Mean – Standard Deviation	0.14	0.26	0.31	0.23	0.31
Mean – Skewness	0.21	0.22	0.25	0.15	0.20
Mean – Kurtosis	-0.04	-0.03	0.00	0.02	0.00
Mean - Corr S&P	0.16	0.22	0.13	0.18	0.17
Mean - Corr Bonds	0.21	0.18	0.17	0.18	0.17
Standard Dev - Skewness	0.19	0.03	0.01	0.02	-0.06
Standard Dev - Kurtosis	0.01	0.15	0.14	0.08	0.11
Standard Dev – Corr S&P	0.14	0.30	0.40	0.43	0.41
Standard Dev – Corr Bonds	0.10	-0.10	0.07	0.13	0.12
Skewness – Kurtosis	-0.35	-0.34	-0.40	-0.60	-0.65
Skewness – Corr S&P	-0.18	-0.30	-0.40	-0.41	-0.48
Skewness – Corr Bonds	0.26	0.13	0.13	0.18	0.14
Kurtosis – Corr S&P	-0.02	0.08	0.08	0.16	0.18
Kurtosis – Corr Bonds	-0.16	-0.16	-0.19	-0.23	-0.26
Corr S&P – Corr Bonds	0.13	0.15	0.27	0.27	0.36

**Table 2: Average Sample Statistics Different Strategies**

Strategy	Mean	Standard Dev.	Skewness	Kurtosis	Corr S&P
Long/Short Equity	1.24	5.65	-0.01	5.36	0.34
Emerging Markets	0.24	7.62	-0.76	7.86	0.42
Global Macro	0.77	5.03	0.77	6.82	0.13
Relative Value	0.69	2.31	-0.72	6.85	0.10
Event Driven	1.04	2.29	-0.75	8.03	0.32

**Table 3: Survivorship Bias Mean Return**

<b>N</b>	<b>5%</b>	<b>10%</b>	<b>25%</b>	<b>50%</b>	<b>75%</b>	<b>90%</b>	<b>95%</b>
1	0.18	0.26	0.18	0.13	0.12	0.11	0.08
2	0.31	0.27	0.21	0.14	0.14	0.12	0.12
3	0.30	0.20	0.18	0.16	0.16	0.17	0.22
4	0.18	0.21	0.16	0.13	0.12	0.14	0.18
5	0.18	0.22	0.19	0.17	0.15	0.11	0.04
6	0.13	0.16	0.19	0.18	0.16	0.13	0.14
7	0.15	0.18	0.16	0.14	0.12	0.11	0.09
8	0.17	0.20	0.21	0.18	0.17	0.16	0.10
9	0.18	0.19	0.17	0.16	0.16	0.14	0.12
10	0.18	0.18	0.17	0.16	0.12	0.11	0.13

**Table 4: Survivorship Bias Standard Deviation**

<b>N</b>	<b>5%</b>	<b>10%</b>	<b>25%</b>	<b>50%</b>	<b>75%</b>	<b>90%</b>	<b>95%</b>
1	-0.13	-0.17	-0.63	-0.60	-0.42	-0.58	-2.10
2	-0.46	-0.65	-0.43	-0.23	-0.15	0.05	-0.03
3	-0.45	-0.41	-0.38	-0.43	-0.45	-0.40	-0.33
4	-0.21	-0.14	-0.11	-0.18	-0.10	-0.10	-0.17
5	-0.10	-0.11	-0.22	-0.21	-0.26	-0.26	-0.35
6	-0.11	-0.12	-0.05	-0.12	-0.07	-0.19	-0.16
7	-0.17	-0.13	-0.17	-0.03	-0.02	-0.07	-0.08
8	-0.21	-0.13	-0.14	-0.20	-0.10	-0.22	-0.22
9	-0.17	-0.19	-0.11	-0.13	-0.01	-0.22	-0.39
10	-0.18	-0.21	-0.19	-0.25	-0.08	-0.23	-0.47

