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Simple and Effective Market Timing with Tactical Asset Allocation

Part 2 - Choices

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Abstract

In Part 1 a simple market timing algorithm was described that switches from an exchange traded fund representing U. S. equities (**SPY**) to one holding treasury long bonds (**TLT**) every month on the last day, the switch being made to whichever ETF has the greatest ratio of current adjusted closing price to adjusted closing price μ months earlier. The parameter μ was determined so as to maximize total return and minimize the total number of trades. It was demonstrated that, over the 10-year period ending on 12/31/13, this model produced a cumulative annualized growth rate (CAGR) and a maximum monthly (daily) draw down, respectively, of 13.9 and 17.3 (19.0)%; note that these values differ slightly from those in the original paper because a more conservative estimate of trading costs is now included.

In the present work, this model is continued to the present day but also modified by extending the two-ETF comparison to one that includes 5 ETFs. The 3 new ETFs considered track MSCI developed market equities outside the U. S. and Canada (**EFA**), the NASDAQ 100 (**QQQ**), and MSCI emerging markets (**EEM**). The extended model is shown, to date, to deliver 74% higher CAGR than the two-ETF model, but with no increase in draw down despite the increased volatility of the 3 new ETFs in comparison to the two original.

A third option is also examined in which an additional constraint is added to the algorithm, namely that unless all 5 ETFs produce positive returns over the μ-month period, the end-of-month choice reverts to cash or a cash surrogate. If the cash surrogate chosen is the ETF tracking the 7-10 year treasury bond (**IEF**), the maximum monthly draw down to date is shown to be less than half that of the two-ETF model and the CAGR to be actually slightly better.

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1.0 Introduction

The so-called weak form of efficient-market theory (EMT) holds that future stock prices cannot be predicted on the basis of past stock prices[1]. Many advocates of this theory believe that the best strategy for the long-term investor is to "buy the market", by which they generally mean to invest in an index fund that represents all, or a significant segment of, the equity market. The claim is that past performance has shown that, in the long run, buying and holding this class of asset will outperform any active management scheme.

One problem with this approach is the definition of the term long run. To paraphrase the famous British economist John Maynard Keynes, " … in the long run we're all dead". In fact, many investors would consider a 5 -15 year investment as long-term whereas some would choose a period as long as 30 years and others as short as 6 months. A brief look at the large cap growth ETF (**QQQ**) that tracks the NASDAQ 100 (which consists of the largest non-financial securities listed on the Nasdaq Stock Market) exhibits what can happen over a long run. An investor purchasing this fund at its inception in March 1999 would have seen her investment more than double in the first year. Two and a half years later, by September 2002, this would have dropped by more than a factor of 5 and her holdings would be down to less than half the initial investment. It would take 5 more years for this investor to recoup the original investment, not including the interest she would have made had she remained in cash. And then her willpower would be once again tested as she watched the collapse of the financial markets in 2008 by the end of which the value of the initial investment would be once again halved.

It is this scenario that tactical asset allocation seeks to mitigate. The main idea is simply to diversify portfolio assets and employ a market timing solution. But what kind of solution? The literature is replete with different approaches. Our goal here is not to compare the many ideas that have been suggested[2] but rather to focus on 3 very simple strategies, the first of which was described in detail earlier[3].

In what follows we first review the pair switching (**PS**) strategy, that involves choosing either the ETF that tracks the massively popular US index, the S&P 500 (**SPY**) or that tracks the 20+ year US Treasury Bond (**TLT**), the choice between the two being based on which has the higher return over the past μ months. Next we generalize this strategy by including 3 additional ETFs to provide increased diversification, and show that the value of the parameter μ that was determined to be best for the **PS** strategy is also best for the 5 ETF version, which we term quint switching (**QS**). Although the latter is shown to have much higher returns than **PS**, without increase in market risk, the risk involved with either may be too high for many conservative investors. We next show how a simple filter applied to the **QS** strategy can substantially reduce the draw down and still provide a double digit return, equivalent to that of the **PS** model. The performance of this latter model, termed **QSF**, is then compared with that of the other two, with special emphasis on the statistics of draw down, and the limitation of all 3 models is discussed.

2.0 Definitions and Strategy Rules

First, a few definitions are in order. Let the value of the switching portfolio on day $\boldsymbol{n}$ be $\boldsymbol{v(n)},\quad 1 \le \boldsymbol{n} \le N$ and the normalized value be $\boldsymbol{V(n)} = \boldsymbol{v(n)} / \boldsymbol{C}$, where $\boldsymbol{C}$ is the cost basis and N is the total number of trading days since inception of the last originating ETF. Also, let $\tau(\boldsymbol{n})$ be the number of trades, where either a buy or a sell is considered a trade.

