Random Walk Hypotheses and Profitability of Momentum Based Trading Rules

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ABSTRACT

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The main conclusion of this thesis is that for all assets examined here momentum based trading rules yield superior risk adjusted returns compared to buy-and-hold strategies under both weekly and monthly time periods. Furthermore, for weekly data from the CRSP NYSE-AMEX equal-weighted index, the CRSP NASDAQ value-weighted index, the CRSP NASDAQ equal-weighted index, small cap stocks, and certain sectors, technical trading rules outperform the buy-and-hold strategies before adjusting for risk and after adjusting for transaction costs. The consequence of these conclusions is that technical trading rules are useful.

The first chapter of this thesis largely serves to update and refine the results of Lo and MacKinlay's 1988 article on testing Random Walk Hypotheses. Chapter 2 and Chapter 3 address the main results summarized above. The profitability of momentum based trading rules, specifically the filter rule, applied to market indexes, decile portfolios, and sector-sorted portfolios are examined with the help of several risk adjusted measures. Furthermore, the connection between returns to the filter rule and lag one autocorrelation is established. Chapter 4 then serves to complete our assessment of the profitability of technical trading rules, which we do by examining the performance of the MACD indicator and the Moving Average strategy.

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Introduction

The central aim of this thesis is to examine the following question "Are past prices indicative of future prices?" Although this question indirectly depends on the model for prices, historically the majority of research has focused on two areas, test for autocorrelation in the return series and the performance of trading strategies.

We begin this dissertation with an analysis of the "Random Walk Hypothesis" along the lines of Lo and MacKinlay (1988). Our aim is two-fold; first, we extend their analysis by including asset return data that have become available since the time of their tests and secondly, we address issues that were not considered by Lo and MacKinlay by performing a sector-by-sector analysis of Lo and MacKinlay's random walk hypothesis.

Data for this exercise and the rest of the thesis are the weekly and monthly values from the CRSP NYSE-AMEX value-weighted index, CRSP NYSE-AMEX equal-weighted index, S&P 500 index, CRSP NASDAQ value-weighted index, CRSP NASDAQ equal-weighted index, ten size-sorted portfolios and ten sector-based portfolios. From the analysis of weekly data four key observations emerge from the results.

- For data corresponding to 1962-2001 from the major market indexes we find that the Lo and MacKinlay's random walk hypothesis is overwhelmingly rejected by the CRSP NYSE-AMEX equal-weighted index which has a lag 1 autocorrelation of approximately 26%. The most significant rejections though occur for the CRSP NASDAQ equal-weighted index which has a lag 1 autocorrelation of approximately 37%.

- Among size-sorted portfolios, Decile 1 (portfolio of smallest firms) exhibited the strongest evidence against the Lo and MacKinlay's random walk hypothesis and the evidence became weaker as we proceed from the lower deciles to the higher deciles.

- Further, for sector-sorted portfolios formed with equal-weighting of stocks, all sectors except the Utilities sector showed strong evidence against the Lo and MacKinlay's random walk hypothesis and in particular the lag 1 autocorrelation for the Services sector was 32% for the overall period 1962-2001.

- Rather remarkably it appears that behavior of the market as a whole has moved towards the random walk behavior after 1985. This follows from the fact that for all the assets examined here, the evidence against Lo and MacKinlay's random walk hypothesis has either dropped considerably or completely vanished in the post Lo and MacKinlay (1988) period, 1986-2001.

The statistically significant rejections of the Lo and MacKinlay's random walk hypothesis suggests the possibility of economically meaningful trading rules. The filter rule is probably the trading rule with the richest academic tradition. In the second and third chapter we detail our investigation of the filter rule. The data for this investigation is similar to the data used for testing the random walk hypothesis except that now the returns are adjusted for dividends.

Our approach to assessing the performance of the filter rule is rather comprehensive as we use three metrics: performance measures before adjusting for risk, risk adjusted performance measures, and market timing tests and in all three cases we take the buy-and-hold strategy as the benchmark strategy. Our analysis of the filter rule leads to five interesting observations for weekly data.

- For the 1962-2001 period, the 5%-filter rule outperforms the buy-and-hold strategy before adjusting for risk for data from the CRSP NYSE-AMEX equal-weighted index, the CRSP NASDAQ value-weighted index, and the CRSP NASDAQ equal-weighted index.

- To illustrate the superior performance of the filter rule consider its performance on the CRSP NASDAQ value-weighted index. The terminal value of a $1 investment as a result of following the filter rule is 6.58 times the amount that results from using the buy-and-hold strategy and at lower risk. Furthermore, the one-way break even transaction cost is 1.70%, a rather large number considering the fact that most academic studies typically use 1/20 of 1%.

- After accounting for risk, the 5%-filter rule performs at least as well as the buy-and-hold strategy for all the indexes except the S&P 500 index. In fact, if one uses the maximum drawdown as the risk measure, then the 5%-filter rule has significantly lower risk than the buy-and-hold strategy for all the indexes.

- For the size-sorted portfolios we find that the 5%-filter rule significantly outperforms the buy-and-hold strategy for all portfolios except Decile 10 the portfolio of the largest firms before adjusting for risk.

- For data from the sector-based portfolios, before adjusting for risk, the 5%-filter rule does at least as well as the buy-and-hold strategy for data from Basic Industries, Construction, Durables, Utilities, Trade, Finance, Oil and Coal, and Services. After adjusting for risk, the 5%-filter rule beats the buy-and-hold strategy for all sectors.

An important observation that arises from the results to the filter rule is the strong relationship between lag one autocorrelation of weekly returns and the excess returns (difference between annualized returns to the filter rule and the annualized returns to the buy-and-hold strategy). Similar to our observations while examining the random walk hypothesis, wherein for all assets examined there was a considerable drop-off in the evidence between 1962-1985 and 1986-2001, we see that the performance of the filter rule declines as we move from the 1962-1985 period to the 1986-2001 period. Proceeding along the lines of Corrado and Lee (1992) we regressed the excess returns on the lag one autocorrelation to find that a strong linear relationship ($R^2 = 50\%$) exists between them. Furthermore, we find that for a 10% increase in lag one autocorrelation there is a 2.39% increase, on average, in the excess returns. These results serve confirm our intuition about the relationship between autocorrelation in returns and profitability of momentum based rules which aim to exploit *trends in prices.*

Finally, in Chapter 4 we continue the investigation of momentum strategies, and in particular we analyze the moving average convergence divergence indicator and a moving average strategy. In essence, the filter rule appears to dominate the two strategies considered, except in the following two scenarios.

- We find that for weekly data from the S&P 500 index the 40-period moving average strategy outperforms the buy-and-hold strategy with a one-way break even transaction cost of 0.48% which is different from the results to the moving average convergence divergence indicator and the filter rule, both of which fail to beat the buy-and-hold strategy.

- Unlike the results to the major market indexes and size-sorted portfolios for data from sector-based portfolios there is no single strategy that seems to dominate. Before adjusting for risk, the 40-period moving average strategy dominates on the basis of one-way break even transaction costs for five out of ten sectors, but after adjusting for risk the moving average convergence divergence indicator dominates.

In summary, the results to the random walk hypothesis, the filter rule and the results for the MA and MACD strategies do confirm the ability of past prices to forecast future prices at least for weekly data from the CRSP NYSE-AMEX equal-weighted index, the CRSP NASDAQ indexes, size-sorted portfolios Deciles 1–9 and certain sector-based portfolios. Furthermore, we find that on risk-adjusted basis the momentum strategies earn superior returns compared to buy-and-hold strategies for almost all portfolios.

Chapter 1

Random Walk Hypotheses : An Extended and Refined Empirical Investigation

The main goal of this chapter is to extend and to refine the analysis of Lo and MacKinlay (1988). First, to gain some basic experience, we simply replicate the analysis of Lo and MacKinlay (1988) with two small twists. Specifically, we extend the time frame to include asset return data that have become available since the time of their tests, and we also examine ten size-sorted portfolios instead of five considered by Lo and MacKinlay.

The second part of our analysis is more substantial, and it addresses issues that were not considered by Lo and MacKinlay (1988). Specifically, we perform a sector-by-sector analysis of Lo and MacKinlay's random walk hypothesis, and we test Lo and MacKinlay's random walk hypothesis for the CRSP NASDAQ equal-weighted index, the CRSP NASDAQ value-weighted index and the S&P 500 index.

This chapter is organized in six sections, and in the first of these we briefly describe several variations of the random walk hypothesis that have been considered earlier, with particular attention to the Lo and MacKinlay version of the random walk hypothesis. This section also summarizes the major findings of Lo and MacKinlay (1988) and defines the variance ratio test that is central to the remaining analysis of the chapter. In Sections 1.2 and 1.3 we test the Lo and MacKinlay version of the random walk hypothesis for several market indexes and size-sorted portfolios, while Sections 1.4 and 1.5 report results of testing on sector-sorted portfolios and other market indexes. Finally in Section 1.6 we offer some concluding remarks.

1.1 Random Walk Hypotheses and The Lo-MacKinlay approach

If P_t, $t = 0, 1, 2, \ldots$, denotes a sequence of prices of a financial asset, then the *random walk hypothesis* for that asset is the assertion that the log-price process $p_t = \log P_t$ satisfies a model of the form

$$p_t = \mu + p_{t-1} + \epsilon_t \, , \tag{1.1}$$

where μ is understood to be a constant and where the terms ϵ_t, $t = 0, 1, 2, \ldots$, are understood to represent a noise process that can be specified in several different ways. To be sure, any test of such a hypothesis requires one to make assumptions that fully specify the process $\{\epsilon_t\}$, and, if one follows the lead of Campbell, Lo, and MacKinlay (1997, pp. 31-33), then there are at least three models one should consider.

If we denote these models by RWH-I, RWH-II, and RWH-III, then they may be summarized as

$$\begin{aligned}
&\text{RWH-I} &&: \ \epsilon_t \ \text{i.i.d}, \ \epsilon_t \sim N(0, \sigma^2)\, , \\
&\text{RWH-II} &&: \ \epsilon_t \ \text{independent}, \quad E(\epsilon_t) = 0\, , \quad E(\epsilon_t^2) = \sigma_t^2 < \infty\, , \\
&\text{and} && \\
&\text{RWH-III} &&: \ \epsilon_t \ \text{possibly dependent with} \quad E(\epsilon_t) = 0\, , \\
& && \quad E(\epsilon_t^2) = \sigma_t^2 < \infty\, , \ \text{and} \quad E(\epsilon_t \epsilon_{t-k}) = 0 \quad \text{for all } k = 1, 2, \ldots \, .
\end{aligned}$$

Motivating the Lo-MacKinlay Model

These models are of increasing generality, so a rejection of RWH-III automatically entails rejection of RWH-I and RWH-II. Lo and MacKinlay (1988) began their analysis by considering RWH-I, and they quickly observed that RWH-I is far too restrictive to be of much interest since it fails to capture some basic features of price processes. First, the daily return processes $p_t - p_{t-1}$ are in most cases empirically found to be significantly leptokurtic, and, second, the daily volatility $\text{Var}(\epsilon_t)$ in the return processes is often observed to change significantly over time. For these reasons, Lo and MacKinlay (1988) turned their attention to a model that is more elaborate than RWH-I and RWH-II, yet which stops short of the fully general model RWH-III. The problem is that such a general model does not lend itself to effective testing. The Lo and MacKinlay version of the random walk hypothesis limits the generality of RWH-III by allowing for only certain types of heteroskedasticity in the noise process, which we will make precise below.