**Table 5: Survivorship Bias Skewness**

<b>N</b>	<b>5%</b>	<b>10%</b>	<b>25%</b>	<b>50%</b>	<b>75%</b>	<b>90%</b>	<b>95%</b>
1	0.94	0.60	0.24	0.06	-0.03	-0.03	0.26
2	0.67	0.30	0.01	-0.05	0.01	-0.08	0.02
3	0.33	0.11	0.04	-0.03	-0.04	-0.01	0.08
4	0.70	0.56	0.21	0.08	0.06	0.14	0.08
5	0.21	0.00	0.01	-0.01	0.04	0.00	0.07
6	0.58	0.32	0.16	0.05	0.03	-0.15	-0.17
7	0.24	0.22	0.07	0.08	0.02	-0.01	0.01
8	0.26	0.19	0.08	0.03	0.05	0.11	0.20
9	0.21	0.17	0.07	0.09	0.15	0.09	0.19
10	0.20	0.23	0.08	0.06	0.03	0.00	-0.02

**Table 6: Survivorship Bias Kurtosis**

<b>N</b>	<b>5%</b>	<b>10%</b>	<b>25%</b>	<b>50%</b>	<b>75%</b>	<b>90%</b>	<b>95%</b>
1	-0.09	-0.19	-0.26	-0.51	-1.55	-2.25	-3.44
2	-0.04	0.03	-0.11	-0.15	-0.90	-3.47	-3.14
3	-0.03	-0.04	-0.16	-0.19	-1.05	-0.93	-2.23
4	-0.03	-0.02	-0.03	-0.44	-1.31	-3.03	-3.70
5	0.09	0.12	-0.07	-0.22	-0.49	-1.04	-1.82
6	0.05	-0.06	-0.08	-0.10	-0.92	-2.00	-2.99
7	0.02	-0.09	-0.18	-0.18	-0.70	-1.10	-1.27
8	-0.10	-0.13	-0.27	-0.45	-0.55	-1.46	-1.67
9	-0.12	-0.21	-0.08	-0.41	-0.58	-1.31	-1.57
10	-0.06	0.00	-0.09	-0.48	-1.01	-1.12	-1.99

**Table 7: Survivorship Bias Correlation S&P 500**

<b>N</b>	<b>5%</b>	<b>10%</b>	<b>25%</b>	<b>50%</b>	<b>75%</b>	<b>90%</b>	<b>95%</b>
1	-0.01	-0.02	-0.01	0.02	0.01	0.03	0.04
2	0.09	0.09	0.05	0.05	0.03	0.05	0.10
3	0.04	0.10	0.05	0.05	0.04	0.06	0.07
4	0.09	0.08	0.05	0.05	0.05	0.05	0.04
5	0.04	0.01	0.04	0.05	0.04	0.07	0.06
6	0.01	0.05	0.08	0.04	0.01	0.01	0.04
7	-0.04	0.02	0.04	0.01	0.01	0.03	0.05
8	-0.04	0.03	0.03	0.04	0.04	0.06	0.04
9	-0.01	-0.03	0.03	0.02	0.02	0.04	0.05
10	-0.03	-0.02	0.03	0.02	0.03	0.05	0.04

**Table 8: Survivorship Bias Correlation Salomon Brothers Bond Index**

<b>N</b>	<b>5%</b>	<b>10%</b>	<b>25%</b>	<b>50%</b>	<b>75%</b>	<b>90%</b>	<b>95%</b>
1	0.00	0.02	0.02	0.01	0.01	0.02	0.01
2	0.02	0.01	0.00	0.00	-0.01	0.01	0.03
3	0.02	0.02	0.02	0.02	0.02	0.01	0.03
4	0.03	0.02	0.02	0.02	0.02	0.01	0.01
5	0.05	0.05	0.02	0.01	0.01	0.02	0.02
6	0.02	0.03	0.01	0.02	0.02	0.01	0.01
7	0.02	0.03	0.02	0.01	0.01	0.02	0.02
8	0.05	0.03	0.03	0.03	0.02	0.01	0.01
9	0.02	0.01	0.01	0.02	0.02	0.02	0.02
10	0.01	0.01	0.01	0.02	0.02	0.03	0.03