For a buy and hold (BAH) strategy with an individual ETF, $ETF(i)$, the normalized value on day n is simply $V_{ETF(i)}(n) = P_{ETF(i)}(n) / P_{ETF(i)}(1)$, where $P_{ETF(i)}(n) = C$ is the adjusted closing price on day $n \geq 1.$ Next, let the ratio of the normalized value on day n to the value on day $n - \hat{\mu}$ be:

$$\rho_{ETF(i)}(n) = V_{ETF(i)}(n) / V_{ETF(i)}(n - \hat{\mu}) \tag{1}$$

where $\hat{\mu}$ is the daily equivalent of μ, the number of "look-back" months of interest.

Then, the generalized switching rule is simply:

Move to $ETF(i)$ on end-of-month day n if and only if

$$\rho_{ETF(i)}(n) = \underset{k=1 \to K}{Max}[\rho_{ETF(k)}(n)] \tag{2}$$

where K is the number of ETFs under consideration.

On all other days the previous position is maintained. For the pair switching strategy (**PS**), analyzed earlier[3], $K = 2$, with $ETF(1)$=**SPY** and $ETF(2)$=**TLT**. For the enhanced quint switching strategy (**QS**), $K = 5$ with $ETF(3)$=**EFA**, $ETF(4)$=**QQQ**, and $ETF(5)$=**EEM**.

Note that both the **PS** and **QS** strategies depend only on relative momentum of the various ETFs. Absolute momentum is not involved. A dual momentum strategy[4], for example, might require that, in addition to the rule specified in equation (2), the winning ETF would need to have a positive ratio, otherwise the position would switch to cash or a cash surrogate. Modifying the **QS** strategy in this way is not advised since back testing can be shown to produce slightly lower CAGR and slightly increased draw down. However, although both the **PS** and **QS** strategies produce maximum draw downs that are far less than any buy-and-hold strategy, some conservative investors might still consider them too high. In this case, there is a dual momentum strategy that modifies **QS** which will be shown to produce less than half the maximum draw down of either **PS** or **QS,** but still yields (double digit) returns better than **PS**. This third strategy, which we will call **QSF** adds a filter rule to equation (2), namely

Move to $ETF(i)$ on end-of-month day n if and only if equation (2) is satisfied <u>and</u>

$$\underset{k=1 \to K}{Min}[\rho_{ETF(k)}(n)] > 1 \tag{3}$$

otherwise move to the cash surrogate $ETF(6)$=**IEF**.

Again, the previous position is maintained on all other days. Equations (2) and (3) combined state that, with the **QSF** strategy, a new position in $ETF(i)$ is chosen only if its ratio is greater than any of the other 4 ratios and, in addition, all 5 ratios are positive. We note here that **IEF** is preferred as a surrogate to cash itself because back testing shows that not only is the return less with cash but the maximum draw down is actually higher as well.

In all three strategies trading costs of 0.1% are assumed to apply for each buy and sell order. Although nominal trading costs are now nearly negligible, the 0.1% number is generally considered a good approximation to account for slippage.

3.0 Performance of the 3 Strategies

To find the best value of μ to use for **QS** we first look to maximize total return, $V(N)-1$, or equivalently the cumulative annualized growth rate over the entire period, $CAGR(N)$, defined as:

$$CAGR(n) = \{[\exp((\log(V)/(n/250))] - 1\} \times 100 \tag{4}$$

(expressed as a percentage) and we have taken a trading year to consist of 250 trading days. Figure 1 depicts $CAGR_{QS}(N)$, as a function of the look back period, μ. Also shown is maximum daily draw down, $DDD_{\max}$.

