Filtered Market Statistics and Technical Trading Rules

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Abstract

In statistical sampling, error-prone outliers are usually treated as candidates to be left out. However, for time series of daily returns of broad equity market indexes, we argue that the central crowd around zero mean should be filtered, such that we can better explore market in-efficiencies to improve rules-based market timing results. We demonstrate that the daily return data of some of the most widely followed stock indexes (like S&P 500, Russell 3000, FTSE 100, Euro Stoxx 50, TOPIX, Hang Seng Index, all from 1990 to 2012) around zero are noisy or less directionally informative, and contributing little to the long term return drift.

We propose a filtering threshold for daily returns (gains or losses) at around 20% level of the daily return standard deviation. Within the threshold, daily returns are close to having a uniform distribution or white noise, whereas the statistics of the remaining daily returns (20% to 30% smaller in sample size) largely resemble that of the original full set. Such *structural separation* of index daily returns is important for end-of-day type of technical trading in practice. The nature of the application is to *exclude* all filtered (nearly flat) market trading days in the day-counting scheme of any relevant technical analysis trading rules.

To back-test investment performance of the daily data filtering proposal, extensive daily technical trading schemes, such as very short term mean-reversion, intermediate term trend following, and non-Markov longer term timing scheme, etc., should be considered. We focus on three families of well-known technical trading rules and apply them to daily data of the most liquid and tradable S&P 500 Index (*SPX*). The time span of back-tests covers the past 23 years (1990-2012), which can be further separated as two sub-periods of low and high volatility regimes: the first 10 years (1990-1999) and the next 13 years (2000-2012). Test examples are:

1. *Daily Runs* long/short switching trading scheme, e.g., a naïve *2-day Runs* trading: long when market has two down days and short when market has two up days;
2. *Dual Moving Average Cross* (*DMAC*) trading scheme, e.g. from 5 to 50-day/200-day simple moving average cross-over to switch long/short or long/flat positions;
3. *Price-Channel* based long/short trading scheme, e.g. a channel defined by maximum and minimum *SPX* price levels in the past 200 daily closes.

Regardless using an in-the-sample fixed daily standard deviation or an out-of-sample dynamic volatility estimation in the filtering process, technical trading rules with filtering out-performs the same rule without filtering, in all three rule examples, over all time period and sub-periods, and for all parameter variations tested.

The largest difference that the filter rule makes is from the simple *2-day Runs* trading example, which has a dynamic implied volatility (daily close quote of *CBOE VIX* index) based filter to count out "nearly flat" days. Over the recent 13 years (2000-2012), it adds about 7% in annualized return to the naïve scheme without filter; it beats the passive *SPX* index holding by 16% in average return per year; and it has much better overall risk-adjusted returns. The choice of *2-day runs* is interestingly the random walk outcome derived from the classical *distribution theory of runs* by Mood (1940), and is also expected using Fama (1965)'s approach of *ex post* serial correlation examination. However, the superior performance of recent decade in back-test deviates from the original random walk assumption and questions Fama's very conclusion of market efficiency almost half a century ago.

Market index based technical trading or market timing is essentially trying to explore price in-efficiency in the broad market. By filtering out "nearly flat" days as unimportant due to very little market-moving information content or simply being noisy, we argue that rules based technical trading has better chance to succeed. Sizable market index moves on information-intensive days probably reflects macro-economic surprise or misinterpretation, so they are more on the side of market in-efficiency to be focused on. Market participants or institutions with fundamental views are usually patient to wait out the "information light" days or periods, until their targets are met or macro-surprise and market action change their investment policy. Thus, from information efficiency and market structural arguments, our index daily data filter proposal should have broad potential for technical trading rule design. By dynamically calibrating market trend or mean reversion by volatility-based filtering "day-in and day-out", a rules-based technical trader or an active investor can win the long run investing "game"!

Introduction

In science and engineering, extreme outliers in a statistical pool are usually subjected to scrutiny. They are highly suspected as spurious samples due to measurement errors, and are often left out of the sampling process ultimately. Similarly, for stock market price returns, early theorists (e.g. Bachelier, 1900) tended to ignore observations of large price move outliers. This way the sampling data can fit closer to the more elegant statistical distributions under the hypothesized random walk framework (Campbell, *et al* 2005). However, days of large market price moves, no matter crashing or rallying, cannot be overlooked in investment management practice, as they have the largest impact on investment performance results. Market crash or price jump may fit into the textbook symptom of an *in-efficient market.* Still they incur the most risks or opportunities for an active investor, whose market timing premise roots in the ability to explore market in-efficiencies.

On the other hand, opportunities from market inefficiency are reflected in the information content of market price moves. Correct interpretation of price implied information to predict future market is the key to technical analysis. Market technicians developed a plethora of technical trading rules only based on price histories (Murphy, 1986), which can be further translated into return time series and their sampling or autoregressive statistics. Usually the technical trading rules have time scale parameters as number of trading days – not only for purpose of smoothing data, but also reflecting one of more expected market cycle length. A rarely asked but important question *against* the full sampling approach of day-counting in technical trading rules is:

Can some market days be filtered out in the day-counting to improve expected performance?

The success of this will depend on the design of the filtering rule to screen out noise. Still it has to include days with significant market-moving information content, capture price opportunities of an inefficient market, and improve prediction of relevant market cycle length. The tail event days with large daily gain or loss need to be retained.

That naturally leads us to consider the "nearly flat" days as candidates to be filtered out. These "nearly flat" days are usually information light and contribute little to investment results. But they impacts prediction of market cycle length in the technical rules. Such impact could be important in very short term trading rules when one single day being counted-in or out matters; or in long term day-counting rules when many "nearly flat" days are a significant portion of the total number of look-back days counted. Also in non-parametric type of day-counting technical rules, such as that only "up" or "down" day matters to trading position being taken, filtering out "nearly flat" days helps to reduce uncertainties in the end-of-day type trading execution.

If filtering out "nearly flat" days improves a technical trading rule in predicting market cycle lengths, market structure or micro-structural reasons might help to explain. Rather than strictly following calendar day-counting, fundamentals based investors or financial institutions will most probably be patient to wait out these information light "near flat" days until fundamental information basis or accumulated market price action causes them to change investment policy. Due to the size of the institutional investor group, alignment with the logic of counting out light days might help technical trading rules predicting future market move. For the short term daily technical rules, counting out "nearly flat" days might also help to match with the positions from the index futures trading limit orders that have multi-day entry or exit price targets.

Besides these qualitative arguments, we will examine market index daily sampling statistics and develop the filter rules systematically in this study. Short term mean-reverting, longer term trend-following, and non-Markov channel trading rules will be back-tested. We intend to demonstrate day-counting filter not only improve the out-of-sample performance of a broad range of technical trading rules, but also make them more robust in term of sensitivities to parameter choice or avoiding data snooping bias . We will make discussions based on the examples' in-the-sample and out-of-sample back-test results. Finally we conclude the filter treatment of technical trading rules and map out future work.