Mixing Processes

The critical issue is the specification of the degree and type of heteroskedasticity that one allows, and here Lo and MacKinlay take their lead from the heteroskedasticity-consistent methods of White (1980) and White and Domowitz (1984) where mixing processes are used to help express the type of heterogeneity and the amount of dependence in the noise process. Before we can define the proposed model we consider two kinds of dependence measures and the associated notion of mixing.

Definition 1.1 (Measures of Dependence). *If $(\Omega, \mathcal{F}, P)$ is a probability space, and $\mathcal{A}$ and $\mathcal{B}$ are two sub-σ-fields of $\mathcal{F}$, we have the dependence measures:*

$$\begin{aligned} \alpha(\mathcal{A}, \mathcal{B}) &= \sup |P(A \cap B) - P(A)P(B)| \,,\; A \in \mathcal{A}\,, B \in \mathcal{B}\,. \\ \phi(\mathcal{A}, \mathcal{B}) &= \sup |P(B|A) - P(A)| \,,\; A \in \mathcal{A}\,, B \in \mathcal{B}\,, P(A) > 0\,. \end{aligned}$$

Definition 1.2 (Mixing Processes). *Let $\{X_t \,:\, t \in \mathbb{Z}\}$ denote a sequence of random variables defined on the probability space $(\Omega, \mathcal{F}, P)$, and for $-\infty \leq J \leq L \leq \infty$*
$\mathcal{F}_J^L = \sigma(X_J, X_{J+1}, \ldots, X_L)$, and

$$\alpha(n) = \sup_n \alpha(\mathcal{F}_{-\infty}^J, \mathcal{F}_{J+n}^{\infty})\,,$$

and

$$\phi(n) \quad = \quad \sup_n \phi(\mathcal{F}_{-\infty}^{J}, \mathcal{F}_{J+n}^{\infty})\,.$$

The sequence $\{X_t : t \in \mathbb{Z}\}$ *is then said to be* α*-mixing if* $\lim_{n\to\infty} \alpha(n) = 0$ *and* ϕ*-mixing if* $\lim_{n\to\infty} \phi(n) = 0$.

Definition 1.3 (Size of Dependence). *For* $\lambda \in \mathbb{R}$ *we say that a sequence* $\{X_t : t \in \mathbb{Z}\}$ *is* α*-mixing of size* λ *provided that for some* $\epsilon > 0$ *one has* $\alpha(n) = O(n^{-\lambda-\epsilon})$. *Similarly, we say that a sequence* $\{X_t : t \in \mathbb{Z}\}$ *is* ϕ*-mixing of size* λ *provided that for some* $\epsilon > 0$ *one has* $\phi(n) = O(n^{-\lambda-\epsilon})$.

A high degree of dependence in the random sequence is associated with small values of λ, while small degree of dependence is associated with large values of λ. For a more extensive discussion of mixing processes and properties of mixing processes the reader is referred to White (2001, pp. 46–53) and Eberlein and Taqqu (1986, pp. 165–192), but these definitions are all we need to specify the models that follow.

The Lo-MacKinlay Model, or the RWH-LM

Now that we have recalled the notions of mixing processes, we can formalize the Lo-MacKinlay model (or the RWH-LM for short). Precisely, for integer N, a log-price process $p_t = \log P_t,\ t = 0, 1, 2, \ldots, N$ is said to be consistent with the RWH-LM provided that it satisfies the following five conditions:

1. For all t and all $k \neq 0$, we have $\mathrm{E}(\epsilon_t) = 0$ and $\mathrm{E}(\epsilon_t \epsilon_{t-k}) = 0$,
2. For all t, $\mathrm{E}(\epsilon_t^2 \epsilon_{t-j} \epsilon_{t-k}) = 0$ for each nonzero j and k where $j \neq k$,
3. $\lim_{N\to\infty} \frac{1}{N} \sum_{t=1}^{N} \mathrm{E}(\epsilon_t^2) = \sigma_0^2 < \infty$,
4. The process $\{\epsilon_t : t \geq 1\}$ is ϕ-mixing of size $r/(2r-1)$, for $r > 1$.
5. The process $\{\epsilon_t : t \geq 1\}$ is such that for all t and for any $k \geq 0$, there exists some $\delta > 0$ for which $\mathrm{E}\{|\epsilon_t \epsilon_{t-k}|^{2(r+\delta)}\} < \Delta < \infty$.

Here we should note that one can replace the ϕ-mixing assumption with the assumption that

4$'$. The process $\{\epsilon_t : t \geq 1\}$ is α-mixing with size $r/(r-1)$, for $r > 1$.

.

While condition (1) retains the essential property of RWH-III that the noise process is uncorrelated, conditions (3), (4) and (5) are used to limit the degree of dependence in the noise process so that versions of central limit theorems and laws of large numbers still apply. On the other hand, condition (2) is more technical and it is assumed — at least in part — because it helps to simplify the computation associated with the variance ratio statistic which is developed in the next subsection.

The Variance Ratio Test

Consider a set of $N+1$ observations $p_0, p_1, \ldots, p_N$ of the log price process $\{p_t\}$, and further assume that for integers $n \geq 1$ and $q > 1$, the number of observations N satisfies $N = nq$ so that the observations can be broken into n blocks each of size q. The fundamental inputs to the variance ratio test are the single period return $r_t = p_t - p_{t-1}$ and the associated q-period return $r_t(q) = p_t - p_{t-q} = r_t + r_{t-1} + \cdots + r_{t-q+1}$. We will analyze the behavior of r_t and r_{t-q} in terms of the autocorrelation coefficient $\rho(k)$ between r_t and r_{t+k}, given by

$$\rho(k) = \frac{\mathrm{Cov}(r_t, r_{t+k})}{\sqrt{\mathrm{Var}(r_t)\mathrm{Var}(r_{t+k})}} \, , \quad 0 \leq k \leq N \, ,$$

We now specify the theoretical version of the variance ratio test. Lo and MacKinlay (1988) defined the theoretical variance ratio VR(q) by the formulation

$$\mathrm{VR(q)} \quad \equiv \quad \frac{\mathrm{Var}(r_t(q))}{q\mathrm{Var}(r_t)} = 1 + 2\sum_{k=1}^{q-1}\big(1 - \frac{k}{q}\big)\rho(k) \, . \tag{1.2}$$

In the simplest case when $q = 2$, the variance ratio VR(2) is the ratio of the two-period return to twice the variance of a one-period return. Formally, from equation (1.2) we see that

$$\text{VR}(2) \quad = \quad \frac{\text{Var}(r_t(2))}{2\text{Var}(r_t)} = 1 + \rho(1)\,. \tag{1.3}$$

In particular, if asset returns satisfy RWH-LM then VR(2)=1 since RWH-LM $\rho(k) = 0$ for all $k \geq 1$. Furthermore, from formula 1.3 we see that the variance ratio will exceed one if the return process exhibits positive autocorrelation, and the variance ratio will be less than one if the return process exhibits negative autocorrelation.

Sample Version

In essence the sample version of the variance ratio test simply takes the definition of the theoretical VR(q) and replaces its numerator and denominator by appropriate analogs. Still, before we can make this definition precise, we need a few additional statistics. Here one should note that the statistics used will all depend on the sample size parameter depend on $N = nq$, but this dependence will be suppressed here to maintain consistency with Lo and MacKinlay (1988).

1. The estimate $\hat{\mu}$ of the drift term μ is defined as

$$\hat{\mu} \quad = \quad \frac{1}{nq}\sum_{k=1}^{nq}(p_k - p_{k-1}) = \frac{1}{nq}(p_{nq} - p_0)\,.$$

2. Two estimates for the volatility in the process $\{\epsilon_t\}$ are given by the statistics $\bar{\sigma}_a^2$ and $\bar{\sigma}_c^2(q)$. The statistic $\bar{\sigma}_a^2$ is defined as

$$\bar{\sigma}_a^2 \quad = \quad \frac{1}{nq-1}\sum_{k=1}^{nq}(p_k - p_{k-1} - \hat{\mu})^2\,,$$

   and the statistic $\bar{\sigma}_c^2(q)$ is defined as

$$\begin{aligned}\bar{\sigma}_c^2(q) \quad &= \quad \frac{1}{m}\sum_{k=q}^{nq}(p_k - p_{k-q} - q\hat{\mu})^2, \quad \text{where} \\ m \quad &= \quad q(nq - q + 1)(1 - \frac{q}{nq})\,.\end{aligned}$$

3. The variance ratio statistic $\overline{\mathrm{VR}}(q)$, the sample version of the theoretical ratio (1.2) that defines VR(q), is defined as the ratio of the two volatility estimates,

$$\overline{\mathrm{VR}}(q) = \frac{\bar{\sigma}_c^2(q)}{\bar{\sigma}_a^2}\,. \tag{1.4}$$

4. The sample autocorrelation coefficient between r_t and r_{t+k} is represented using $\hat{\rho}(k)$, where

$$\hat{\rho}(k) = \frac{\frac{1}{N-k}\sum_{t=k}^{N}(r_t - \overline{r}_N)(r_{t-k} - \overline{r}_N)}{\frac{1}{N}\sum_{t=1}^{N}(r_t - \overline{r}_N)^2}\,, \quad 1 \leq k < N\,,$$

where $\overline{r}_N = \frac{1}{N}\sum_{t=1}^{N} r_t$.

5. A sample version of the relationship between the variance ratio statistic and the estimated autocorrelation in returns given by equation (1.2) is

$$\overline{\mathrm{VR}}(q) \xrightarrow{P} 1 + \sum_{k=1}^{q-1} \frac{2(q-k)}{q}\hat{\rho}(k)\,, \tag{1.5}$$

where $\xrightarrow{P}$ denotes convergence in probability.

6. For $1 \leq j \leq q-1$, let $\delta(j) = \lim_{n\to\infty} \mathrm{Var}(\hat{\rho}(j))$, the variance associated with the limiting distribution of the sample autocorrelation coefficient. A heteroskedasticity-consistent estimator $\hat{\delta}(j)$ of the parameter $\delta(j)$ is given by

$$\hat{\delta}(j) \quad = \quad \frac{\sum_{k=j+1}^{nq}(p_k - p_{k-1} - \hat{\mu})^2(p_{k-j} - p_{k-j-1} - \hat{\mu})^2}{\left[\sum_{k=1}^{nq}(p_k - p_{k-1} - \hat{\mu})^2\right]^2}.$$

7. With the help of the estimator $\hat{\delta}(j)$ we can define a heteroskedasticity-consistent estimator of the parameter $\theta(q) = \lim_{n\to\infty} \mathrm{Var}(\overline{\mathrm{VR}}(q))$, the variance associated with the limiting distribution of $(\overline{\mathrm{VR}}(q))$, as

$$\hat{\theta}(q) \quad = \quad \sum_{j=1}^{q-1}\left[\frac{2(q-j)}{q}\right]^2 \hat{\delta}(j)\,.$$

Finally, the variance ratio test denoted by $z^*(q)$ is defined as

$$z^*(q) = \frac{\sqrt{nq}(\overline{\mathrm{VR}}(q) - 1)}{\sqrt{\hat{\theta}}}. \tag{1.6}$$

Furthermore, Lo and MacKinlay (1988) argue that the variance ratio test $z^*(q)$ used to test the RWH-LM is asymptotically standard normal, that is $z^*(q) \overset{\mathrm{d}}{\to} N(0,1)$.