Figure 2: Frequency Distributions of Sample Standard Deviation

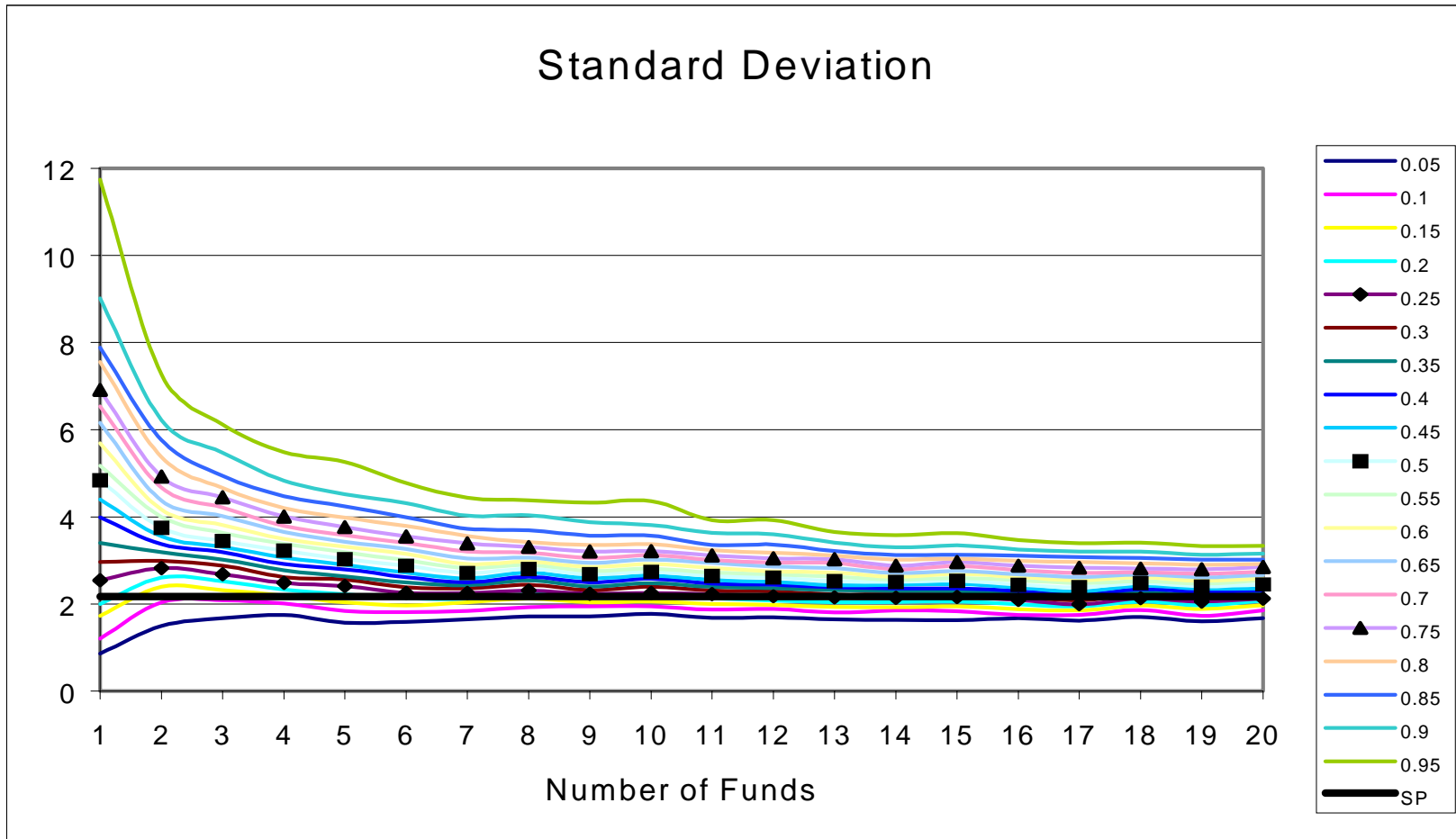


Figure 3: Frequency