Filtered Market Statistics

Examination of market index sampling statistics with and without filtering is for the purpose of adjusting technical trading rules. Most of technical trading rules were developed during or before the 1980's (Murphy, 1986) and applied successfully in commodity futures trading. When extended to liquid stock index futures trading, it was noticed that some of the technical rules lost effectiveness in the 1990's bull market (Taylor, 2005). Since early 1990's, we witnessed the popularization of exchange based stock index futures trading , the reduction of index transaction costs due to the introduction of no-load index mutual funds and ETF's, and the advent of broad based electronic trading. All these market structural factors turn stock indexes into investable liquid financial assets, rather than just some mathematically computed time series of their component stocks. This in turn can also impact the efficacy of index based technical trading rules.

For these reasons, we will focus on daily data of liquid stock indexes in the last 23 years (1990-2012) for the *filter* study. Given a sample period, our method of filtering first computes a filter *threshold* for daily returns. It can be around 20% of sample daily return's standard deviation of the *full set*. With the *threshold*, we separate the *full set* of daily returns into a *filtered set* and a *retained set*. The *filtered set* contains the daily return samples whose magnitude is less than the *threshold* level, regardless of a daily gain or loss. The rest of the daily returns constitute the time series of the *retained set*, which essentially skips the *nearly flat* trading days whose daily return magnitude is within the *threshold*.

Table 1(a), (b) and (c) shows the summary statistics of S&P 500 Index (*SPX*)'s daily return over 1990 – 2012, and two sub-periods 1990 – 1999 and 2000 – 2012 respectively. The 23 year time span (1990-2012) has total 5797 trading days of daily returns in the *full set*. After filtering at a threshold of 0.25% (21% of the full set's standard deviation), 27% of the full set – a total of 1566 daily returns go to the *filtered set.* The *full set*'s excess Kurtosis is 8.5. That explains why *filtered set* is larger than what it would have been, about 17% of the *full set* if the full set has a normal distribution[1]. Some observations in the summary statistics in Table 1 worth noting:

First, the low ratio (< 3%) of (*mean/standard deviation*) of both the *full set* and the *retained set* indicates daily return samples are close to a *Martingale* (zero return drift) process;

Second, *retained set* has similar statistics as the original *full set*: close to zero return drift, similar level of standard deviation, small skew and large excess kurtosis – since the central crowd around zero mean (the *filtered set*) are truncated from the distribution, the *retained set* has somewhat larger standard deviation and kurtosis than the original *full set*;

Third, the *filtered set* has a near uniform distribution [2](see Figure 1's histogram of the *filtered set*) or spreads like white noise within the bound of daily return *threshold*. The mean return is

[1] The size of the *filtered set* can be approximately calculated using the *Cornish-Fisher* expansion with the moments listed in Table 1(a).

[2] A χ^2 hypothesis test can verify the uniform distribution at 95% confidence level.

even smaller than the drift of the *retained set* or *full set*. We call them "nearly flat" days as they probably have little net market-moving information content.

For the two sub-periods 1990-1999 and 2000-2012, the summary statistics have similar characteristics as the full period except that the filtering *thresholds* are different. As filter *thresholds* are scaled by the sampled standard deviation, it does not seem to make a difference on the structural separation of daily returns, no matter the sample has the 1990's bull market's lower daily standard deviation or the higher realized volatility of the 2000-2012's full market cycle.

Appendix 1 lists summary statistics other well-known stock indexes with and without daily return filter. The effects of filtering and distribution characteristics are similar to those of the S&P 500 Index. TOPIX stands out with negative long term return drift and STOXX has the most drastic reversal for the two periods (1990's and after 2000) in daily mean return, although their other sampling statistics are similar to the other indexes.

We also examine the impact of filtering on autoregressive statistics. Table 2 lists the S&P 500 Index daily return serial correlation coefficients for lag one-day through five days[3]. Filtered daily returns within the threshold are taken out the time series. The lag one-day through five-day serial correlation coefficients are also computed on the *retained set*. The most visible effect of filtering is that the lag-2 day serial correlation are reduced by the most amount (to further negative) among the five lags. That is true for whole period 1999-2012 and two sub-periods.

Runs Long/Short Switching Trading Rule

[3] Fama (1965) presents an extensive empirical analysis of US daily, four-day, nine-day, and sixteen-day stock returns from 1956 to 1962, and concludes that, "there is no evidence of important dependence from either an investment or statistical point of view".

The "*Runs*" is defined as consecutive gaining or losing trading days. It is the simplest non-parametric (that the magnitude of gain or loss does not matter) pattern for a daily return time series. The asymptotic distribution properties of "*Runs*" are among the earliest statistical tests of random walk hypothesis and market efficiency theory (Campbell *et al*, 2005). "Up" or "Down" day-counting is critical in a trading scheme designed to take advantage of any pervasive *Runs* pattern. The simplest, somewhat naïve scheme[4] can be a mean-reversion trading rule on a single stock index like the S&P 500:

Long 100% in *SPX* at the market close of a trading day when the index has been *down* for *n* days (including the trading day)[5]; switch to 100% *short* in *SPX* at the market close of a trading day when the index has been *up* for *n* days (including the trading day). The 100% *long* or *short* position in *SPX* is continued if *n*-day runs condition for switching has not been satisfied.

To choose the single parameter *n* to decide the length of *runs* sequence to trade with, we recall the *Distribution Theory of Runs* (Mood, 1940) that in *N* daily returns time series sample, the expected number of switching of *runs* sequence is:

$$E(S_{runs}) = 2Np(1-p) + p^2 + (1-p)^2$$

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[4] Position sizing scheme and risk management such as stop limits can help to make the naïve trading on *runs* sequence a more practical market timing strategy. Theoretically, Bayesian probability and Markov chain techniques can be used for sizing leveraged or partial long or short positions in the *runs* sequence. A data-mining approach to select the trading parameters can also be used on an out-of-sample basis. These practical variations are out of the scope of the current study, although we believe the current filtered day-counting proposal is also applicable.

[5] This is a typical same-day end-of-day trading scheme. As the close quote for trade decision is assumed as the same transaction price, it can be hard to implement in practice. For example, some no-load index mutual funds require a 3:45PM cut-off to submit trade order to get the same-day execution. The index level at 3:45PM can be significantly different from the 4:00PM close price. This can make the early trade decision deviate or outright opposite to what it should have been. However, one can use the E-mini futures contracts to trade as the futures trading closes at 4:15PM. *SPX* index futures might be the world's most liquid contracts. Futures trading provide ability to leverage as well.

where p is the probability that single daily return is positive – the *up*-day probability and $(1 - p)$ is the *down*-day probability. From summary statistics of Table 1 and Appendix 1, we know that stock index daily return process is close to *Martingale* and thus p is about ½.