The Findings of Lo and MacKinlay

Lo and MacKinlay used their version of the variance ratio test to study the hypothesis that a log-price process p_t satisfies RWH-LM for weekly and monthly data for the CRSP NYSE-AMEX value-weighted index and the CRSP NYSE-AMEX equal-weighted index from 1962-1985. In addition to looking at indexes that represent the overall market, Lo and MacKinlay also used data from 5 size-sorted portfolios and 625 individual securities. Among their conclusions five seem to be particularly noteworthy.

1. The authors find strong evidence against RWH-LM in the overall period 1962-1985 and in all sub-periods.

2. On the basis of the weekly returns of the NYSE-AMEX market indexes for the 1962-1985 period and all sub-periods the RWH-LM is strongly rejected.

3. Further, on the basis of the weekly returns of five size-sorted portfolios formed using assets from the NYSE-AMEX universe for the 1962-1985 period and all sub-periods the RWH-LM is strongly rejected.

4. On the other hand, the monthly returns of the NYSE-AMEX market indexes offered no evidence against the RWH-LM in any sample period.

5. Based on the results of five size-sorted portfolios, the authors infer that the rejection of the RWH-LM is primarily due to the effect of small stocks.

1.2 Test of RWH-LM for Market Indexes

In the first of the new analyzes considered here, we examined the RWH-LM using return data from the CRSP NYSE-AMEX value-weighted index, the CRSP NYSE-AMEX equal-weighted index, and the 10 size-sorted portfolios for the period 1962-2001. We will briefly describe the data collection and construction process before giving a detailed report of our analysis. [1]

Data

Our test of the RWH-LM focuses on the 2059 week time span from July, 1962 to December, 2001, and we consider both weekly and monthly returns. Daily data were not used because, as Lo and MacKinlay (1988) observe, such data can suffer from serious biases due to infrequent trades in some stocks.

Since the CRSP database consists of daily and monthly data for all the CRSP market indexes and the S&P 500 index, we had to use the daily return files to construct weekly return data for all the return indexes used in this dissertation. The weekly return data were computed here in a way that parallels the method used by Lo and MacKinlay (1988); specifically the weekly return for a financial asset is defined as the return from Wednesday's closing price through the following Wednesday close, with a more elaborate rule[2] employed should following Wednesday close not be available.

We use only nominal returns in this chapter following the lead of Lo and MacKinlay (1988), who argue that "since the volatility of weekly nominal returns is so much larger than that of the inflation and Treasury-bill rates, the use of nominal, real, or excess returns in a volatility-based test will yield practically identical inferences."

[1] We note that both the data collection process and the computation of the test statistics are carried out using SAS programs which are run in an Unix environment. For further details about the computing environment and for a copy of the SAS programs please contact the author.

[2] Specifically, when the following Wednesday's closing price was unavailable we used the following Thursday's closing price. If both the following Wednesday's price and the following Thursday's price were unavailable we used the following Tuesday's closing price. In case all three closing prices were unavailable we assigned a missing value to the corresponding week's return.

Presentation of the Results

In each of the tables given in this chapter, we report for $q = 2$, $q = 4$, and $q = 8$ the values of the variance ratios $\overline{\mathrm{VR}}(q)$ and the corresponding test statistic $z^*(q)$. Moreover, each table contains results for both weekly and monthly data, and each table is subdivided into three major columns with each column corresponding to a particular time period. The first column displays the results for the entire sample period 1962-2001, while the second corresponds to the first sub-period 1962-1985 and is designed to match closely with the overall time period of Lo and MacKinlay (1988). Finally the third column provides the analysis of the sub-period 1986-2001 which updates the Lo-MacKinlay analysis to the present.

CRSP NYSE-AMEX equal-weighted index

From Table 1.1 there are three observations that seem noteworthy.

- For weekly data the RWH-LM is rejected for the overall period 1962-2001 and the lag 1 autocorrelation for the weekly returns is approximately 26%, a notably large value.
- The values obtained in the first sub-period 1962-1985 match closely the values obtained in Lo and MacKinlay (1988).
- Even though the RWH-LM continues to be rejected with data for the second sub-period 1986-2001, one finds that the rejections are lower than those of the first sub-period.

Detailed Results

From the table one sees that the RWH-LM is rejected at a 5% significance level for weekly return data of the CRSP NYSE-AMEX equal-weighted index for the overall period 1962-2001. The value of the variance ratio for $q = 2$ for the time-period 1962-2001 is 1.26, so, from equation (1.5) and the first entry in Table 1.1 we can infer[3] that $\hat{\rho}(1)$ is approximately

[3] We note that while $\overline{\mathrm{VR}}(2) - 1$ can be interpreted as lag 1 autocorrelation coefficient, the relationship between $\overline{\mathrm{VR}}(q) - 1$ and $\hat{\rho}(q)$ for $q > 2$ is not straightforward. For further details the reader is referred to Lo

Table 1.1: $\overline{VR}$ and Z-scores: CRSP NYSE-AMEX equal-weighted index

The table reports the values of the variance ratio statistic and corresponding z-scores for returns of the CRSP NYSE-AMEX equal-weighted index for the entire sample period 1962-2001, the sub-period 1962-1985, and the sub-period 1986-2001. The observed variance ratios $\overline{\text{VR}}(q)$ are reported in the main row, with the corresponding heteroskedasticity-robust test statistics $z^*(q)$ reported just below in parenthesis. Under RWH-LM the variance ratios should equal 1 and the test statistic is asymptotically standard normal. Variance ratios significantly different from 1 have corresponding test statistics marked with an asterisk. The parameter q corresponds to the return period used to form the variance ratios; for example when $q = 2$ the variance ratio is the ratio of variance of two-period returns to one-period returns.

Periods	1962-2001 Overall Time Period			1962-1985 The Lo-MacKinlay period			1986-2001 The post Lo-MacKinlay period		
q values	2	4	8	2	4	8	2	4	8
Observations	2059			1226			833		
Weekly Data	1.261 (5.489)*	1.542 (6.776)*	1.803 (7.348)*	1.293 (7.473)*	1.640 (8.888)*	1.941 (8.507)*	1.200 (1.706)	1.362 (1.905)	1.56 (2.338)*
Observations	474			282			192		
Monthly Data	1.173 (3.408)*	1.194 (2.052)*	1.173 (1.160)	1.160 (2.553)*	1.209 (1.750)	1.325 (1.706)	1.210 (2.509)*	1.159 (1.097)	0.843 (-0.726)

26% for the weekly returns of the CRSP NYSE-AMEX equal-weighted index. The variance ratio test statistic given below is statistically significant with a z-score of 5.48. The bottom line is that there is strong evidence against RWH-LM.

Results for Sub-periods

The results for the period 1962-1985 are consistent with those obtained in Lo and MacKinlay (1988). The lag 1 autocorrelation $\hat{\rho}(1)$ in weekly returns is approximately 29% during the period 1962-1985, a value that is in keeping with the value of 30% reported by Lo and MacKinlay (1988).

Perhaps the most striking inference to be drawn from Table 1.1 is that for the sub-period 1986-2001 we find no evidence of deviation from the RWH-LM for the CRSP equal-weighted index. The lack of persistence in the results across sub-periods is in stark contrast with the findings of Lo and MacKinlay (1988) who find the rejections of the RWH-LM for the CRSP NYSE-AMEX equal-weighted index to be pervasive over all sub-periods. Furthermore, we note that the lack of significance against RWH-LM in the later sub-period 1986-2001 is an indication that the behavior of the market is consistent with RWH-LM and is unlike the

and MacKinlay (1988)

market behavior in the earlier sub-period 1962-1985.

Monthly Return Data

The results for monthly data of the CRSP NYSE-AMEX equal-weighted index provide a different picture. Specifically, they show only weak evidence against the RWH-LM in all the sample periods and they are much more in keeping with the earlier findings of Lo and MacKinlay (1988). The lag 1 autocorrelation $\hat{\rho}(1)$ for the monthly returns of the CRSP NYSE-AMEX equal-weighted index is approximately 17% for the period 1962-2001, and this does yield a corresponding statistically significant z-score of 3.51, but this significance in z-score does not persist when one considers different lags and different time periods.

CRSP NYSE-AMEX value-weighted index

From Table 1.2 there are three key observations to be made, and they are:

- The results shows no evidence against the RWH-LM for weekly return data both in the overall time-period, and in the sub-period 1986-2001.
- However, for the sub-period 1962-1985, the evidence against the RWH-LM is consistent with the findings of Lo and MacKinlay (1988). The lag 1 autocorrelation $\hat{\rho}(1)$ in weekly returns is approximately 8% with a corresponding statistically significant z-score of 2.26.
- For monthly data there is no evidence against the RWH-LM both in the overall period and in any of the sub-periods.

1.3 Test of RWH-LM for Size-sorted Portfolios

Lo and MacKinlay (1988) argue that one motivation for the study of size-sorted portfolios comes from the disparity in the behavior of the equal-weighted and value-weighted indexes. Specifically, one wants to gain some insight in the rejection of the RWH-LM between the CRSP NYSE-AMEX equal-weighted index and the CRSP NYSE-AMEX value-weighted

Table 1.2: $\overline{VR}$ and Z-scores: CRSP NYSE-AMEX value-weighted index

The table reports the values of the variance ratio statistic and corresponding z-scores for returns of the CRSP NYSE-AMEX value-weighted index for the sample period 1962-2001, the sub-period 1962-1985, and the sub-period 1986-2001. The observed variance ratios $\overline{\text{VR}}(q)$ are reported in the main row, with the corresponding heteroskedasticity-robust test statistics $z^*(q)$ reported just below in parenthesis. Under RWH-LM the variance ratios should equal 1 and the test statistic is asymptotically standard normal. Variance ratios significantly different from 1 have corresponding test statistics marked with an asterisk. The parameter q corresponds to the return period used to form the variance ratios; for example when $q = 2$ the variance ratio is the ratio of variance of two-period returns to one-period returns.

Periods	1962-2001 Overall Time Period			1962-1985 The Lo-MacKinlay period			1986-2001 The post Lo-MacKinlay period		
q values	2	4	8	2	4	8	2	4	8
Observations	2059			1226			833		
Weekly Data	1.04 (1.132)	1.068 (1.083)	1.088 (0.970)	1.082 (2.260)*	1.157 (2.311)*	1.214 (2.019)*	0.99 (-0.143)	0.961 (-0.341)	0.938 (-0.400)
Observations	474			282			192		
Monthly Data	1.041 (0.755)	0.994 (-0.058)	0.998 (-0.013)	1.054 (0.799)	1.043 (0.338)	1.184 (0.910)	1.026 (0.284)	0.905 (-0.592)	0.71 (-1.245)

index. From the results of the previous section a similar disparity continues to persist even after including data from the 1986-2001. Following the lead of Lo and MacKinlay (1988) we test the RWH-LM with the help of ten size-sorted portfolios.