Distributions of Sample Skewness

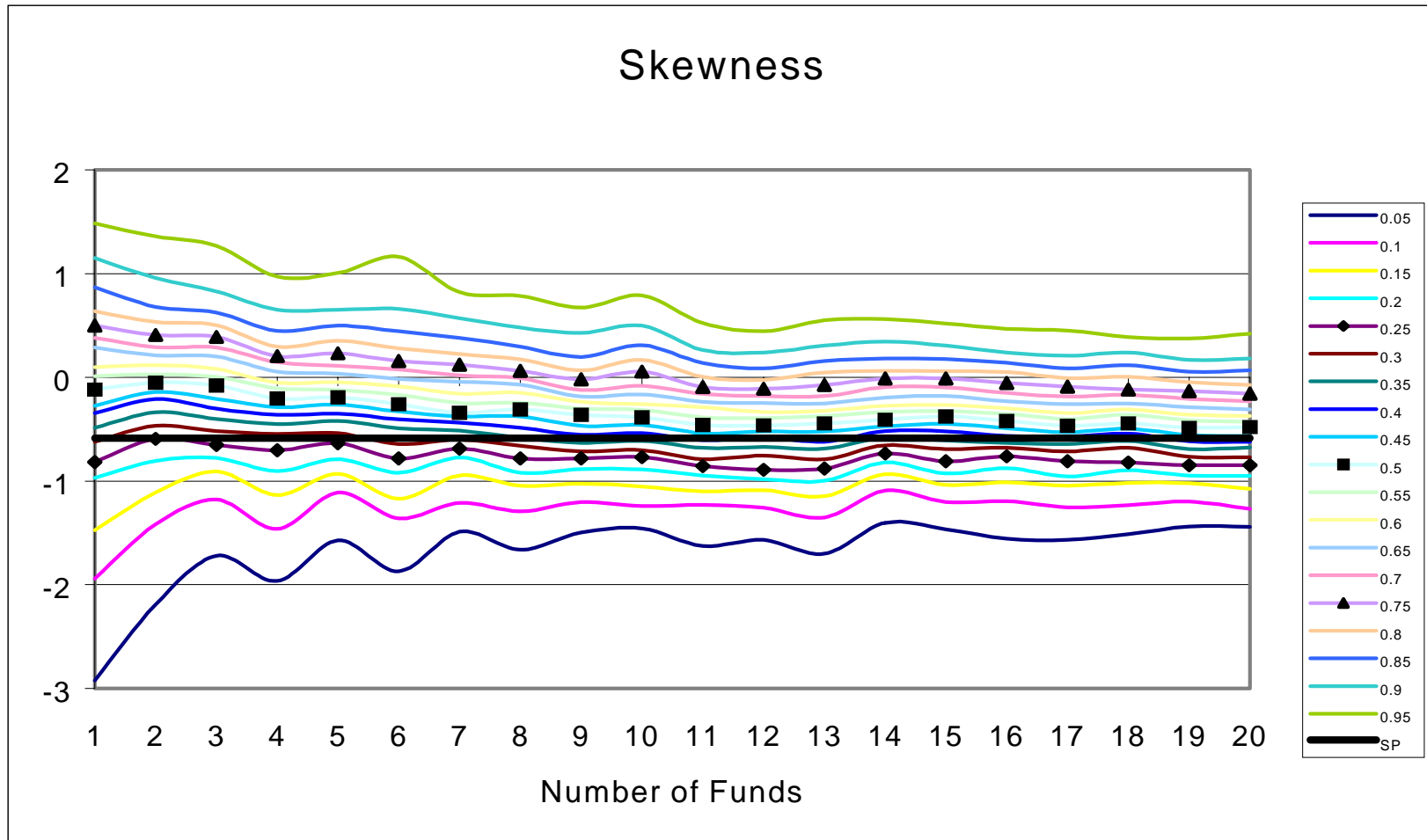


Figure 4: Frequency Distributions of Sample Kurtosis