When the sample period for *SPX* spans over a decade that N is large (N >2500), the expected number of *runs* switching from the above formulae is about half of N. Then the expected average *runs* length n of *SPX* is 2 days. So we will study only a 2-day *runs* trading scheme in this paper.

On *ex post* basis, Table 2 shows lag 2-day serial correlation of *SPX* daily returns is the most negative in most cases, which supports empirically the choice of 2-day *runs* mean-reversion trading scheme. Table 2 also reminds us the value added to the negative 2-day serial correlation by the filter rule of daily returns. The daily return filter rule can be easily introduced to the *runs* trading scheme: just skip a "nearly flat" day in the *runs* day-counting and resume when a normal day (with daily return beyond threshold magnitude) comes. Still the small returns of these "nearly flat" days will be included in the trading scheme's total accumulated returns, since a long or short position is taken in those days.

We study how to choose a daily return filter threshold for the 2-day *runs* trading scheme. We first use a constant filter threshold approach. Figure 2(a) shows, for two sub-periods 1990-1999 and 2000-2012, the annualized returns of the 2-day *runs* scheme when the absolute level of fixed filter threshold is changed. The level of optimal constant threshold depends on the sample period. Figure 2(b) scales the constant filter threshold by each sub-period's daily return standard deviation respectively. The results show that 20% and 22% daily return standard deviation of the respective sample period is optimal to maximize the annualized returns. It is obvious that the 2-day *runs* trading scheme performs better (with higher annualized returns) in 2000-2012 than in

1990-1999. Compared to the un-filtered original *2-day runs* scheme, the out-performance in annualized return is over 5% in 2000-2012 and 3% in 1990-1999, also shown in Table 3(a) – (b). The number of long/short switching trades is also reduced due to the filter rule. For example, during 2000-2012, it is down from 533 trades for the unfiltered case to 393 trades when a d = 0.3% daily return filter threshold is used.

Two simple out-of-sample dynamic choice of filter threshold level for *runs* trading day-counting scheme is also considered:

1. *Filter Threshold d* = 20% of *SPX* daily return standard deviation in the 60-day look-back rolling window (such that the threshold calculation is updated daily);
2. *Filter Threshold d* = 22% of the current *SPX* index option implied volatility, which we use the same-day *CBOE VIX* Index close quote / ($100\sqrt{252}$) (also updated daily).

Table 3(b) summarizes the performance metrics of the dynamic filter rule in comparison to fixed filter choices. The *VIX* based dynamic filter performs best in annualized return and risk adjusted returns for the total period 1990-2012 and sub-period 2000-2012. Although this study is not aiming for volatility forecasting, the dynamic filter based on implied future volatility has stood out in performance. The 2-day *runs* trading scheme by nature is playing the very short term market mean-reverting expectation "game". The out-performance of the *VIX* based filtered *runs* scheme over the recent 13 years (2000-2012) is substantial. As shown in Table 3, it adds about 7% in annualized return compared to the original 2-day *runs* scheme without filter, and beats buy-and-hold *SPX* Index by over 16% per year in return.

Annual returns from 2000 to 2012 from back-tests are listed in Table 4 for each case. Figure 3 shows the account value growth comparison among *SPX* Index, 2-day *runs* trading without filtering, and with *VIX* based filter when all starts at the end of 1999 with 100$.

The value added by day-counting filter to the 2-day *runs* trading scheme is obvious. From Table 3, over 23 years (1990-2012), all filtered schemes have better annualized returns by about 2% to 4%, higher risk adjusted returns (ratio of annualized return/standard deviation) by about 0.1 to 0.2, and lower maximum drawdown than the unfiltered case. Passively holding *SPX* index over 1990-2012 can only achieve similar annualized return and risk adjusted return as the unfiltered 2-day *runs* scheme, but it has much larger maximum drawdown as indicated in Table 3. However, over the ten year period 1990-1999, *SPX* index out-performs all 2-day *runs* trading scheme significantly. Without any sophisticated position sizing and risk management, the simple 2-day *runs* scheme expects short term mean reversion. It is simply not suitable in a strong trending bull market like the 1990's. Still two out of three filtered *runs* scheme tested out-performs the un-filtered *runs* scheme and have annual returns from 5% to 6% over the ten years.

Dual Moving Average Cross Trading Rule

Dual Moving Average Cross (DMAC) is a well-known technical trading rule that involves most of today's trending following system (Murphy, 1986). It calculates two price moving averages at different look-back lengths. For example, the rule of *Golden Cross* on S&P 500 Index compares 50-day simple (arithmetic) *price* moving average of *SPX* against a longer 200-day *SPX* moving average. When Shorter Moving Average (SMA) crosses below or above Longer Moving Average (LMA), a long/short or long/flat position on the index is switched.

Compared to runs trading, DMAC has much longer time scale as it tries to signal change of intermediate to longer term market trend (Brock *et al*, 1992). For example, the 50-day and 200-day SMA and LMA only crossed 21 times in the past 22 years (1991-2012). However, day-counting is also important in a DMAC trading rule as it implies an expected cycle length of market trend.

The daily return based filter rule can also be used to adjust the DMAC trading rule. Take 0.25% as the threshold to filter daily returns of *SPX* when computing SMA or LMA. If a "nearly flat" day is within the range of look-back for simple moving average calculation, the index price of that day is ignored. Then the look-back day range has to be extended to backfill the closet earlier "essential" day whose daily return is beyond magnitude of the threshold. That earlier day's close price becomes a new component of the moving average calculation. The total number of daily close prices in the moving average calculation is still the same as the stated look-back length. Just all the prices of the nearly flat days are skipped and replaced with the same number of those closest earlier "essential" days as needed. The net effect is that the filtering process expands moving average information to further back-ward time at the expense of excluding recent nearly flat days, which could be just noise.

As back-test examples, we focus on Dual Moving Average Cross trading rule on the *SPX* index. We fix the longer moving average (LMA) look-back length as 200 days, and vary the shorter moving average (SMA) look-back length as 5, 10, 20, 25, 30, 40 and 50 days. When SMA is above LMA, a 100% long position is taken in the S&P 500 index the same day at market close; on the other hand when SMA < LMA, we test the variations of *flat, 50% short* or *100% short* in the index.

As shown in Table 5, for the past 22 years (1991-2012), filtered DMAC out-performs non-filtered DMAC in all 21 cases. In one case (25-day for SMA and 100% short when SMA < LMA) the difference in annualized return is 4.67%! DMAC without daily return filtering exhibits high sensitivity to the parameter of look-back length of SMA – only three out of the 21 cases have better annualized return performance better buy-and-hold S&P 500 Index passively.

In contrast, 18 out of the 21 cases of filtered DMAC have higher annualized return than *SPX*. The three under-performing cases are all in the group of 100% short when SMA < LMA, and on the short end of SMA look-back length. The lags in annualized returns from *SPX* are less than 1%. It is known that moving average trading rule has a lagging effect shortcoming. DMAC can be trapped in a whip-saw market on false prediction of a bearish trend. This reflects more on the trend following effectiveness of DMAC, rather than too much about the adjustment using the day-counting filter rule.