Portfolio Construction

Using stock return data on individual securities from the CRSP database, we construct a ten-asset group consisting of size-sorted portfolios. At the end of each month (or week for weekly data) all NYSE stocks were sorted by size (shares outstanding times price per share) to determine the NYSE decile breakpoints. Subsequently, all NYSE, AMEX, and NASDAQ stocks were allocated on the basis of their size to the ten size portfolios formed using the breakpoints that had been determined by the NYSE stocks. Here, as usual, Decile 1 represents the portfolio of the smallest of firms while Decile 10 represents the portfolio of the largest of firms.

Index values for each decile are constructed using both equal-weighting and value-weighting of assets within each decile portfolio. Here, we only report the results for deciles formed with value-weighting of stocks within each decile portfolio[4].

[4] Results for equal-weighted portfolios are very similar to those obtained for value-weighted portfolios and

Table 1.3: $\overline{VR}$ and Z-scores: Return Data by Decile

The table reports the values of the variance ratio statistic and corresponding z-scores for weekly and monthly returns of the decile portfolios constructed using stocks from the NYSE, AMEX, and NASDAQ exchanges for the sample period 1962-2001, the sub-period 1962-1985, and the sub-period 1986-2001. The observed variance ratios $\overline{\text{VR}}(q)$ are reported in the main row, with the corresponding heteroskedasticity-robust test statistics $z^*(q)$ reported just below in parenthesis. Under RWH-LM the variance ratios should equal 1 and the test statistic is asymptotically standard normal. Variance ratios significantly different from 1 have corresponding test statistics marked with an asterisk. The parameter q corresponds to the return period used to form the variance ratios; for example when $q = 2$ the variance ratio is the ratio of variance of two-period returns to one-period returns.

Periods	1962-2001			1962-1985			1986-2001		
q value	2	4	8	2	4	8	2	4	8
Weekly Return Data		2059			1226			833	
Decile 1	1.374	1.816	2.247	1.368	1.84	2.315	1.388	1.783	2.153
(Small)	(7.819)*	(10.13)*	(11.23)*	(8.605)*	(10.82)*	(11.18)*	(3.577)*	(4.463)*	(5.103)*
Decile 2	1.296	1.612	1.905	1.307	1.673	2.006	1.28	1.527	1.772
	(5.979)*	(7.441)*	(8.165)*	(7.864)*	(9.349)*	(9.150)*	(2.542)*	(2.979)*	(3.431)*
Decile 3	1.257	1.514	1.74	1.275	1.59	1.855	1.234	1.414	1.596
	(5.523)*	(6.546)*	(6.894)*	(7.277)*	(8.366)*	(7.861)*	(2.343)*	(2.546)*	(2.840)*
Decile 4	1.231	1.468	1.659	1.263	1.568	1.799	1.194	1.348	1.501
	(4.991)*	(5.974)*	(6.174)*	(7.144)*	(8.230)*	(7.462)*	(2.049)*	(2.248)*	(2.492)*
Decile 5	1.21	1.406	1.578	1.251	1.543	1.798	1.167	1.26	1.35
	(4.281)*	(4.915)*	(5.192)*	(6.921)*	(8.001)*	(7.593)*	(1.737)	(1.649)	(1.707)
Decile 6	1.176	1.342	1.467	1.23	1.484	1.667	1.118	1.19	1.261
	(3.989)*	(4.556)*	(4.531)*	(6.441)*	(7.214)*	(6.387)*	(1.393)	(1.356)	(1.412)
Decile 7	1.151	1.275	1.377	1.206	1.422	1.594	1.092	1.119	1.152
	(3.496)*	(3.718)*	(3.685)*	(5.753)*	(6.283)*	(5.689)*	(1.123)	(0.867)	(0.831)
Decile 8	1.125	1.216	1.276	1.179	1.365	1.489	1.07	1.066	1.064
	(3.055)*	(3.062)*	(2.794)*	(5.144)*	(5.536)*	(4.724)*	(0.921)	(0.517)	(0.374)
Decile 9	1.081	1.132	1.175	1.14	1.273	1.372	1.025	0.997	0.986
	(2.127)*	(1.990)*	(1.851)	(3.929)*	(4.100)*	(3.565)*	(0.366)	(-0.030)	(-0.090)
Decile 10	0.991	0.986	0.985	1.034	1.06	1.075	0.949	0.909	0.894
(Large)	(-.271)	(-.251)	(-.169)	(0.923)	(0.867)	(0.689)	(-0.980)	(-0.980)	(-0.790)
Monthly Return Data		474			282			192	
Decile 1	1.218	1.286	1.314	1.215	1.328	1.531	1.23	1.21	0.935
	(4.292)*	(3.038)*	(2.150)*	(3.305)*	(2.730)*	(2.812)*	(2.884)*	(1.413)	(-.289)
Decile 2	1.191	1.209	1.195	1.18	1.245	1.402	1.216	1.145	0.846
	(3.877)*	(2.272)*	(1.352)	(2.882)*	(2.069)*	(2.125)*	(2.739)*	(1.015)	(-.719)
Decile 3	1.164	1.152	1.11	1.153	1.209	1.338	1.192	1.064	0.762
	(3.454)*	(1.699)	(0.769)	(2.531)*	(1.823)	(1.806)	(2.506)*	(0.450)	(-1.08)
Decile 4	1.168	1.133	1.079	1.161	1.193	1.33	1.185	1.042	0.723
	(3.507)*	(1.475)	(0.555)	(2.673)*	(1.668)	(1.760)	(2.345)*	(0.290)	(-1.26)
Decile 5	1.158	1.115	1.059	1.176	1.207	1.332	1.14	0.987	0.699
	(3.305)*	(1.275)	(0.413)	(2.974)*	(1.821)	(1.801)	(1.750)	(-.089)	(-1.35)
Decile 6	1.128	1.086	1.02	1.138	1.169	1.266	1.12	0.974	0.701
	(2.621)*	(0.940)	(0.139)	(2.257)*	(1.441)	(1.401)	(1.507)	(-.180)	(-1.36)
Decile 7	1.118	1.064	1.024	1.137	1.166	1.313	1.096	0.924	0.637
	(2.410)*	(0.703)	(0.168)	(2.232)*	(1.401)	(1.626)	(1.217)	(-.528)	(-1.63)
Decile 8	1.084	1.027	0.954	1.098	1.104	1.172	1.07	0.914	0.662
	(1.736)	(0.297)	(-.313)	(1.677)	(0.900)	(0.903)	(0.840)	(-.572)	(-1.50)
Decile 9	1.083	1.006	0.955	1.105	1.081	1.192	1.054	0.887	0.632
	(1.650)	(0.062)	(-.301)	(1.679)	(0.663)	(0.978)	(0.656)	(-.765)	(-1.64)
Decile 10	1.021	1.007	1.067	1.037	1.042	1.199	1.005	0.95	0.885
	(0.355)	(0.069)	(0.417)	(0.462)	(0.288)	(0.920)	(0.058)	(-.313)	(-.485)

Decile-to-Decile Behavior

From Table 1.3 four important observations emerge.

- For weekly return data Decile 1 exhibits the strongest evidence against the RWH-LM for the overall period 1962-2001.
- Evidence against the RWH-LM drops significantly as on moves from the smallest to the largest decile.
- In fact, the portfolio of largest firms Decile 10 is the only decile portfolio that shows no evidence against RWH-LM in any of the time periods.
- Furthermore, similar to what we observed with market indexes the evidence against the RWH-LM is significantly weaker in the second sub-period 1986-2001.

Detailed Results

For weekly return data the evidence against RWH-LM is strongest for Decile 1. In fact, for Decile 1 the value of the variance ratio test statistic $z^*(q)$ is 7.82 and is highly significant in the overall period 1962-2001. However, as we proceed through the decile portfolios the evidence against RWH-LM becomes weaker.

As in the case of market indexes, we may obtain estimates of the lag 1 autocorrelations for returns on the size-sorted portfolios using the value of variance ratio for $q = 2$. The lag 1 autocorrelation $\hat{\rho}(1)$ for Decile 1 in the overall period 1962-2001 is approximately 37%. However, the lag 1 autocorrelation drops as one moves towards larger firms, and in fact the lag 1 autocorrelation for Decile 10 is only -0.01%.

Results for Sub-periods

Compared to the first sub-period 1962-1985 the evidence against RWH-LM is lower in the second sub-period 1986-2001 even though the test statistics continue to be significant.

can be obtained from the author.

For example, for $q = 2$, $z^*(2)$ for 1962-1985 is 8.61 compared to 3.58 for the period 1986-2001.

Starting with Decile 5 there is no evidence against RWH-LM for the sub-period 1986-2001 while the overall period and the first sub-period continue to show strong evidence against RWH-LM. Furthermore, between Deciles 5 and 9 there appears to be a large difference in the magnitude of the lag 1 autocorrelations between the first sub-period 1962-1985 and the second sub-period 1986-2001.

Also, unlike Deciles 1–9 which exhibit strong evidence against RWH-LM in at least one time period, the portfolio of largest firms Decile 10 shows no evidence against RWH-LM in any of the time periods. The evidence against RWH-LM is weak even during the 1962-1985 period during which Deciles 1–9 show significant evidence against RWH-LM.

Monthly Return Data

For monthly return data evidence against RWH-LM disappears completely for all periods for almost all deciles. The smallest of firms represented by Decile 1 is the only asset that still exhibits significant autocorrelation in returns in the overall period 1962-2001 and the first sub-period 1962-1985. The lag 1 autocorrelation $\hat{\rho}(1)$ for Decile 1 during the period 1962-2001 is 22% and is consistent in terms of magnitude across all lags. Also, as in the weekly returns case, the test statistic values drop in magnitude in the sub-period 1986-2001 when compared to the overall period 1962-2001 and the first sub-period 1962-1985.

1.4 Test of RWH-LM for Sector-sorted Portfolios

The use of sector-sorted portfolios and other indexes to test the RWH-LM is the key difference between the results here and those of Lo and MacKinlay (1988). One reason for the use of sector-sorted portfolios here follows from the lead of Fama and French (1988) who observe that since industry portfolios contain firms of different sizes, size-sorted portfolios and sector-sorted portfolios are not proxies for each other and provide independent evidence in any analysis[5].

Portfolio Construction

Using the Standard Industrial Classification (or SIC) codes we form 10 sector-based portfolios. The 10 sectors are Basic Industries, Construction (includes Mining), Durables, NonDurables, Transportation (includes Communication), Utilities, Trade, Finance (including Real Estate and Insurance), Oil and Coal, and Services. As with decile portfolios we used the weekly and monthly return data to construct index values for each sector. Also, within each sector we construct both equal-weighted and value-weighted portfolios. Similar to decile portfolios, the sector-based portfolios are continuously changing and are updated every month (or week for weekly data).

Sectors formed with Equal-weighting of Stocks

We begin by highlighting key observations from Table 1.4.