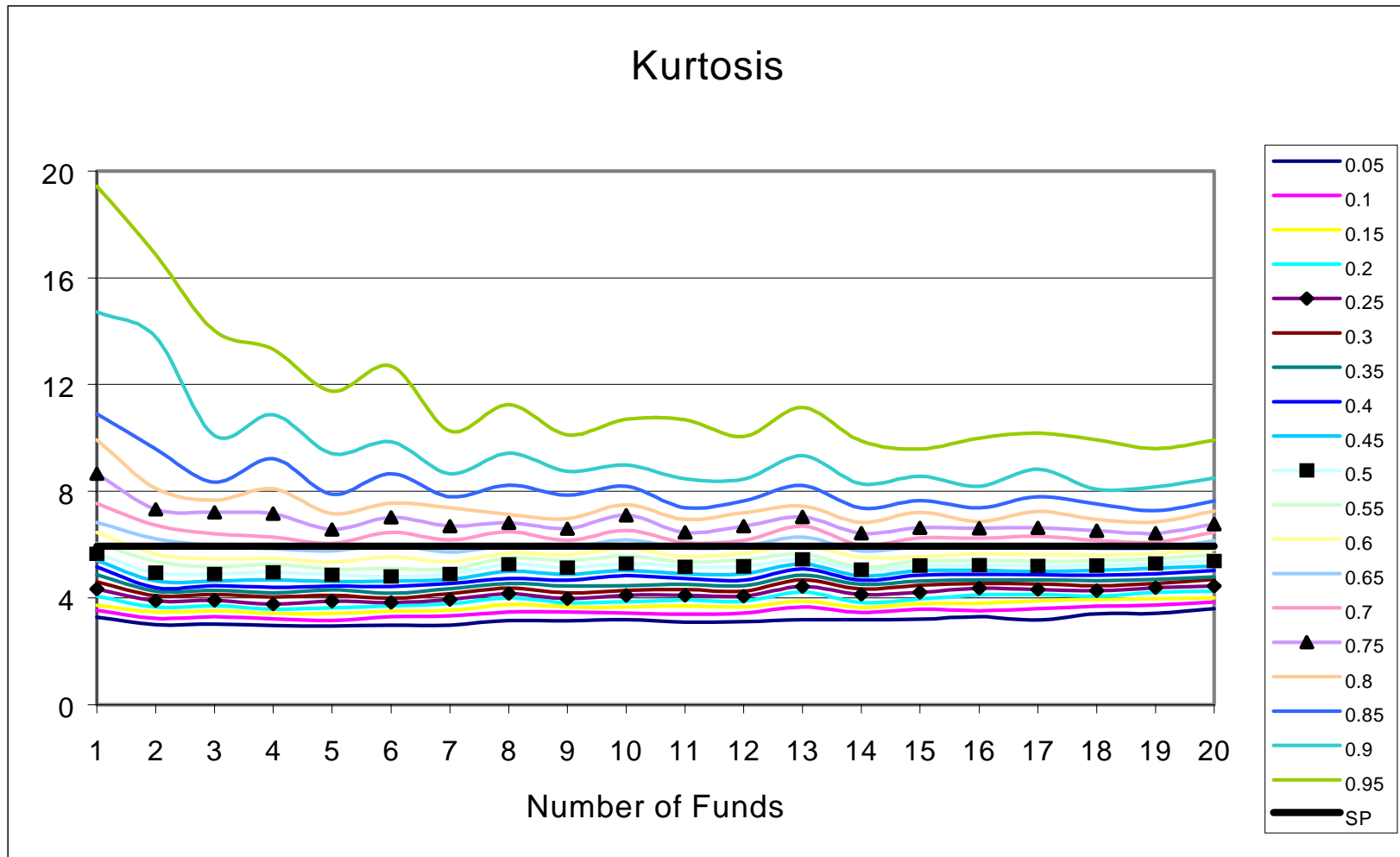


Figure 5: Frequency Distributions of Sample Correlation with the S&P 500