With daily return filter, DMAC also shows robustness on parameter variations. When SMA look-back length varies from 5-day to 50-day, the annualized return over 22 years (1991-2012) differs less than 1% out of a maximum of 8.6%, as shown in Table 5(a). The big difference in accumulated wealth growth is shown in Figure 4(a). This is a “middle” case that 25 day/200 day DMAC is used and the 50% short position is taken when SMA < LMA. Recall that a 0.25% daily return filter can exclude over 20% of the trading days. To include same number of early “essential” days in the moving average sample, this could be effectively looking at a half quarter (30-day) and one year (250-day) look-back coverage.

Figure 4(b) shows traditional Golden Cross (50-day/200-day) results that filtering makes little difference. Filtered 50-day/200-day comparison can be a quarter (60-day) versus one year

(250-day) look-back coverage, which has a clear financial accounting explanation. On the other hand, Golden Cross parameters could be result of *ex post* optimization after decades of *SPX* data.

Price Channel Trading Rule

Channel trading rule (Lukac *et al*, 1988) has been effective in trading commodity futures. One single parameter of channel look-back length L is involved. For example, L = 200 days can be used for *SPX* index. For every day at close, the highest /lowest index price over the past L = 200 days (excluding the same day) gives an upper and lower bound of the index price. Let us denote at t day close, the upper and lower bound on index price as M_t and m_t respectively:

$$M_t = Max\ (P_{t-1}, P_{t-2}, \ldots, P_{t-L+1}, P_{t-L}) \text{ and } m_t = Min\ (P_{t-1}, P_{t-2}, \ldots, P_{t-L+1}, P_{t-L})$$

where P represents the daily close price and the subscript denotes the day account in look-back.

With time progressing, the rolling bounds form a marching price channel as shown in Figure 5 for past 23 years (1990-2012). The simple Channel Trading Rule of 100% long and short switching is:

When current position (day t) is long, switch to short when $P_t < m_t$ at the day's close, and stay in the long position when $P_t \geq m_t$;

When current position (day t) is short, switch to long when $P_t > M_t$ at the day's close, and stay in the short position when $P_t \leq M_t$.

Essentially the channel breakout trading rule has bifurcated decision branches of long or short depending on the direction of the current position. Thus it is a non-Markov process based market timing scheme. For *SPX* index with a channel look-back length of 200 days, the channel trading rule is a long term trading scheme[6]. It differs in underlying market timing logic from the very short term mean reversion daily runs trading rule and the intermediate term trending-following scheme of dual moving average cross. We introduce the long term channel trading rule to check the effects of the daily return filter.

We apply the daily return filter of threshold d = 0.25% to the *SPX* index. In defining the upper and lower bounds of the channel, prices of the "nearly flat" days are ignored and the look-back window is extended back-ward as necessary to include prices of the same number of earlier "essential" days. The nominal look-back length of the channel is maintained in terms of actual number of daily prices considered after filtering. The actual rolling window look-back coverage of the channel is changing due to volatilities of short term daily returns.

The daily return filter improves the channel trading scheme substantially compared to the non-filtered original 200-day look-back channel scheme on *SPX* index over the last 23 years. The major difference occurs during the past 2.5 years by the end of 2012, when the filtered channel trading yields better market timing effectiveness. As shown in Figure 6, the accumulated assets of channel trading more than double just due to filtering adjustment over the last 23 years (1990-2012). Due to the number of "nearly flat" days filtered out, the 200-day look-back in channel definition after filtering extend the average window to about 250 days (one calendar year). This matches standard accounting cycle statistically.

The robustness of the channel trading scheme is also improved due to day-filtering in the channel definition. We vary the nominal channel look-back lengths by a 25-day step from L =

[6] Over the past 23 years (1990-2012), the 200-day look-back *SPX* channel trading incurs only 7 long/short position switching indicated by Figure 5.

150 days to 250 days. As shown in Table 6, filtered channel trading rule out-performed the non-filtered rule for all look-back lengths by from about 0.7% to 4% in annualized returns. Also every filtered channel trading rule in Table 6 out-performs the passive *SPX* index over the past 23 years in annualized return. In comparison, every unfiltered channel rule using the same nominal look-back length under-performs the *SPX* index. Thus daily return filter can help making the long term channel trading rule viable on *SPX*. The variation among annualized returns for five different channel look-back lengths is also smaller for the filtered rules than the unfiltered channel rules, as shown in Figure 6.

Discussion and Conclusion

Starting by examining the statistical distribution properties of liquid market index's daily returns, we propose a threshold of around 20% of the fixed sample standard deviation or a dynamic volatility measure to filter daily returns. The central crowd of "nearly flat" days is structurally demonstrated as close to white noise and directionally less informative, and may only serve to complicate the choice of time scale parameters in technical trading rules. Thus we propose to filter the daily returns and skip the "nearly flat" days in the day-counting scheme of technical trading rule specification.

We choose three type technical trading rules to back-test the impact of daily return filtering: short term mean reversion, intermediate term trend following and long term channel breakout rules. Specifically, we focus on *SPX* index over the past 23 years (1990-2012) and decade long sub-periods; we tested a 2-day *runs* long/short trading rule, 5 to 50-day/200-day dual moving average cross rule, and 200-day look-back channel trading rule. Filtered technical rules out-performed in almost all cases the un-filtered original technical rules in terms of annualized returns and risk adjusted returns. They also out-perform the passive *SPX* index whereas some of the original unfiltered original technical rules have difficulties, especially in the recent years.

By filtering the "nearly flat" days out, the number of trades is also reduced significantly in a short term trading rule like the 2-day *runs* long/short switching. This makes active trading rules more viable as far as transaction cost and market friction are concerned.

The index based technical rules can be leveraged up easily using future contracts to improve return. However, risk management technique should be considered along with the daily filter rule. For example, preliminary results show 100% leverage can almost double the annualized return of a filtered 2-day *runs* scheme over 2000-2012 and a 10% stop loss limit on both long and short positions can reduce the leveraged rule's maximum drawdown level by the same amount. This type of expansion and the extension of the daily return filter technique to other liquid market indexes and asset classes can be considered as areas of future research.

Finally, we try to explain why the statistically based filtering for market index technical trading rules works or might work in the future. For intermediate and long term technical rules, we saw the conventional day-counting parameters are adjusted towards the quarterly or yearly accounting frequencies after the daily filter process. This may help matching the fundamentals based market moves.

On the other hand, market index based technical trading or market timing is essentially trying to explore price in-efficiency in the broad market. By filtering out "nearly flat" days as unimportant due to very little market-moving information content or simply being noisy, we argue that rules based technical trading has better chance to succeed. Sizable market index moves on information-intensive days probably reflects macro-economic surprise or misinterpretation, so they are more on the side of market in-efficiency to be focused on. Market participants or institutions with fundamental views are usually patient to wait out the "information light" days or periods, until their targets are met or macro-surprise and market action change their investment policy. Thus, from information efficiency and market structural arguments, our index daily data filter proposal should have broad potential for technical trading rule design. By dynamically calibrating market trend or mean reversion through volatility-based filtering "day-in and day-out", a rules-based technical trader or an active investor can win the long run investing "game"!