- For weekly return data, all sectors except Utilities show strong evidence against RWH-LM in all time periods.
- The Basic Industries sector, the Durables sector, the Trade sector, the Finance, Real Estate, and Insurance sector along with the Services sector have weekly lag 1 auto-correlations above 30% for the overall period 1962-2001.
- Similar to results from the previous sections, the magnitude of the rejections of RWH-LM are lower in the second sub-period 1986-2001.
- For monthly return data, the Finance, Real Estate, and Insurance sector is the only one for which the RWH-LM is rejected for all time periods.

Detailed Results

[5]To help us understand the concentration of firms by size within each sector we calculated some simple descriptive statistics for each sector over the period 1962-2001. We noticed that the average decile ranks of the firms within each sector ranged anywhere from 2.0 to 6.0. Further descriptive statistics can be obtained from the author.

Table 1.4: $\overline{VR}$ and Z-scores: Return Data by Sectors (Equal-Weighted)

The table reports the values of the variance ratio statistic and corresponding z-scores for weekly and monthly returns of the sector-based portfolios constructed using equal-weighting of stocks from the NYSE, AMEX, and NASDAQ exchanges for the sample period 1962-2001, the sub-period 1962-1985, and the sub-period 1986-2001. The observed variance ratios $\overline{\text{VR}}(q)$ are reported in the main row, with the corresponding heteroskedasticity-robust test statistics $z^*(q)$ reported just below in parenthesis. Under RWH-LM the variance ratios should equal 1 and the test statistic is asymptotically standard normal. Variance ratios significantly different from 1 have corresponding test statistics marked with an asterisk. The parameter q corresponds to the return period used to form the variance ratios; for example when $q = 2$ the variance ratio is the ratio of variance of two-period returns to one-period returns.

Periods	1962-2001			1962-1985			1986-2001		
q values	2	4	8	2	4	8	2	4	8
Weekly Return Data	2059			1226			833		
Basic Industries	1.305	1.651	2.050	1.343	1.779	2.258	1.248	1.461	1.732
	(6.730)*	(8.623)*	(10.14)*	(8.744)*	(10.86)*	(11.46)*	(2.592)*	(2.993)*	(3.686)*
Construction	1.255	1.551	1.833	1.258	1.608	1.968	1.249	1.447	1.625
	(6.021)*	(7.773)*	(8.599)*	(6.960)*	(8.721)*	(9.162)*	(2.650)*	(3.004)*	(3.316)*
Durables	1.302	1.646	1.968	1.318	1.707	2.077	1.286	1.583	1.862
	(6.549)*	(8.275)*	(8.987)*	(8.181)*	(9.865)*	(9.841)*	(3.157)*	(3.905)*	(4.356)*
NonDurables	1.286	1.596	1.884	1.311	1.690	2.010	1.261	1.505	1.769
	(5.150)*	(6.533)*	(7.356)*	(7.953)*	(9.562)*	(9.213)*	(2.434)*	(2.918)*	(3.494)*
Transportation	1.253	1.532	1.803	1.272	1.589	1.885	1.237	1.484	1.745
	(6.087)*	(7.353)*	(7.697)*	(7.744)*	(9.041)*	(8.770)*	(3.147)*	(3.753)*	(4.078)*
Utilities	1.218	1.414	1.528	1.293	1.607	1.745	1.111	1.141	1.214
	(5.584)*	(6.193)*	(5.615)*	(7.042)*	(8.032)*	(6.507)*	(1.487)	(1.155)	(1.335)
Trade	1.337	1.730	2.163	1.368	1.841	2.353	1.300	1.598	1.942
	(6.772)*	(8.771)*	(10.31)*	(8.767)*	(11.02)*	(11.67)*	(2.987)*	(3.658)*	(4.468)*
Fin, RE, Ins	1.319	1.687	2.097	1.330	1.730	2.137	1.294	1.590	2.022
	(7.366)*	(9.222)*	(10.34)*	(7.490)*	(9.162)*	(9.391)*	(2.802)*	(3.488)*	(4.733)*
Oil and Coal	1.244	1.479	1.692	1.236	1.479	1.686	1.261	1.491	1.730
	(7.567)*	(8.201)*	(7.843)*	(6.473)*	(6.909)*	(6.338)*	(4.177)*	(4.607)*	(4.795)*
Services	1.325	1.705	2.072	1.329	1.758	2.234	1.323	1.656	1.918
	(7.788)*	(9.579)*	(10.06)*	(8.646)*	(10.57)*	(11.09)*	(4.174)*	(4.916)*	(4.880)*
Monthly Return Data	474			282			192		
Basic Industries	1.260	1.408	1.517	1.261	1.444	1.749	1.251	1.297	0.982
	(5.064)*	(4.383)*	(3.581)*	(4.079)*	(3.743)*	(3.968)*	(3.035)*	(2.083)*	(-.087)
Construction	1.161	1.234	1.231	1.201	1.305	1.409	1.101	1.119	0.974
	(3.485)*	(2.577)*	(1.561)	(3.378)*	(2.514)*	(2.038)*	(1.356)	(0.910)	(-.130)
Durables	1.208	1.229	1.149	1.192	1.260	1.365	1.237	1.206	0.922
	(4.196)*	(2.425)*	(1.013)	(3.131)*	(2.208)*	(1.951)	(2.899)*	(1.328)	(-.331)
NonDurables	1.191	1.204	1.138	1.170	1.230	1.352	1.221	1.170	0.883
	(3.879)*	(2.248)*	(0.981)	(2.678)*	(1.915)	(1.848)	(2.877)*	(1.227)	(-.565)
Transportation	1.198	1.207	1.229	1.182	1.241	1.445	1.223	1.188	1.056
	(3.674)*	(1.987)*	(1.428)	(2.988)*	(2.054)*	(2.367)*	(2.444)*	(1.063)	(0.211)
Utilities	1.080	1.057	1.188	1.083	1.047	1.233	1.062	1.017	0.988
	(1.570)	(0.605)	(1.238)	(1.279)	(0.388)	(1.170)	(0.782)	(0.118)	(-.054)
Trade	1.256	1.373	1.361	1.251	1.441	1.685	1.268	1.266	0.874
	(4.964)*	(3.917)*	(2.445)*	(3.654)*	(3.431)*	(3.437)*	(3.508)*	(1.940)	(-.590)
Fin, RE, Ins	1.245	1.387	1.621	1.223	1.344	1.656	1.308	1.494	1.567
	(4.243)*	(3.699)*	(3.823)*	(3.089)*	(2.618)*	(3.198)*	(3.629)*	(3.394)*	(2.583)*
Oil and Coal	1.140	1.315	1.515	1.132	1.330	1.632	1.152	1.293	1.316
	(2.641)*	(3.186)*	(3.262)*	(2.062)*	(2.703)*	(3.185)*	(1.648)	(1.758)	(1.227)
Services	1.230	1.286	1.326	1.259	1.445	1.745	1.201	1.097	0.845
	(4.089)*	(2.694)*	(2.002)*	(3.986)*	(3.711)*	(3.941)*	(2.078)*	(0.522)	(-.556)

As in the case of market indexes and size-sorted portfolios, we may obtain estimates of the lag 1 autocorrelations in returns on these size-sorted portfolios using variance ratios corresponding to $q = 2$. For example, the weekly returns from the Services sector has a lag 1 autocorrelation $\hat{\rho}(1)$ of approximately 33% in the overall time-period 1962-2001. The Basic Industries sector, the Durables sector, the Trade sector, the Finance, Real Estate, and Insurance sector along with the Services sector have weekly lag 1 autocorrelations above 30% for the overall period 1962-2001.

Results for Sub-periods

The evidence in the results for the sub-periods shows the same pattern that we observed in the previous sections. There is a large drop off in the values of the test statistics for the sub-period 1986-2001 among all sectors, and the most strongest evidence against RWH-LM occurs in the first sub-period 1962-1985.

As we noted earlier the Utilities sector is the only one that shows a change in the evidence against the RWH-LM. For the sub-period 1986-2001 the Utilities sector shows no evidence against RWH-LM even though it shows substantial evidence against RWH-LM both in the overall period 1962-2001 and in the sub-period 1962-1985. A reasonable explanation for this phenomenon could be the deregulation that occurred in the Utilities sector in the early 1990's.

Rather remarkably for the Oil and Coal sector, the lag 1 autocorrelations of weekly return data for the second sub-period 1986-2001 are higher than those for the fist sub-period 1962-1985. An explanation for this requires further investigation and we plan to address this in a future study.

Monthly Return Data

For monthly return data, the Basic Industries sector, the Trade sector, the Finance, Real Estate, and Insurance sector, the Oil and Coal sector, and the Services sector exhibit significant evidence against RWH-LM during the overall period 1962-2001. However, the Finance, Real Estate and Insurance sector is the only sector that has significant $z^*(q)$ values over all periods confirming significant evidence against RWH-LM.

Interestingly, the value of lag 1 autocorrelations for the Finance, Real Estate and Insurance sector during the second sub-period is higher than those for the first sub-period. This is similar to the jump in the value of lag 1 autocorrelations from the first sub-period to the second sub-period that we observed for the Oil and Coal sector using weekly data.

Sectors formed with Value-weighting of Stocks

We begin with a summary of the most interesting observations from Table 1.5.

- The results for sectors formed with value-weighting of stocks tell a significantly different story from the results obtained using sectors formed with equal-weighting of stocks within each sector.

- For weekly return data only 5 out of the 10 sectors show significant evidence against RWH-LM in the overall period 1962-2001.

- Also, alarmingly, none of the sectors show significant evidence against RWH-LM for the sub-period 1986-2001, while almost all of the sectors show significant evidence against RWH-LM for the sub-period 1962-1985.

- For monthly return data, none of the sectors are significant in any of the time periods, a clear indication of lack of evidence against RWH-LM.

The difference in the results found for sectors formed with equal-weighting of stocks within each sector and sectors formed with value-weighting of stocks within each sector is surprising given that typically the sector-sorted portfolios are well diversified within each sector with respect to size.

1.5 Test of RWH-LM for Other Market Indexes

Here we examine the RWH-LM using data from the NASDAQ indexes and the S&P 500 index. The CRSP database contains the daily and monthly returns of the CRSP NASDAQ

Table 1.5: $\overline{VR}$ and Z-scores: Return Data by Sectors (Value-Weighted)

The table reports the values of the variance ratio statistic and corresponding z-scores for weekly and monthly returns of the sector-based portfolios constructed using value-weighting of stocks from the NYSE, AMEX, and NASDAQ exchanges for the sample period 1962-2001, the sub-period 1962-1985, and the sub-period 1986-2001. The observed variance ratios $\overline{\text{VR}}(q)$ are reported in the main row, with the corresponding heteroskedasticity-robust test statistics $z^*(q)$ reported just below in parenthesis. Under RWH-LM the variance ratios should equal 1 and the test statistic is asymptotically standard normal. Variance ratios significantly different from 1 have corresponding test statistics marked with an asterisk. The parameter q corresponds to the return period used to form the variance ratios; for example when $q = 2$ the variance ratio is the ratio of variance of two-period returns to one-period returns.