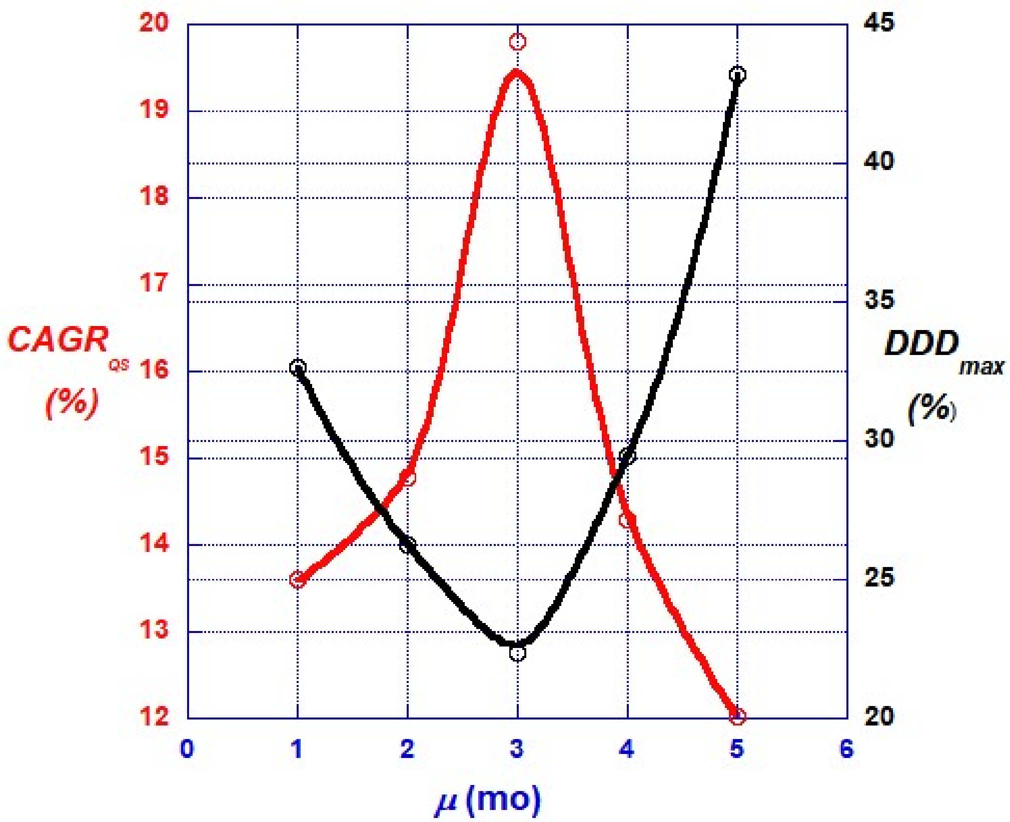

Fig. 1 Cumulative annualized growth rate for the **QS** algorithm for the period beginning on 4/14/2003 and ending 12/16/2017 as a function of look-back period. Also shown on the right ordinate axis is the maximum daily draw down for each value of μ. The results are essentially the same, independent of the ending date.

In contrast to the results for **PS** shown earlier[3], where the CAGR was nearly equal for $3 < \mu < 5$ months, figure 1 displays a sharp maximum at $\mu = 3$ months for CAGR and a sharp minimum for $DDD_{\max}$.

Figure 2 displays the **QS** portfolio value as a function of time from inception of **EEM** (4/14/2003) through 2/1/2018, compared with the buy-and-hold values of the 5 individual ETFs that the strategy utilizes. It is remarkable that, over this almost 15 year period, **QS** produces over a 1400% return which is 2.5 - 6 times the value of the individual ETFs and, as seen in Table 1 below, it does this with less market risk (draw down) than any of them.