Table 1: Summary Statistics of S&P 500 Index Daily Returns

a. Full period: 1990-2012

1990 -2012	Full Set	Retained Set (>0.25%)	Filtered Set (≤0.25%)
mean	0.0309%	0.0397%	0.0072%
std dev	1.171%	1.368%	0.143%
skew	-0.0433	-0.0563	-0.0335
excess kurt	8.5784	5.5245	-1.1789

b. Sub-period: 1990-1999

1990 -1999	Full Set	Retained Set (>0.2%)	Filtered Set (≤0.2%)
mean	0.0603%	0.0799%	-0.0010%
std dev	0.888%	1.017%	0.114%
skew	-0.2501	-0.2766	0.0410
excess kurt	4.9094	3.0854	-1.1468

c. Sub-period:2000-2012

2000-2012	Full Set	Retained Set (>0.3%)	Filtered Set (≤0.3%)
mean	0.0144%	0.0142%	0.0151%
std dev	1.343%	1.596%	0.165%
skew	0.0153	0.0135	-0.1342
excess kurt	8.5170	5.1893	-1.1056

Table 2: *SPX* Daily Return Serial Correlation Coefficients

Filtering Threshold d = 0.25%

	Full Set			Filtered Set		
	1999-2012	2000-2012	1990-1999	1999-2012	2000-2012	1990-1999
lag 1	-0.059	-0.085	0.017	-0.048	-0.075	0.030
lag 2	-0.045	-0.058	-0.006	-0.076	-0.090	-0.037
lag 3	0.003	0.022	-0.053	0.023	0.048	-0.054
lag 4	-0.006	-0.006	-0.008	-0.027	-0.028	-0.026
lag 5	-0.044	-0.047	-0.039	-0.046	-0.053	-0.029

Figure 1: Histogram of S&P 500 Index Daily Return *Filtered Set*

(1990-2012) and Filtering Threshold d = 0.25%

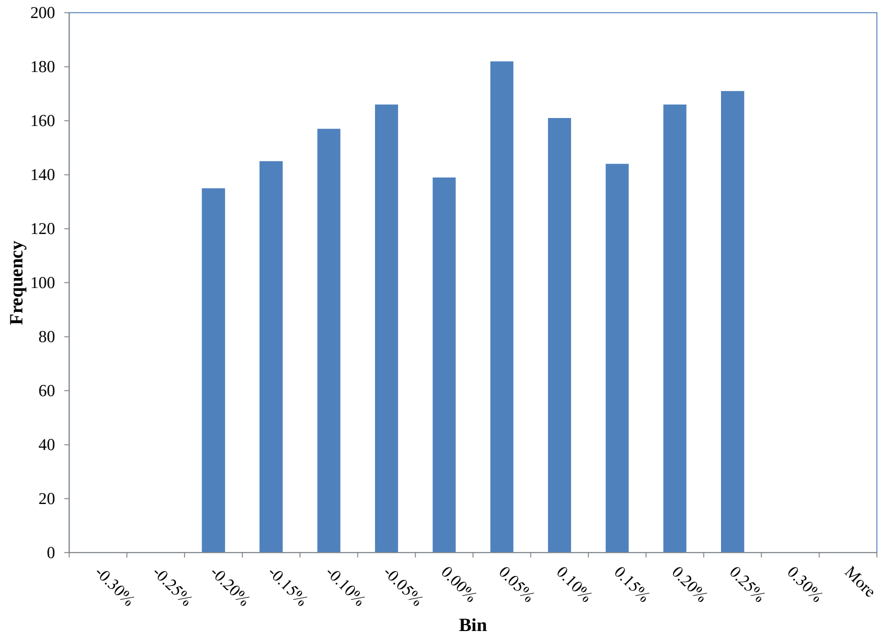
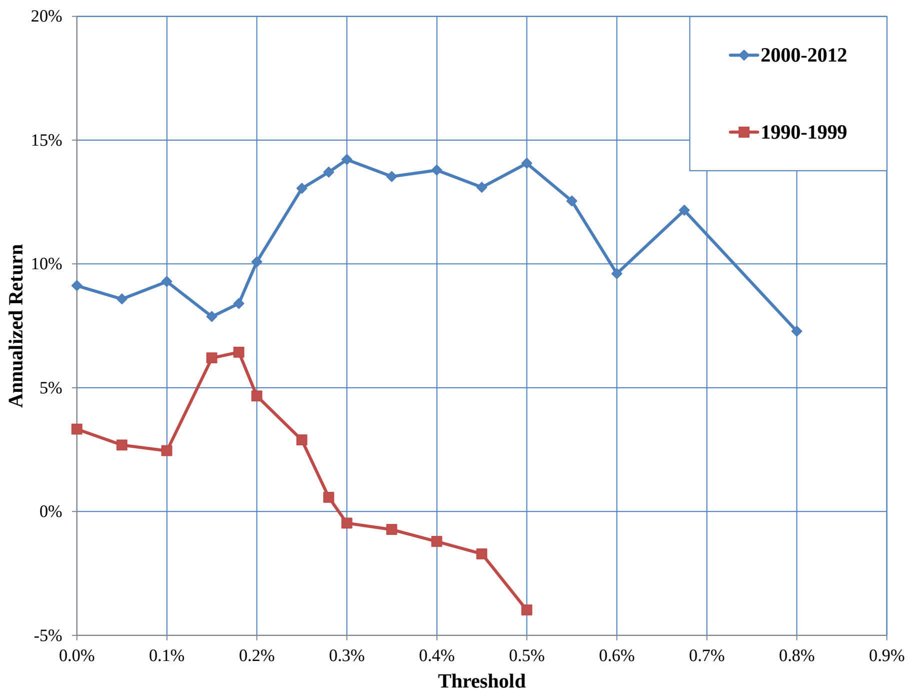