Periods	1962-2001			1962-1985			1986-2001		
q values	2	4	8	2	4	8	2	4	8
Weekly Return Data		474			282			192	
Basic Industries	1.109	1.251	1.424	1.133	1.339	1.58	1.085	1.161	1.265
	(2.869)*	(3.662)*	(4.239)*	(3.703)*	(4.858)*	(5.259)*	(1.222)	(1.322)	(1.545)
Construction	1.135	1.288	1.357	1.164	1.391	1.569	1.101	1.165	1.113
	(3.530)*	(4.382)*	(3.783)*	(4.760)*	(5.873)*	(5.386)*	(1.357)	(1.352)	(0.682)
Durables	1.042	1.101	1.173	1.091	1.185	1.298	1.004	1.038	1.08
	(1.124)	(1.541)	(1.806)	(2.656)*	(2.862)*	(2.962)*	(0.061)	(0.348)	(0.521)
NonDurables	1.015	1.024	0.993	1.054	1.073	1.044	0.962	0.958	0.921
	(0.416)	(0.389)	(-.080)	(1.432)	(1.044)	(0.406)	(-0.560)	(-0.360)	(-0.510)
Transportation	1.042	1.071	1.128	1.074	1.161	1.214	1.018	1.005	1.067
	(1.367)	(1.223)	(1.433)	(2.571)*	(2.820)*	(2.347)*	(0.378)	(0.052)	(0.480)
Utilities	1.105	1.196	1.218	1.202	1.396	1.449	0.992	0.963	0.948
	(3.333)*	(3.463)*	(2.586)*	(5.268)*	(5.620)*	(4.140)*	(-0.150)	(-0.410)	(-0.400)
Trade	1.064	1.133	1.249	1.133	1.28	1.457	0.996	0.99	1.05
	(1.697)	(2.013)*	(2.642)*	(4.036)*	(4.233)*	(4.334)*	(-0.060)	(-0.090)	(0.316)
Fin, RE, Ins	1.084	1.146	1.2	1.137	1.271	1.369	1.011	0.977	0.971
	(2.778)*	(2.664)*	(2.427)*	(4.280)*	(4.413)*	(3.777)*	(0.193)	(-0.230)	(-0.210)
Oil and Coal	1.068	1.104	1.169	1.097	1.169	1.264	1.034	1.029	1.054
	(2.018)*	(1.738)	(1.918)	(3.008)*	(2.690)*	(2.629)*	(0.538)	(0.265)	(0.350)
Services	1.12	1.253	1.376	1.171	1.391	1.592	1.067	1.113	1.161
	(3.153)*	(3.813)*	(3.911)*	(4.847)*	(5.839)*	(5.646)*	(0.967)	(0.961)	(0.980)
Monthly Return Data		474			282			192	
Basic Industries	1.188	1.212	1.268	1.233	1.386	1.644	1.128	0.969	0.768
	(3.625)*	(2.297)*	(1.860)	(3.165)*	(3.006)*	(3.299)*	(1.825)	(-.235)	(-1.10)
Construction	1.025	0.984	0.92	1.111	1.12	1.161	0.91	0.809	0.627
	(0.472)	(-.161)	(-.491)	(1.636)	(0.907)	(0.769)	(-1.04)	(-1.21)	(-1.44)
Durables	1.094	1.106	1.114	1.126	1.17	1.258	1.07	1.047	1.015
	(1.692)	(0.996)	(0.693)	(2.017)*	(1.440)	(1.365)	(0.785)	(0.277)	(0.056)
NonDurables	0.989	0.932	0.972	0.964	0.9	1.059	1.025	0.947	0.752
	(-.172)	(-.610)	(-.173)	(-.457)	(-.693)	(0.278)	(0.246)	(-.304)	(-.994)
Transportation	1.051	1.094	1.216	1.052	1.043	1.132	1.055	1.134	1.294
	(0.927)	(0.907)	(1.307)	(0.834)	(0.361)	(0.689)	(0.654)	(0.846)	(1.174)
Utilities	1.02	0.934	1.025	1.047	0.95	1.071	0.973	0.871	0.901
	(0.409)	(-.707)	(0.161)	(0.757)	(-.415)	(0.359)	(-.342)	(-.884)	(-.424)
Trade	1.164	1.179	1.091	1.177	1.269	1.356	1.151	1.045	0.696
	(2.894)*	(1.736)	(0.575)	(2.608)*	(2.095)*	(1.752)	(1.557)	(0.265)	(-1.23)
Fin, RE, Ins	1.114	1.11	1.188	1.171	1.201	1.385	1.03	0.957	0.882
	(2.109)*	(1.121)	(1.222)	(2.370)*	(1.510)	(1.835)	(0.372)	(-.297)	(-.542)
Oil and Coal	1.089	1.115	1.203	1.109	1.173	1.411	1.058	1.036	0.936
	(1.451)	(1.051)	(1.247)	(1.440)	(1.248)	(1.939)	(0.566)	(0.206)	(-.252)
Services	1.128	1.178	1.198	1.188	1.336	1.563	1.055	0.983	0.772
	(2.426)*	(1.832)	(1.292)	(2.965)*	(2.865)*	(2.993)*	(0.622)	(-.101)	(-.892)

Table 1.6: $\overline{VR}$ and Z-scores: CRSP NASDAQ equal-weighted index

The table reports the values of the variance ratio statistic and corresponding z-scores for weekly returns of the CRSP NASDAQ equal-weighted index for the sample period 1962-2001, the sub-period 1962-1985, and the sub-period 1986-2001. The observed variance ratios $\overline{\text{VR}}(q)$ are reported in the main row, with the corresponding heteroskedasticity-robust test statistics $z^*(q)$ reported just below in parenthesis. Under RWH-LM the variance ratios should equal 1 and the test statistic is asymptotically standard normal. Variance ratios significantly different from 1 have corresponding test statistics marked with an asterisk. The parameter q corresponds to the return period used to form the variance ratios; for example when $q = 2$ the variance ratio is the ratio of variance of two-period returns to one-period returns.

Periods	1962-2001 Overall Time Period			1962-1985 The Lo-MacKinlay period			1986-2001 The post Lo-MacKinlay period		
q values	2	4	8	2	4	8	2	4	8
Observations	1511			678			833		
Weekly Data	1.374 (6.749)*	1.834 (8.711)*	2.281 (9.505)*	1.469 (8.826)*	2.168 (11.925)*	2.864 (12.863)*	1.324 (4.072)*	1.663 (4.872)*	1.979 (5.158)*
Observations	348			156			192		
Monthly Data	1.228 (3.747)*	1.251 (2.133)*	1.167 (0.920)	1.256 (3.271)*	1.419 (2.752)*	1.608 (2.498)*	1.215 (2.465)*	1.146 (0.868)	0.907 (-0.361)

equal-weighted index and the CRSP NASDAQ value-weighted index from 1973-2001. To construct weekly CRSP NASDAQ data, we use the same procedure that we outlined when investigating weekly data of the CRSP NYSE-AMEX market indexes.

The reason for considering additional market indexes like the NASDAQ indexes, is primarily due to the results of Lo, Mamaysky and Wang (2000). Specifically, the authors find that daily stock returns conditioned on specific technical indicators provide incremental information when compared to the unconditional daily stock returns and more importantly, the incremental information is significantly higher for NASDAQ stocks than NYSE-AMEX stocks.

Other Market Indexes

Tables 1.6, 1.7, and 1.8 display the results for the CRSP NASDAQ equal-weighted market index, the CRSP NASDAQ value-weighted market index and the S&P 500 index for both weekly and monthly data. The most interesting observations that one can draw from these tables are perhaps the following.

- The RWH-LM is strongly rejected for the CRSP NASDAQ equal-weighted index at all time periods and at all lags for weekly data and the lag 1 autocorrelation $\hat{\rho}(1)$ of weekly returns of the CRSP NASDAQ equal-weighted index is approximately 37% for the overall time-period 1962-2001.

- An important observation that is in order here is that the values of the variance ratios and the test statistics for the CRSP NASDAQ equal-weighted index leads us to conclusions similar to those of Lo, Mamaysky, and Wang (2000), namely that the returns to the NASDAQ exchange indexes exhibit higher autocorrelations than returns from the NYSE-AMEX exchange indexes.

- Given what we have seen in the previous sections, not surprisingly, the results are weaker for monthly data. The evidence against RWH-LM is only moderate as the rejections fail to occur at all lags.

- However, the CRSP NASDAQ value-weighted index shows no evidence against RWH-LM for both weekly and monthly data for the overall time-period 1962-2001. Nevertheless, there is some evidence against RWH-LM in the first sub-period 1962-1985 in weekly data but this does not persist in the second sub-period 1986-2001.

- We hasten to add that the pattern in the results here is similar to what we have seen in the previous sections. The evidence against RWH-LM is stronger in the first sub-period 1962-1985 than the second sub-period 1986-2001.

- The S&P 500 index shows no evidence against RWH-LM for both weekly and monthly data and in any of the time-periods. Even during the 1962-1985 sub-period the lag 1 autocorrelation in weekly returns is only 4%.

1.6 Concluding Remarks

The central aim of this introductory chapter was to revisit the analysis of Lo and MacKinlay (1988) and additionally test the Lo-MacKinlay model with the help of data from sector-sorted portfolios and several other market indexes.

Table 1.7: $\overline{VR}$ and Z-scores: CRSP NASDAQ value-weighted index

The table reports the values of the variance ratio statistic and corresponding z-scores for weekly returns of the CRSP NASDAQ value-weighted index for the sample period 1962-2001, the sub-period 1962-1985, and the sub-period 1986-2001. The observed variance ratios $\overline{\text{VR}}(q)$ are reported in the main row, with the corresponding heteroskedasticity-robust test statistics $z^*(q)$ reported just below in parenthesis. Under RWH-LM the variance ratios should equal 1 and the test statistic is asymptotically standard normal. Variance ratios significantly different from 1 have corresponding test statistics marked with an asterisk. The parameter q corresponds to the return period used to form the variance ratios; for example when $q = 2$ the variance ratio is the ratio of variance of two-period returns to one-period returns.

Periods	1962-2001 Overall Time Period			1962-1985 The Lo-MacKinlay period			1986-2001 The post Lo-MacKinlay period		
q values	2	4	8	2	4	8	2	4	8
Observations	1511			678			833		
Weekly Data	1.080 (1.579)	1.212 (2.415)*	1.369 (2.883)*	1.212 (4.714)*	1.537 (6.220)*	1.829 (6.164)*	1.036 (0.541)	1.105 (0.924)	1.223 (1.346)
Observations	348			156			192		
Monthly Data	1.130 (1.830)	1.149 (1.118)	1.172 (0.816)	1.180 (2.161)*	1.259 (1.644)	1.453 (1.798)	1.112 (1.156)	1.106 (0.583)	1.081 (0.282)

We began by making explicit the several versions of the random walk hypothesis that have been considered earlier in the financial literature, and in particular we noted the importance of allowing some form of heterogeneity in the noise process. This brought us to the Lo-MacKinlay model (or RWH-LM), and set the stage for us to develop the variance ratio test that served as our basic tool throughout the chapter.