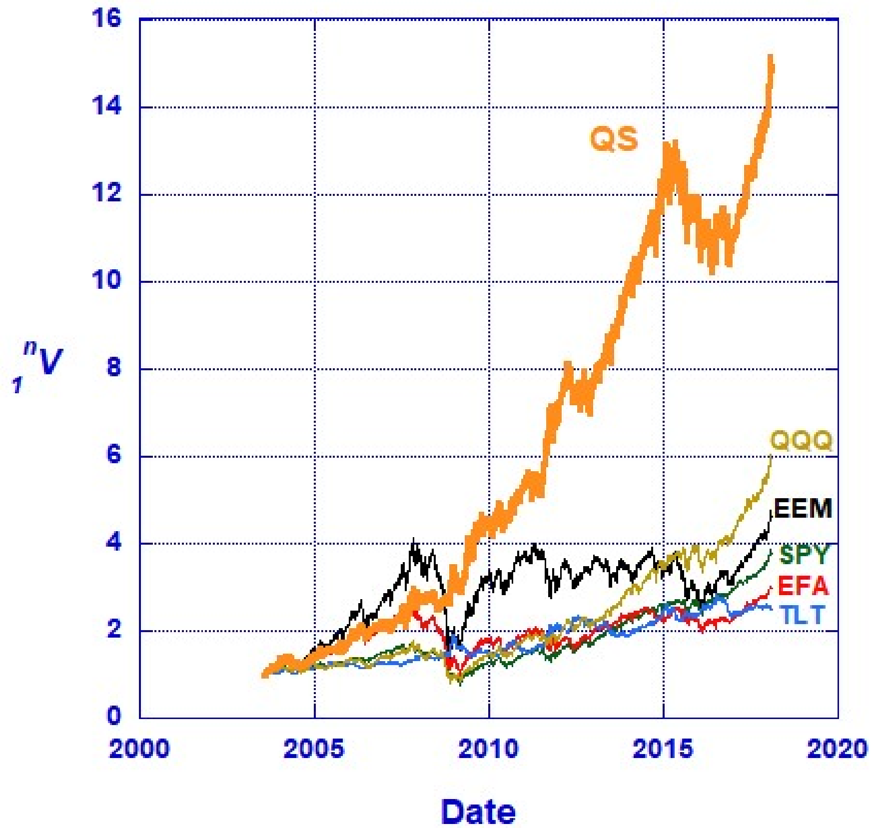

Fig. 2 Portfolio value of **QS** strategy, compared with the individual ETFs that make up that strategy on day $\boldsymbol{n}$, $1 < \boldsymbol{n} \leq N = 3728$, over the almost 15 year period beginning on 4/14/2003 and ending on 2/1/2018.

	QS	SPY	TLT	EFA	EEM	QQQ
$DDD_{\max}$	22.3	55.2	26.6	61.0	66.4	53.4

Table 1 Maximum daily draw down for **QS** strategy compared with buy-and-hold of the individual ETFs that make up the strategy over the period beginning on 4/14/2003 and ending on 2/1/2018.

A few words about draw down are in order at this point. Daily draw down is defined as:

$$DDD(n) = \{\underset{i=1\rightarrow n}{Max}\,[V(i)] - V(n)\} \,/\, \underset{i=1\rightarrow n}{Max}[V(i)], \qquad n = 1,\ldots,N \tag{5}$$

and maximum daily draw down is then

$$DDD_{\max}(n) = \underset{i=1\rightarrow n}{Max}\left[DDD(i)\right] \tag{6}$$

Daily draw downs, and indeed intraday draw downs, are most useful for traders who are focused on profiting from volatility. On the other hand, to be consistent with the strategies discussed in this paper, a monthly time frame is probably more useful since any trades occur, if at all, only on the last day of the month. The monthly draw down, $\boldsymbol{MDD}$, is computed exactly as in eq. (5) except that only end-of-month prices are utilized. This means that any intra-month spikes that might be observed in daily draw downs are not present unless they persist to month's end. Accordingly, monthly draw downs are generally smaller than daily draw downs. In what follows, our focus will be on $\boldsymbol{MDD}$, however whenever maximum draw down values are given, both $\boldsymbol{MDD}$ and $\boldsymbol{DDD}$ will be provided.

Maximum draw downs are not the only issue of interest when market risk is of concern. Two other factors are important, i.e., the frequency at which draw downs of a given magnitude occur and the persistence of large draw downs when they do occur. Both of these features will be addressed at some length in the next section.

Figure 3 compares the relative returns of the three strategies described above.

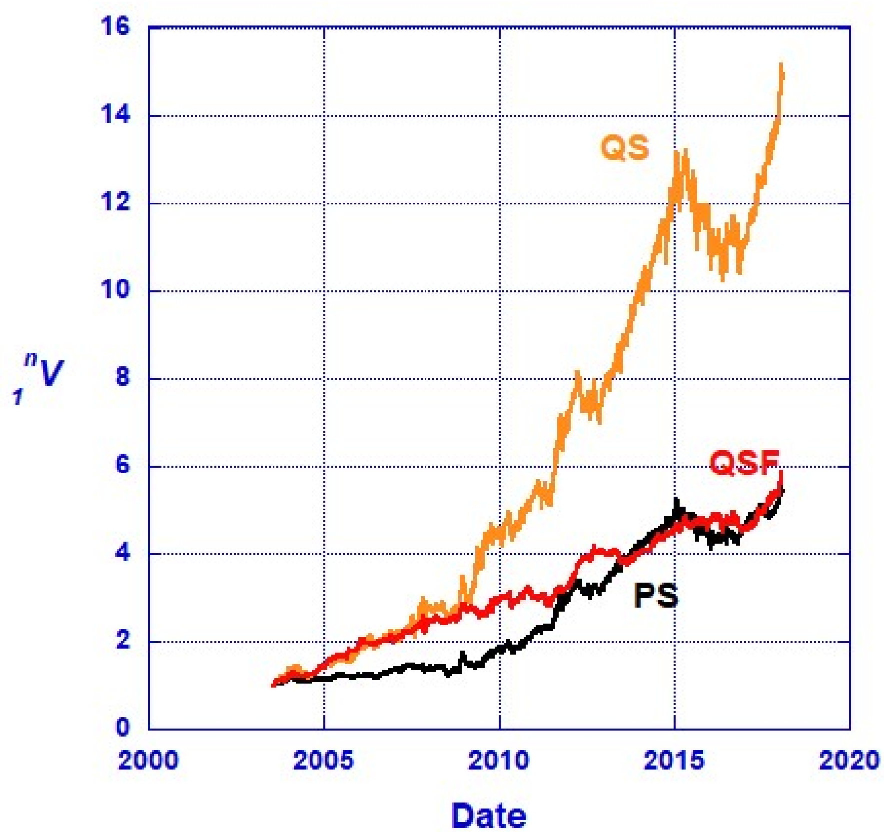

Fig. 3 Comparison of portfolio value of **QS, PS, and QSF** strategies, on day $\boldsymbol{n}, \quad 1 < \boldsymbol{n} \leq \boldsymbol{N} = 3728,$ over the almost 15 year period beginning on 4/14/2003 and ending on 2/1/2018.