Figure 2: Choosing Filter Threshold for 2-day Runs Long/Short Switch Scheme

(a) Varying Absolute Level of Filter Threshold



(b) Varying Filter Threshold relative to Sample Standard Deviation

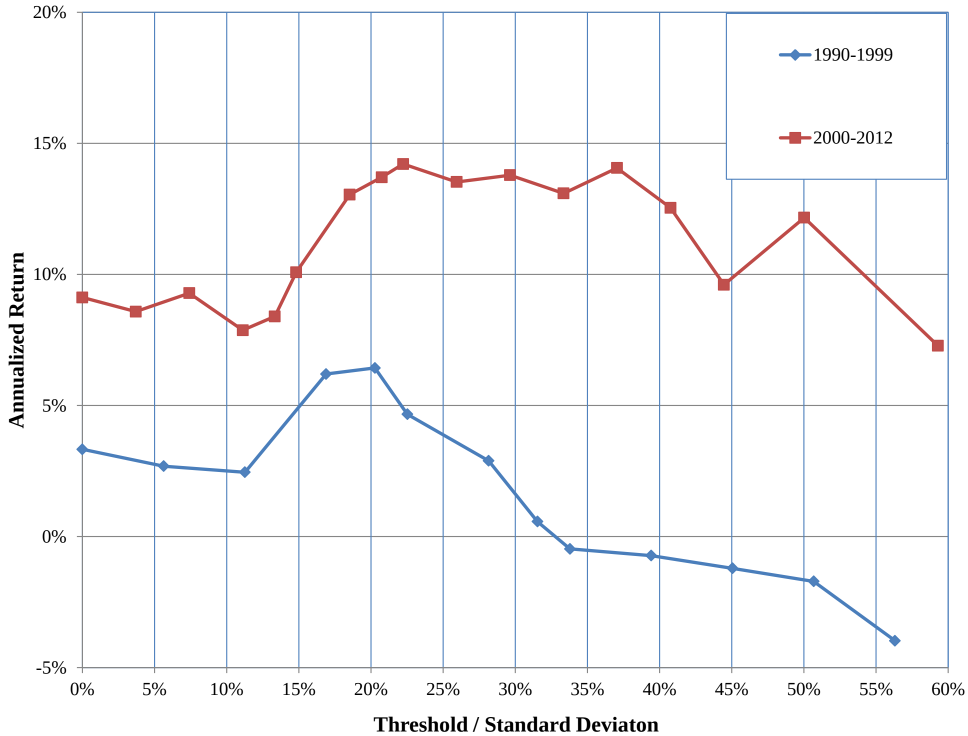


Table 3: Performance Statistics of 2-day Runs Trading Scheme with Filter

(a) Buy and Hold *SPX* Index + No-filter 2-day Runs Scheme

	Buy/Hold *SPX*			No Filter *2-day SPX Runs*		
	1990-2012	1990-1999	2000-2012	1990-2012	1990-1999	2000-2012
Annualized Return	6.25%	15.31%	-0.23%	6.56%	3.33%	9.12%
Std Dev	18.6%	14.1%	21.4%	18.6%	14.1%	21.4%
Risk Adjusted Return	0.336	1.087	-0.011	0.353	0.236	0.426
Maximum Drawdown	56.8%	19.9%	56.8%	31.5%	31.5%	29.9%

(b) Performance Comparison of Different Filter Rules

	Fixed Filter			20% 60-day Rolling Std Dev Filter			22% CBOE VIX Filter		
	d= 0.25%	d= 0.18%	d= 0.30%						
	1990-2012	1990-1999	2000-2012	1990-2012	1990-1999	2000-2012	1990-2012	1990-1999	2000-2012
Annualized Return	8.50%	6.43%	14.21%	9.77%	5.10%	13.53%	10.31%	3.22%	16.13%
Std Dev	18.6%	14.1%	21.4%	18.6%	14.1%	21.4%	18.6%	14.1%	21.4%
Risk Adjusted Return	0.457	0.456	0.664	0.526	0.361	0.632	0.555	0.228	0.754
Maximum Drawdown	30.7%	18.6%	26.7%	26.7%	25.5%	26.7%	30.1%	23.6%	30.1%

Table 4: Comparison of Annual Returns of 2-day *Runs* Filter Rules (2000-2012)

	SPX Price Return	No Filter 2-day Runs	Fixed Filter Runs *d*= 0.3%	20% 60-day Rolling Std. Dev. Filter Runs	22% CBOE VIX Filter Runs
2000	-10.14%	40.17%	30.62%	34.97%	34.84%
2001	-13.04%	-14.48%	19.52%	13.10%	27.26%
2002	-23.37%	33.41%	25.69%	30.06%	24.52%
2003	26.38%	-6.62%	7.70%	4.16%	14.25%
2004	8.99%	0.05%	-3.76%	-2.09%	-2.28%
2005	3.00%	-7.02%	15.54%	-0.14%	5.50%
2006	13.62%	20.90%	25.12%	28.47%	24.67%
2007	3.53%	25.30%	24.56%	2.95%	23.42%
2008	-38.49%	10.66%	3.10%	20.53%	18.24%
2009	23.45%	27.67%	31.74%	37.46%	36.08%
2010	12.78%	5.20%	-3.30%	-0.32%	-6.68%
2011	0.00%	-7.98%	2.12%	11.19%	8.10%
2012	13.41%	7.81%	14.14%	5.61%	10.64%

Figure 3: 2-day Runs Scheme Trading Account Growth (2000 – 2012)

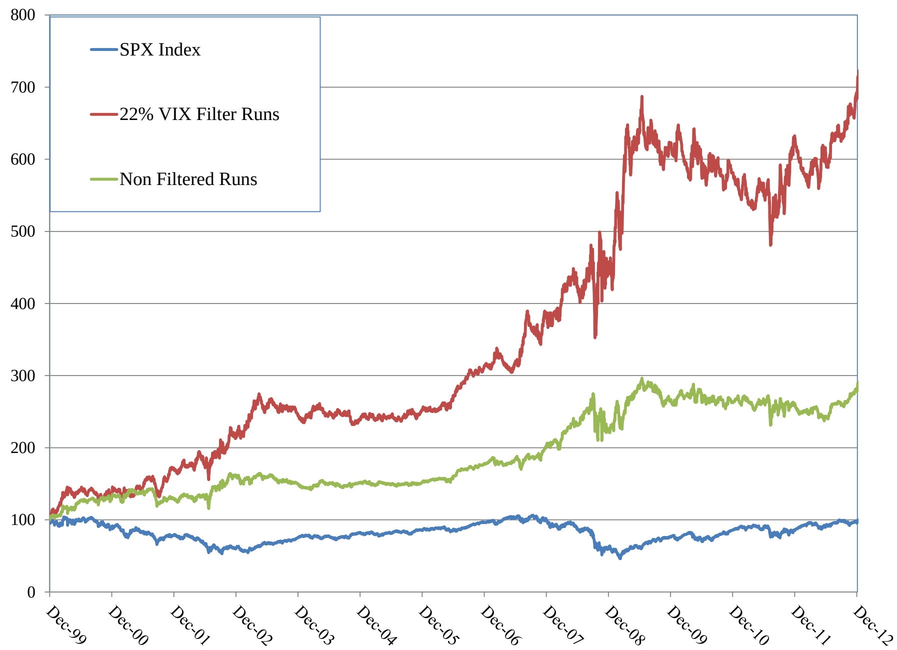


Table 5: Filtering Effect on Dual Moving Average Cross Rule (1991-2012)