With the tools in hand we turned our attention to analyzing the RWH-LM. As our first task we analyzed the RWH-LM by re-examining the results of Lo and MacKinlay (1988) for the period 1962-2001 with the help of weekly and monthly return data obtained from the CRSP NYSE-AMEX equal-weighted index, the CRSP NYSE-AMEX value-weighted index, and the 10 size-sorted portfolios. We then carried out our second task, namely to analyze the RWH-LM using data from sector-sorted portfolios and other market indexes. In short, five noteworthy observations emerged from our results.

- For the overall period 1962-2001, the RWH-LM is overwhelmingly rejected by weekly data from the CRSP NYSE-AMEX equal-weighted index and the value of the lag 1 autocorrelation is approximately 26%.

- For weekly return data of size-sorted portfolios, Decile 1 exhibits the strongest evi-

Table 1.8: $\overline{VR}$ and Z-scores: S&P 500 index

The table reports the values of the variance ratio statistic and corresponding z-scores for weekly returns of the S&P 500 index for the sample period 1962-2001, and sub-periods 1962-1985, the sub-period 1962-1985, and the sub-period 1986-2001. The observed variance ratios $\overline{\text{VR}}(q)$ are reported in the main row, with the corresponding heteroskedasticity-robust test statistics $z^*(q)$ reported just below in parenthesis. Under RWH-LM the variance ratios should equal 1 and the test statistic is asymptotically standard normal. Variance ratios significantly different from 1 have corresponding test statistics marked with an asterisk. The parameter q corresponds to the return period used to form the variance ratios; for example when $q = 2$ the variance ratio is the ratio of variance of two-period returns to one-period returns.

Periods	1962-2001 Overall Time Period			1962-1985 The Lo-MacKinlay period			1986-2001 The post Lo-MacKinlay period		
q values	2	4	8	2	4	8	2	4	8
Observations	2059			1226			833		
Weekly Data	1.008 (0.238)	1.01 (0.158)	1.006 (0.063)	1.045 (1.243)	1.08 (1.183)	1.103 (0.977)	0.969 (-0.520)	0.936 (-0.630)	0.904 (-0.672)
Observations	474			282			192		
Monthly Data	1.01 (0.175)	0.97 (-0.288)	1.004 (0.028)	1.023 (0.328)	1.005 (0.038)	1.151 (0.729)	0.993 (-0.072)	0.903 (-0.605)	0.787 (-0.908)

dence against RWH-LM and the evidence against RWH-LM becomes weaker as we proceed from the lower deciles to the higher deciles.

- All sector-sorted portfolios formed with equal-weighting of stocks except the Utilities sector show strong evidence against the RWH-LM using weekly data and in particular the lag 1 autocorrelations for weekly returns of the Services sector was 32% for the overall period 1962-2001.

- However, the results for weekly return data of sectors formed with value-weighting of stocks are strikingly different with only 5 out of the 10 sectors showing significant evidence against the RWH-LM.

- Among the several other market indexes that were examined, weekly returns from the CRSP NASDAQ equal-weighted index showed strong evidence against the RWH-LM with a value of 37% for the lag 1 autocorrelation.

A common theme that emerges from the results is that the behavior of the market as a whole has moved towards the RWH-LM after 1985. This follows from the fact that for all the assets examined here, the evidence against RWH-LM has either dropped considerably or completely vanished in the second sub-period 1986-2001. We hasten to add that recently, Lo and MacKinlay (1999, pp. 16) observe this fall off in the evidence against the RWH-LM by using data from 1962-1996. Lo and MacKinlay argue that the move towards RWH-LM could be due to the fact that several investment firms have constructed trading strategies that capture the patterns in the autocorrelation observed in Lo and MacKinlay (1988).

Furthermore, the analysis of RWH-LM using sector-sorted portfolios has brought to light another interesting phenomenon which arises due to the differing results between sector-sorted portfolios formed with equal-weighting of stocks within each sector and sector-sorted portfolios formed with value-weighting of stocks within each sector. The presence of the phenomenon is surprising given that typically the sector-sorted portfolios are well diversified within each sector with respect to size and moreover, size-sorted portfolios formed both with value-weighting of stocks within each decile and equal-weighting of stocks within each decile, exhibit little difference in terms of the evidence against RWH-LM. An explanation for the differing behavior of sector-sorted with different weighting schemes requires further investigation and we suspect the presence of some kind of interaction effect between size-sorted portfolios and sector-sorted portfolios.

Another interesting characteristic in the results which is consistent with the results of Lo and MacKinlay (1988), is that in general weekly data show stronger evidence against RWH-LM than monthly data and the degree of autocorrelation varies among assets. This evidence of varying predictability (loosely speaking) across time horizon and assets is similar to that observed in Lo and MacKinlay (1999, pp. 284).

Before we conclude the chapter we would like to draw the attention of the reader to two issues that we have not addressed here. The first issue concerns the possible explanations associated with the deviation from the RWH-LM. An excellent study that examines several explanations is the one by Boudoukh, Richardson, Matthew and Whitelaw (1994). The second issue concerns the reasons for using the variance ratio test over existing unit root tests. A comprehensive investigation of the performance of the variance ratio test versus other commonly used unit root tests can be found in Lo and MacKinlay (1989).

Chapter 2

Risk Adjusted Returns and Profitability of the Filter Rule

The main goal of this chapter is to provide a risk adjusted evaluation of a classical rule — the so-called filter rule. The statistically significant rejections of the RWH-LM that we observed in Chapter 1 suggest the possibility of economically meaningful trading rules, and the filter rule is probably the trading rule with the richest academic tradition.

This investigation of the filter rule is unlike previous studies, as we assess the profitability of the filter rule with the help of three metrics: performance measures before adjusting for risk, risk adjusted performance measures, and market timing tests. In all three cases we take the buy-and-hold strategy as the benchmark strategy. The data for this exercise is similar to the data used in Chapter 1. Specifically, we use weekly and monthly data for the period July 1962 to December 2001 from the CRSP NYSE-AMEX value-weighted index, the CRSP NYSE-AMEX equal-weighted, the S&P 500 index, the CRSP NASDAQ value-weighted index, and the CRSP NASDAQ equal-weighted index.

This chapter is organized in five sections, the first of which frames the filter rule and reviews earlier empirical tests. The second section then explains the technical implementation of the filter rule strategy and offers a brief discussion on the choice of a particular filter rule. We review the performance measures that are used to assess the profitability of the filter rule in the third section, and in the fourth we present a comparison of the filter rule and the buy-and-hold strategy in the context of several market indexes. The final section summarizes the major findings of our risk adjusted analysis of the empirical performance of the filter rule.

2.1 Filter Rules – Definition and Earlier Work

Filter rules were first proposed by Alexander (1961), which is one of the earliest academic works to focus on the possibility that stock prices may exhibit trends which can be exploited by statistical rules. In Alexander's words, "Suppose we tentatively assume the existence of trends in stock market prices but believe them to be masked by the jiggling of the market we might filter out all movements smaller than a specified size and examine the remaining movements."

One way to define such a filter is the following. Let $P_t,\ t = 1, 2, \dots$, denote a sequence of prices[1] of a financial asset and let $0 < \lambda < 1$ be a fixed number. The time points at which the λ-filter rule generates the *buy* and *sell* signals are identified by the following recipe. The time of the first buy signal B_1 is given by

$$B_1 = \min\{t \geq 1 : \frac{P_t - \min_{1\leq i\leq t} P_i}{\min_{1\leq i\leq t} P_i} \geq \lambda\}\,,$$

and the time of the first sell signal S_1, following the first buy signal is given by

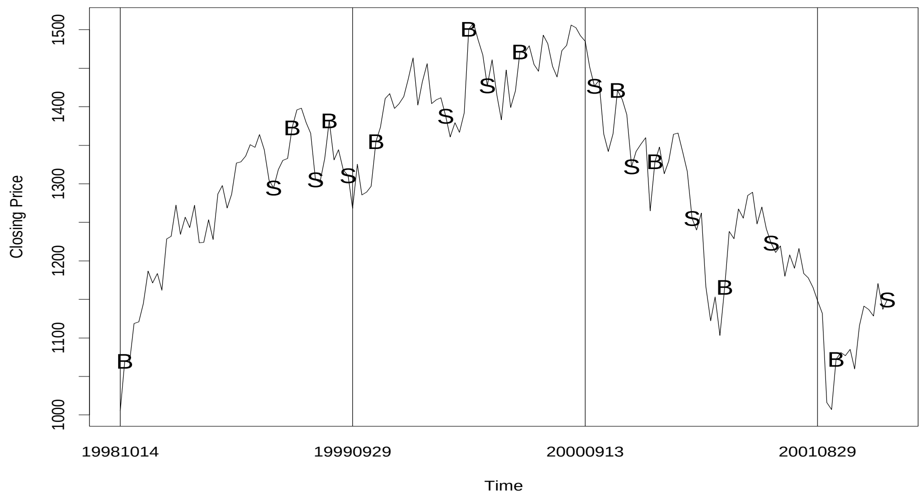
$$S_1 = \min\{t \geq B_1 : \frac{\max_{B_1\leq i\leq t} P_i - P_t}{\max_{B_1\leq i\leq t} P_i} \geq \lambda\}\,.$$

One can define the time points of buy and sell signals that follow in a similar fashion. The time of the v^{th} buy signal B_v is given by

$$B_v = \min\{t \geq S_{v-1} : \frac{P_t - \min_{S_{v-1}\leq i\leq t} P_i}{\min_{S_{v-1}\leq i\leq t} P_i} \geq \lambda\}\,,$$

[1] In common with most empirical studies, our evaluations will be based on closing prices whether daily, weekly or monthly.

Figure 2.1: Plot of 5% Filter Rule applied to Closing Prices of S&P 500 Index



and the time of the v^{th} sell signal S_v is given by

$$S_v = \min\{t \geq B_v : \frac{\max_{B_v \leq i \leq t} P_i - P_t}{\max_{B_v \leq i \leq t} P_i} \geq \lambda\}\,.$$

Figure 2.1 illustrates the signals generated by the $\lambda = 0.05$-filter rule applied to the weekly closing prices of the S&P 500 index from 1998 to 2001.

The above definition reflects what Corrado and Lee (1992) expressed by the verbal recipe: buy the asset when the asset's price rises by $100 * \lambda$ percent above its most recent local low, where the most recent local low is defined as the minimum asset price since the last sell signal. Similarly, sell the asset when the asset's price falls by $100 * \lambda$ percent below its most recent local high, where the most recent local high is the maximum asset price since the last buy signal.

Earlier Experience with Filter Rules

The earliest study of filter rules was by Alexander in 1961 and they have subsequently been studied by Alexander (1964), Fama and Blume (1966), Sweeney (1988), and Corrado and Lee (1992).

Alexander

In his 1961 article Alexander examined filter rules with various values of λ in the range $0.05 \leq \lambda \leq 0.5$ and for the underlying price series he used data on the Dow Jones industrial average from 1897-1929 and the S&P industrial average from 1929-1959. Alexander observed that for both the averages, that the filter rules corresponding to small values of λ performed better than filters with large λ values; moreover, he observed that filters with small values of λ resulted in higher profits than a simple buy-and-hold strategy. Based on these observations Alexander concluded that "stock market prices do have trends, and once a move has begun in the price series it tends to persist."