It can be seen that **QS** far outperforms either of the other two and that both **PS** and **QSF** produce roughly the same returns. Table 2 compares the maximum draw down and **CAGR** for each strategy.

	QS	PS	QSF
MDD_{max}	19.3	18.6	7.9
DDD_{max}	22.3	21.9	15.4
$CAGR$	20.3	11.7	12.8

Table 2 Maximum monthly & daily draw down and CAGR for **QS** , **PS**, and **QSF** strategies over the period beginning on 4/14/2003 and ending on 2/1/2018.

So, the outsized performance of **QS** comes at the price of much higher risk than with **QSF**. The latter, on the other hand, yields higher returns (nearly 500% over the nearly 15 year period shown) than does **PS**, and accomplishes this with much less volatility and less than half the maximum monthly draw down of the latter.

Finally, figure 4 displays the number of trades employed for each strategy (each switch counts for two trades, except the initial purchase). As mentioned earlier, a 0.1% levy is deducted for each trade to account mainly for the cost of slippage (the difference between the adjusted closing price and the price actually obtained in a transaction). Slippage is not a deterministic process and, while bounds may be established using Monte Carlo methods, this is beyond the scope of the present study.

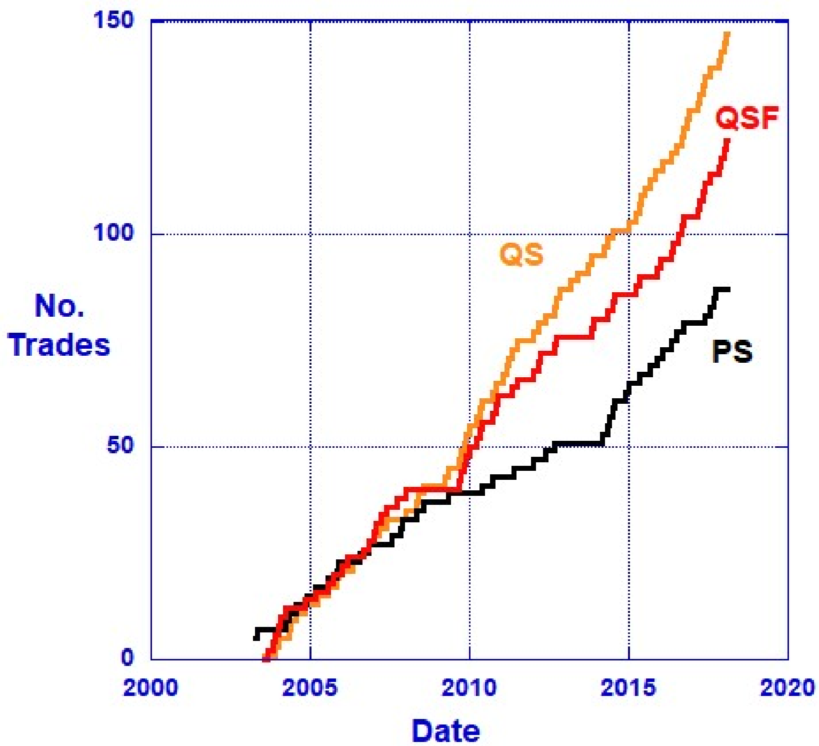

Fig. 4 Comparison of the number of trades made with **QS, PS, and QSF** strategies, on day n, $1 < n \leq N = 3728$, over the almost 15 year period beginning on 4/14/2003 and ending on 2/1/2018. Each switch corresponds to 2 trades.

Note that the **PS** results begin at 5 trades in the figure because the **PS** strategy was implemented from the inception of **TLT** on 7/30/2002 and 5 trades occurred before the date 4/14/2003. Figure 4 shows that the **QS** strategy required 147 trades (73 switches after the initial purchase), which is nearly double that of the **PS** strategiy, but still amounts to only roughly 5 switches per year.

4.0 Statistics of Draw Down

As noted above, maximum draw down is not the only issue of interest when market risk is of concern. Two other factors are important, namely the frequency at which draw downs of a given magnitude occur and the persistence of large draw downs when they do occur. For the strategies outlined in this paper both of these are readily measured by compiling and sorting the draw down results from back tests to compute cumulative distribution functions (CDFs). Figure 5 depicts the monthly draw down CDFs for these three strategies.