(a) Flat When SMA < LMA

SMA Length	Buy/Hold	DMAC (Non-Filtered)	DMAC (Filtered)	Annualized Filtered Out-performance
50	6.88%	8.01%	8.08%	0.07%
40	6.88%	7.58%	7.99%	0.41%
30	6.88%	6.85%	8.30%	1.44%
25	6.88%	6.28%	8.58%	2.30%
20	6.88%	7.19%	7.76%	0.57%
10	6.88%	6.84%	7.88%	1.04%
5	6.88%	6.63%	7.59%	0.96%

(b) 100% Short When SMA < LMA

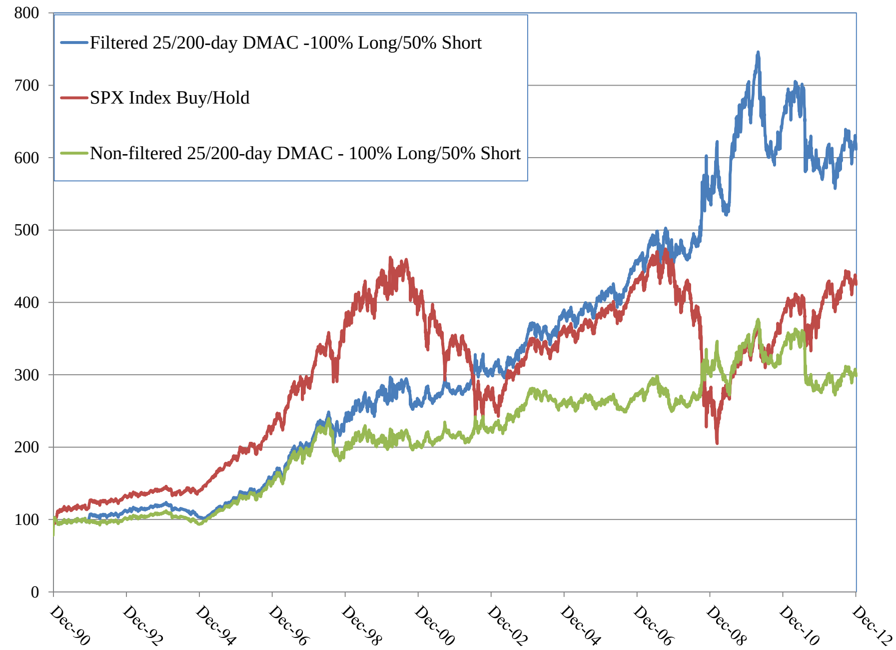
SMA Length	Buy/Hold	DMAC (Non-Filtered)	DMAC (Filtered)	Annualized Filtered Out-performance
50	6.88%	7.04%	7.30%	0.26%
40	6.88%	6.17%	7.08%	0.91%
30	6.88%	4.72%	7.68%	2.96%
25	6.88%	3.55%	8.22%	4.67%
20	6.88%	5.30%	6.58%	1.27%
10	6.88%	4.57%	6.76%	2.19%
5	6.88%	4.13%	6.17%	2.04%

(c) 50% Short When SMA < LMA

SMA Length	Buy/Hold	DMAC (Non-Filtered)	DMAC (Filtered)	Annualized Filtered Out-performance
50	6.88%	7.79%	7.94%	0.15%
40	6.88%	7.14%	7.79%	0.65%
30	6.88%	6.05%	8.25%	2.20%
25	6.88%	5.18%	8.66%	3.49%
20	6.88%	6.52%	7.43%	0.91%
10	6.88%	5.98%	7.59%	1.61%
5	6.88%	5.65%	7.14%	1.49%

Figure 4: *SPX* DMAC Trading Account Growth (1991-2012)

(a) 25-day/200-day Moving Average Cross (100% long/50% short)



(b) 50-day/200-day Moving Average Cross Account Growth

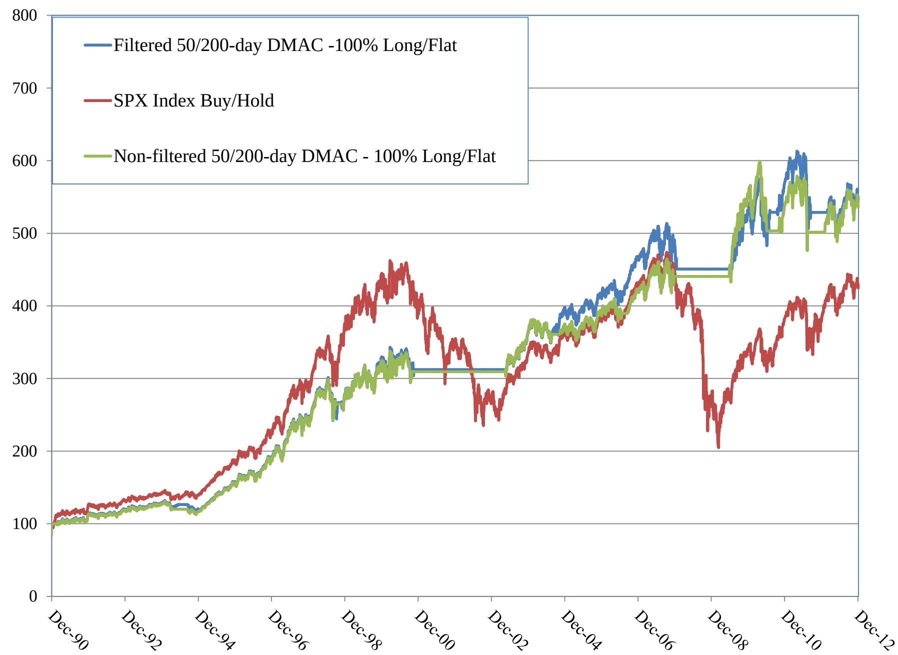


Figure 5: *SPX* 200-day Look-back Price Channel (1990-2012)