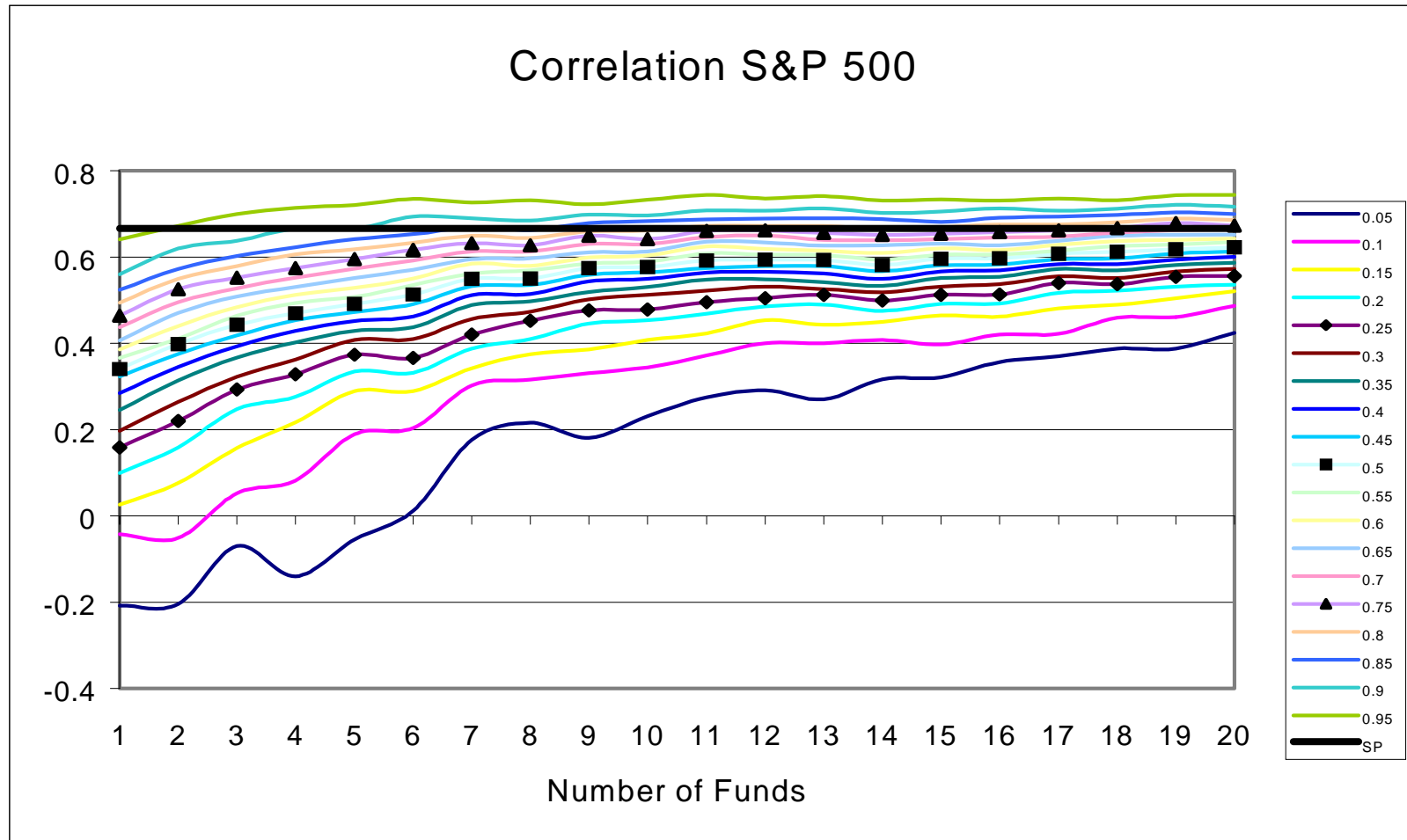


Figure 6: Frequency Distributions of Sample Correlation with the Salomon Brothers Bond Index