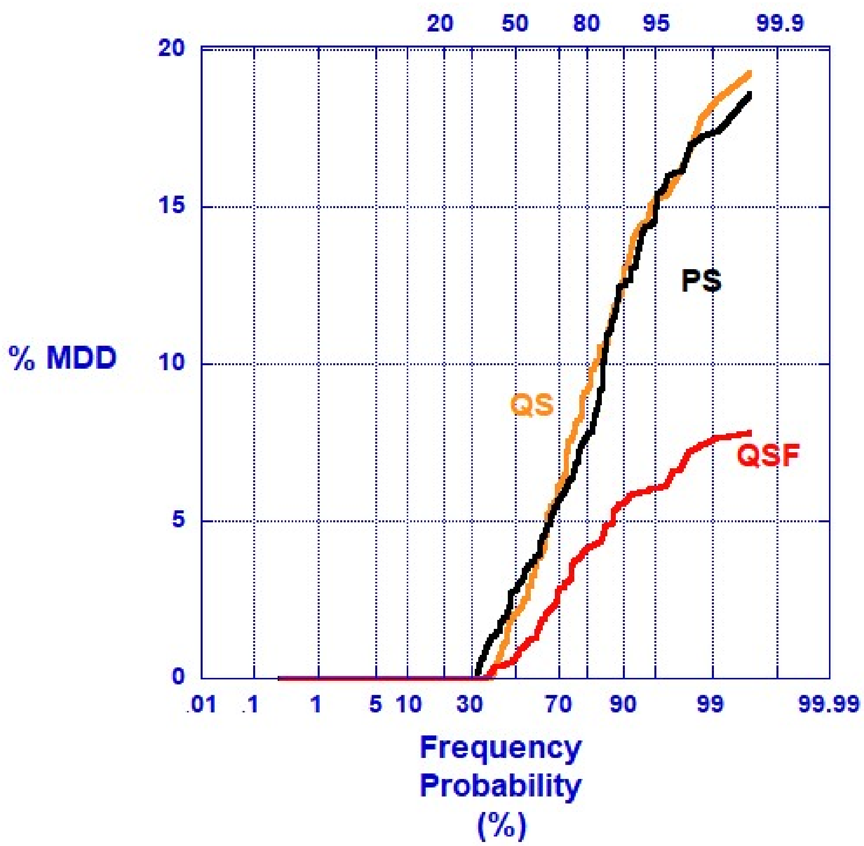

Fig. 5 Cumulative distribution functions of monthly draw downs for **QS, PS, and QSF** strategies, over the almost 15 year period beginning on 4/14/2003 and ending on 2/1/2018. The total number of end-of-month draw down observations in this period is 176.

The scale on the abscissa for this figure is such that a Gaussian CDF would appear as a straight line. Focusing first on the **QSF** strategy, it is observed, for example, that roughly 40% of the end-of-month draw downs (MDD s) are zero, meaning that new highs were recorded at these times. Moreover, 90% of the time MDD s were less than 6% and draw downs exceeding 7.6% would be expected only 1% of the time, or less than twice in 15 years.

The **QS** and **PS** strategies, by contrast, have larger and more frequent MDD s and both exhibit fairly similar draw down statistics. 65% of the time MDD s for these strategies do not exceed 5%, roughly 84% of the time they don't exceed 10% and 95% of the time MDD s would not be expected to exceed 15%.

In addition to the draw down frequency, the persistence and depth of draw downs, when they do occur, is of interest, as is any correlation between the two. Before proceeding to explore these issues, some definitions are in order. We define the draw down period, $\Pi(i)$ to be the number of months between successive end-of-month valuations, $V_k > V_i > V_j$, where $k > j > i$. i.e., the period in months between successive increases in valuation in which at least one month of positive draw down has occurred. Consecutive increases in valuation result in zero draw down, so these periods are ignored. Next, the depth of draw down, $\Delta(i)$ is defined as the maximum local value of draw down that occurs in period $\Pi(i)$. Clearly, $\Delta(i)$ is a subset of $MDD_{\max}(i)$ for all i .

Figure 6 displays the likelihood of draw down periods exceeding Π months for the three strategies described above. Since the ordinate values are integers in this case, a continuous CDF cannot be constructed, so markers are displayed at each discrete level and the curves represent exponential curve fits to the data. Although the data exhibit considerable scatter, the correlation coefficient for the **QS** fit is 0.92, for **PS** is 0.99, and for **QSF** is 0.94. Figure 6 shows, for example, that 90% of draw down periods for **QSF** would be expected to be less than 8 months, for **QS** less than 6 months, and for **PS** less than 12 months. Note, however, that roughly 2% of draw downs for both **PS** and **QS** would be expected to exceed 30 months, which is consistent with the draw downs shown in fig. 3 beginning in March 2015.