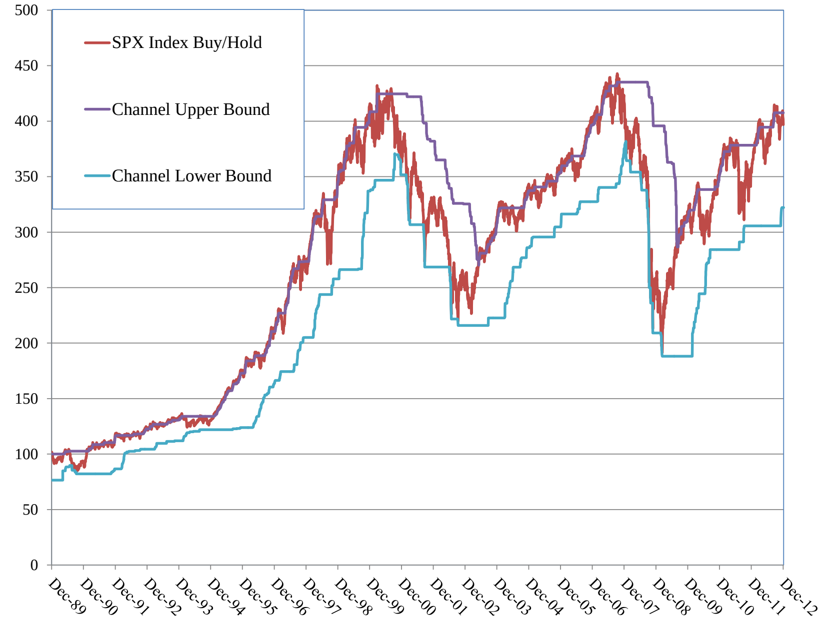


Figure 6: *SPX 200*-day Channel Trading Account Growth w/wo Filter

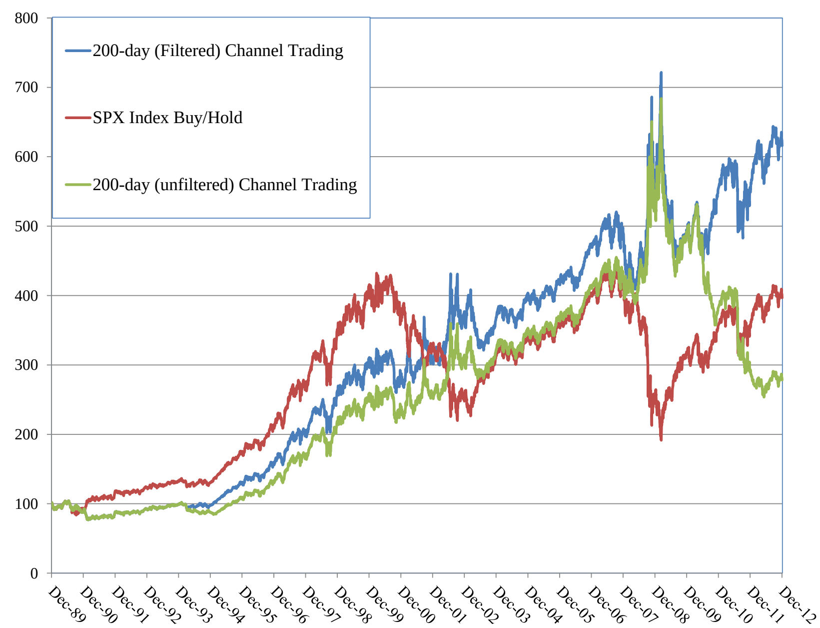


Table 6: Annualized Returns of *SPX* Channel Trading Rule (1990-2012)

Channel Lookback (Days)	Buy/Hold	Channel Trading (Non-Filtered)	Channel Trading (Filtered)	Annualized Filtered Out-performance
250	6.25%	5.70%	6.35%	0.65%
225	6.25%	5.92%	7.44%	1.52%
200	6.25%	4.63%	8.60%	3.97%
175	6.25%	5.41%	7.21%	1.80%
150	6.25%	2.92%	6.43%	3.52%

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Appendix 1: Summary Statistics of Daily Returns of Other Stock Indexes

Full Period 1990-2012; Sub-periods 1990-1999 and 2000-2012; *d* denotes filter threshold

Russell 3000 Index

	1999-2012, *d* = 0.25%			1990-1999, *d* = 0.18%			1999-2012, *d* = 0.3%		
	Full Set	Retained Set	Filtered Set	Full Set	Retained Set	Filtered Set	Full Set	Retained Set	Filtered Set
mean	0.0319%	0.0415%	0.0063%	0.0583%	0.0768%	-0.0019%	0.0115%	0.0099%	0.0159%
std dev	1.17%	1.37%	0.14%	0.84%	0.96%	0.11%	1.37%	1.61%	0.17%
skew	-0.099	-0.106	-0.042	-0.378	-0.391	0.065	-0.014	-0.009	-0.126
excess kurt	8.49	5.43	-1.16	5.21	3.37	-1.17	6.91	4.26	-1.04

FTSE 100 Index

	1999-2012, *d* = 0.25%			1990-1999, *d* = 0.20%			1999-2012, *d* = 0.3%		
	Full Set	Retained Set	Filtered Set	Full Set	Retained Set	Filtered Set	Full Set	Retained Set	Filtered Set
mean	0.0219%	0.0264%	0.0069%	0.0447%	0.0557%	0.0008%	0.0040%	0.0019%	0.0100%
std dev	1.15%	1.31%	0.14%	0.91%	1.01%	0.11%	1.31%	1.51%	0.17%
skew	0.028	0.014	-0.035	0.138	0.092	-0.005	0.019	0.021	-0.055
excess kurt	6.22	4.13	-1.13	2.23	1.21	-1.07	5.87	3.64	-1.11

TOPIX (Tokyo Stock Exchange Index)

	1999-2012, *d* = 0.3%			1990-1999, *d* = 0.28%			1999-2012, *d* = 0.315%		
	Full Set	Retained Set	Filtered Set	Full Set	Retained Set	Filtered Set	Full Set	Retained Set	Filtered Set
mean	-0.0121%	-0.0147%	-0.0034%	-0.0127%	-0.0138%	-0.0091%	-0.0116%	-0.0155%	0.0013%
std dev	1.36%	1.55%	0.17%	1.29%	1.47%	0.16%	1.42%	1.61%	0.18%
skew	0.050	0.049	0.063	0.410	0.362	0.123	-0.159	-0.133	0.012
excess kurt	5.97	3.97	-1.14	4.59	2.82	-1.13	6.59	4.47	-1.14

Euro STOXX 50 Index

	1999-2012, *d* = 0.3%			1990-1999, *d* = 0.225%			1999-2012, *d* = 0.35%		
	Full Set	Retained Set	Filtered Set	Full Set	Retained Set	Filtered Set	Full Set	Retained Set	Filtered Set
mean	0.0243%	0.0314%	0.0044%	0.0631%	0.0811%	0.0059%	-0.0061%	-0.0071%	-0.0035%
std dev	1.37%	1.60%	0.17%	1.04%	1.19%	0.13%	1.59%	1.84%	0.20%
skew	0.079	0.055	-0.009	-0.230	-0.247	-0.103	0.174	0.153	0.070
excess kurt	5.56	3.36	-1.18	5.25	3.34	-1.13	4.39	2.54	-1.21

Hang Seng Index (HSI)

	1999-2012, *d* = 0.35%			1990-1999, *d* = 0.36%			1999-2012, *d* = 0.34%		
	Full Set	Retained Set	Filtered Set	Full Set	Retained Set	Filtered Set	Full Set	Retained Set	Filtered Set
mean	0.0505%	0.0683%	0.0002%	0.0868%	0.1188%	-0.0043%	0.0223%	0.0300%	0.0007%
std dev	1.68%	1.95%	0.20%	1.74%	2.01%	0.20%	1.63%	1.89%	0.19%
skew	0.277	0.213	0.000	0.389	0.290	-0.006	0.164	0.130	0.007
excess kurt	9.79	6.52	-1.15	11.76	8.01	-1.15	7.74	4.99	-1.15