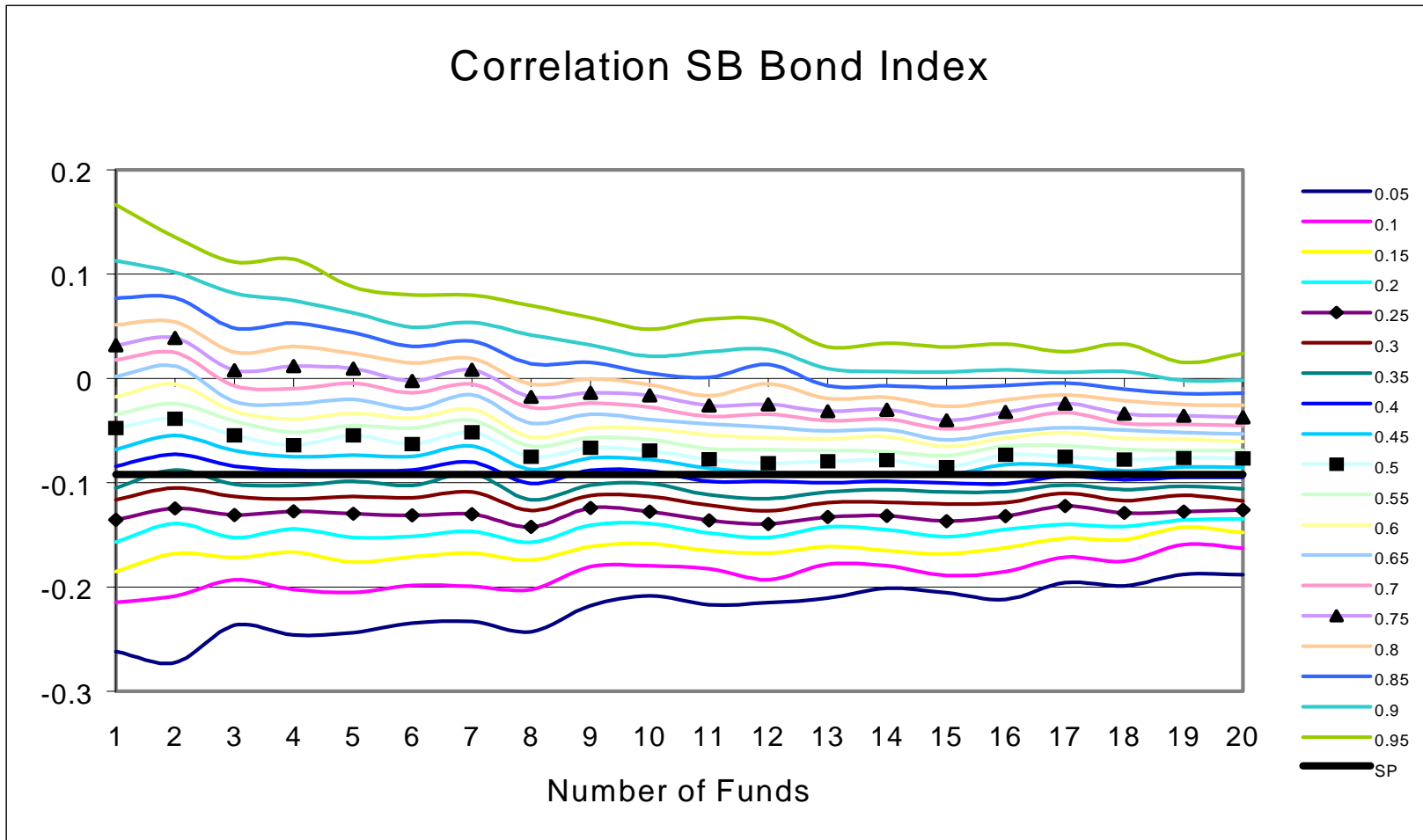


Figure 7: Frequency Distributions of Efficiency Test Results