Figure 7 depicts the likelihood of draw down depths exceeding Δ % for the three strategies. Here we see that, for example, 30% of draw down depths would be expected to be less than 1% for **QSF**, and slightly more than double that for the other two strategies. At 90% probability, Δ is 6.8% for **QSF** and 13.2% for **PS** and **QS**.

Finally, figure 8 plots draw down depth on the abscissa and draw down period on the ordinate. Although it is clear that there is some tendency for increasing period to correlate with increasing depth, the correlation coefficients for the (exponential) curve fits in this case are 0.92 for **QS**, 0.80 for **PS** and 0.85 for **QSF**, and the variance is evidently quite high.

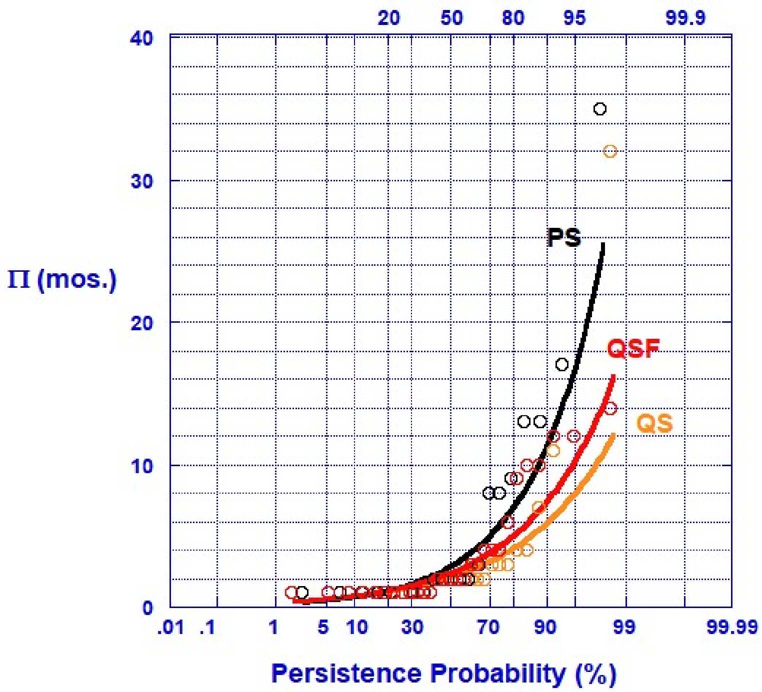

Fig. 6 Cumulative distribution functions of draw down persistence for **QS**, **PS, and QSF** strategies, over the almost 15 year period beginning on 4/14/2003 and ending on 2/1/2018.

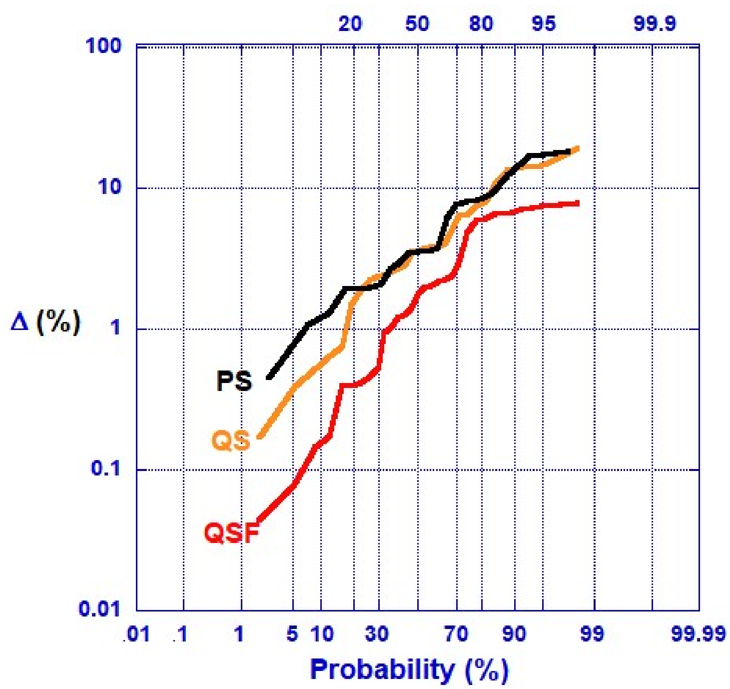

Fig. 7 Cumulative distribution functions of draw down depth for **QS**, **PS, and QSF** strategies, over the almost 15 year period beginning on 4/14/2003 and ending on 2/1/2018.

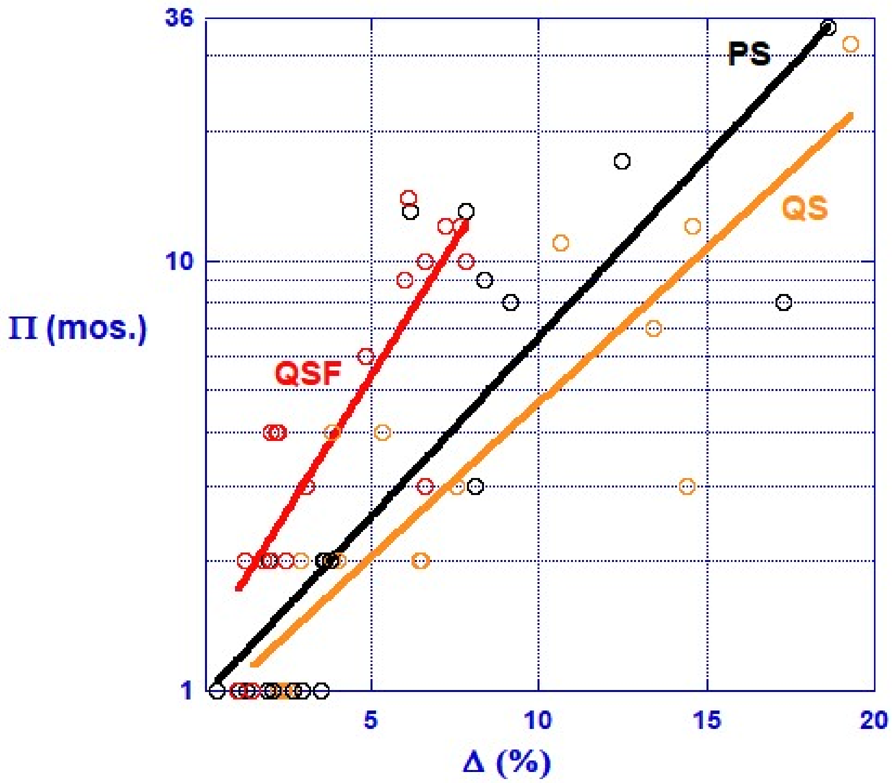

Fig. 8 Draw down period vs draw down depth for **QS**, **PS, and QSF** strategies, over the almost 15 year period beginning on 4/14/2003 and ending on 2/1/2018.

5.0 Discussion

The **QS** algorithm outlined in this paper is a relative momentum strategy that simply chooses at the end of each month from among 5 widely traded and highly diversified ETFs the one the with the highest return over the past 3 months. Back testing of this scheme over the past near 15-year period produced a cumulative annualized growth rate in excess of 20%, which translates to a total return in excess of 1400%. This outstanding performance was achieved with a maximum monthly draw down of less than 20% which, remarkably, is less than the draw down achieved with a buy-and-hold strategy with any of the individual ETFs from which the switching choice is made. However, some conservative investors may still object to 20% draw downs, especially when they persist for an extended period. As seen in figures 2 and 3, the **QS** model experienced a valuation dip commencing in February 2015 and did not fully recover until September 2 years later. The steep recovery beginning near the end of 2016 notwithstanding, an undisciplined investor might be tempted to sell after witnessing a bumpy but steady decline for 15 straight months.

Those investors willing to sacrifice earnings growth for decreased market risk might opt for the variant of the **QS** model that utilizes both relative and absolute momentum. The **QSF** algorithm employs the same switching rule as does **QS** but requires in addition that a switch to any of the 5 ETFs be made only if the 3-month return of all 5 is positive. If not, a 6th ETF is chosen as a surrogate to cash. This additional requirement is quite stringent and results in roughly half as many trades as does **QS**. Although the cumulative annualized growth rate decreased from 20.3 to 12.8%, the **QSF** model also reduces the maximum monthly draw down from 19.3 to 7.9% and the draw down persistence period is markedly reduced as well.

One final caveat - the near 15-year back test period used was based on the fact that the emerging markets ETF employed in the models did not exist until mid-April 2003. Although it is sometimes possible to find (mutual fund or index) proxies that would allow some approximation of what might occur over more extended periods (and this was done in part 1 of this study, with the **PS** model), no satisfactory proxies were considered adequate replacements for some of the ETFs in **QS**/**QSF**. Moreover, the advent of high speed trading, and other innovations introduced in the 21st century, arguably diminish the value of proxy extensions. Thus we are left with the old proviso that past performance may not necessarily be replicated in the future.

6.0 References

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