Alexander's 1964 article essentially replicated the analysis of the 1961 article, except that he made some adjustments that were needed to respond to criticisms of his earlier analysis. As a result of these adjustments, the performance of filter rules were severely dampened, and the filter rules only marginally outperformed the simple buy-and-hold strategy before taking commissions into account.

Almost all empirical studies assume that transactions, buying or selling the asset under investigation, are executed at closing prices, but in Alexander (1961) it was inappropriately assumed that all assets could be purchased at a price P_T, for which one has the equality

$$\frac{P_T - \min_{1 \leq i \leq T} P_i}{\min_{1 \leq i \leq T} P_i} = \lambda \quad ,$$

or sold at a price P_T where P_T satisfies the equality

$$\frac{\max_{1 \leq i \leq T} P_i - P_T}{\max_{1 \leq i \leq T} P_t} = \lambda \, .$$

If one assumes constant monitoring of a continuous real time price process, this trading assumption may be reasonable but to be more in keeping with traditional analysis the 1964 paper used the closing prices.

Fama and Blume

The filter rule was next taken up in Fama and Blume (1966) which studied the performance of filter rules for data which extended the series considered by Alexander. Specifically, it reports on the analysis of the filter rule with λ ranging from 0.005 to 0.5, for the daily closing prices of the thirty individual Dow stocks for January 1956 to September 1962. Fama and Blume make four basic observations:

- Filter rules are easily triggered at ex-dividend dates, and, an adjustment of the price series for dividends on ex-dividend days leads to improved performance of filter rules.
- Before commissions, for almost all securities the annualized return (adjusted for dividends) the annualized return from a buy-and-hold strategy is greater than the annualized return[2] (adjusted for dividends) which one obtains from the filter strategy.
- The best performing filter rule on each of the 30 stocks was the $\lambda = 0.005$-filter rule and even for this filter rule, the short positions produced disastrous returns for all the assets.
- Filter rules with small values of λ generated large number of transactions, and this fact explains why the filter rule produced poor returns after one adjusts for transaction costs; for example, the $\lambda = 0.005$-filter rule generated an average of 84 transactions per stock per year.

Sweeney

The analysis of Fama and Blume (1966) was not followed up for almost twenty years, but then Sweeney (1988) considered the performance of the $\lambda = 0.005$-filter rule for the

[2]For each asset the annualized return for the filter strategy is computed by averaging the annualized return over all values of λ.

fourteen stocks that had the best performance in Fama and Blume (1966). Sweeney used daily closing prices from 1970 to 1982, and since short positions performed poorly in the study of Fama and Blume, Sweeney considered only long positions. That is, whenever the $\lambda = 0.005$-filter rule issued a sell signal, the asset currently being held was sold, and a risk-free asset was purchased which was then held until the next buy signal. Sweeney's main finding is that for all the stocks under consideration, the $\lambda = 0.005$-filter rule yields better returns than the buy-and-hold strategy on a risk adjusted basis. Moreover, Sweeney found that one has excess returns even after one accounts for one-way transaction costs of 1/20 of 1 percent for each one-way trade.

Corrado and Lee

The most recent investigation of the filter rule to judge its usefulness as a trading strategy is that of Corrado and Lee (1992) which examined the relationship between returns to the filter rule and the autocorrelation in daily stock returns. The authors applied the $\lambda = 0.005$-filter rule to the 30 Dow stocks that were initially examined in Fama and Blume (1966), and they also analyzed additional stocks from the S&P 100 index. Using daily data for a set of 120 stocks from January 1963 to December 1989, the authors find that a 1% increase in the daily stock return autocorrelation *ceteris paribus* leads to an estimated 3.84% increase in daily filter rule returns on the average. Corrado and Lee note that, the difference between the cross-sectionally averaged annualized return on days invested in the stock and the cross-sectionally averaged annualized return on days not invested in the stock is statistically significant.

2.2 Filter Rule Implementation

The analysis of a trading strategy such as the filter rule ultimately depends on a number of specific decisions which do not necessarily address the basic idea of the strategy, but which are nevertheless essential when the time comes to do the implementation. Here in our implementation of the filter rule we assume the following:

- For each asset, the first position taken is a long position in the risk free asset.
- The risk free asset is held until the filter rule issues a buy signal, then the risk free asset is sold and a long position is taken in the risky asset.
- The long position in the risky asset is held until the filter rule issues a sell signal, after which the risky asset is sold and a long position is taken in the risk free asset. [3]
- Any open position is closed at the end of the sample period.
- Further, we assume that all transactions are executed at closing prices which also form the inputs to the filter rule.

The buy-and-hold strategy is straightforward to implement; we simply start with a long position in the risky asset, and we hold it until the end of the sample period.

Choice of filter rule and Data Snooping

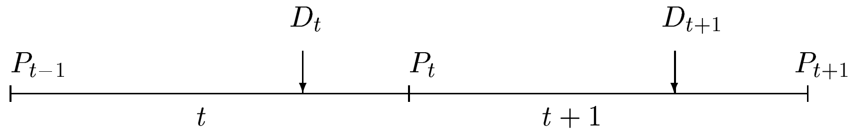
The choice of a filter rule presents a potential data-snooping problem, and, in fact, such a problem persists any time one uses information from data to guide subsequent research. Here, there are two cases that are particularly relevant.

1. Research that is influenced by the successes and failures of previous research may be subject to the data snooping correction (Lo and MacKinlay (1999, pp. 213). This category covers several issues, some of which are, the use of data corresponding to a particular period, the choice of portfolios, and the choice of parameter values for a trading strategy. The studies of Sweeney (1988) and Corrado and Lee (1992) are subject to this criticism, since they use the best performing filter rule from Fama and French (1966), namely the $\lambda = 0.005$-filter rule.

2. The use of a set of observations to fine tune a particular methodology, for example, use the data to obtain the optimum choice of λ for the filter rule, and subsequently report the performance of the optimized methodology on the same data.

[3] We purposefully avoid short positions given their poor performance in Fama and Blume (1966).

Figure 2.2: Dividend Timing Convention



In general, it is virtually impossible to avoid any data-snooping bias. Here, in order to limit the data snooping bias we consider an arbitrary value for λ, $\lambda = 0.05$, as the basis for our empirical investigation and consciously avoid the $\lambda = 0.005$ filter which has worked well in the past. Furthermore, we note that the $\lambda = 0.05$ is the only rule we investigate, and more importantly we remind the reader that our goal here is to examine the risk adjusted performance of a filter rule strategy and not to determine the optimum filter rule.

2.3 Performance Measures: A Brief Review

Any analysis of a trading strategy must be based on one or more performance measures, and it is certainly best for such measures

1. be made completely explicit,
2. be appropriate to both the trading strategy and the benchmark,
3. account, to the extent possible, for risk, and
4. account, to the extent possible for transaction costs.

Here, we review some tools that are commonly used to asses the performance of trading rules. As before, we let $P_t,\ t = 1, 2, \ldots, T$, denote a sequence of closing prices of a financial asset. Here, we assume that the asset's dividend payment announced between $t-1$ and t denoted D_t are paid at time t, so, P_t denotes the *ex-dividend* price at date t and is as shown in Figure 2.2 (adapted from Campbell, Lo and MacKinlay (1997, pp. 12)). The return on the asset for the period $[t-1, t]$ may be defined as

$$R_t = \frac{P_t + D_t - P_{t-1}}{P_{t-1}} \quad .$$

To distinguish between a risky asset's return and the return on the risk-free asset we denote the return on the risk-free asset for the period $[t-1, t]$ as R_t^f.

In order to review the performance measures we need several other notations and we state them for a general trading strategy rather than the filter rule.

- Let T denote the total number of observations for the asset.
- For weekly return data let $K = 52$, and for monthly return data let $K = 12$.
- We consider here only those strategies that divide the sample period into periods when we are invested in the risky asset (long periods) and periods when we are invested in the risk-free asset. To capture this division we define two indicator variables $I_{\text{in}}(\cdot)$ and $I_{\text{out}}(\cdot)$, where $I_{\text{in}}(t) = 1$ when we are long the risky asset at time t and zero otherwise. Analogously, $I_{\text{out}}(t) = 1$ when we are long the risk-free asset and zero otherwise, so, implicitly we have $I_{\text{in}}(t) * I_{\text{out}}(t) = 0 \quad \text{for all } t$.[4]
- Denote the number of periods that we are long the risky asset by T_{in}, so in symbols $T_{\text{in}} = \sum_{t=1}^{T} I_{\text{in}}(t)$. The number of periods when we are invested in the risk-free asset is then denoted by T_{out} and we obviously have $T_{\text{out}} = T - T_{\text{in}}$.
- Let N_{buy} and N_{sell} denote the number of buy signals and sell signals that the trading strategy generates, so one has $N_{\text{buy}} = \sum_{t=2}^{T} I_{\text{out}}(t-1) I_{\text{in}}(t)$. Note that, the filter rule definition is such that the first buy signal cannot occur at $t = 1$. Analogously, $N_{\text{sell}} = \sum_{t=2}^{T} I_{\text{in}}(t-1) I_{\text{out}}(t)$.
- Finally, we let N denote the total number of one-way transactions, so $N = N_{\text{buy}} + N_{\text{sell}}$.

We proceed to consider some simple return measures which helps us assess the performance of a trading strategy.

[4]In long hand, if $I_{\text{in}}(t-1) = 0$ and $I_{\text{in}}(t) = 1$ we did not own the asset during the time period $t-1$ but we bought it at the end of the period $t-1$ and held it at least to the end of the period t.

Performance Measures Not Adjusted for Risk

Terminal value of a \$1 investment For such an in-out strategy Lo and MacKinlay (1997) note that the terminal value of a \$1 investment is given by

$$V_T = \prod_{t=1}^{T} \Big[(1 + R_t) I_{\text{in}}(t) + (1 + R_t^f) I_{\text{out}}(t) \Big] \ ,$$

where the index t denotes weekly or monthly time periods.

Annualized returns The annualized return R for a trading strategy is given by the formula

$$R = \Big([V_T]^{K/T} - 1 \Big) \ . \tag{2.1}$$

Note that, the terminal value has a running index t which denotes weekly or monthly time periods. Moreover, for weekly data the $K = 52$ and for monthly return data $K = 12$.

Annualized return standard deviation The annualized return standard deviation S for a trading strategy is defined by

$$S = \sqrt{K} * \left(\left[\frac{1}{T-1} \sum_{t=1}^{T} (R_t - \overline{R}_t)^2 \right]^{1/2} \right) \ , \tag{2.2}$$

where $\overline{R}_t = \frac{1}{T} \sum_{t=1}^{T} R_t$. Here again, index t denotes weekly or monthly time periods. This formula with the parameter K in front does look peculiar. To clarify, suppose T represents the total number of trading weeks per year, the formula (2.2) without $\sqrt{K}$ represents the standard deviation of the weekly returns. Along with $\sqrt{K}$, the formula gives the standard deviation of K-weekly returns assuming they are independent. Of course, this assumption of independence is a rather strong one, but is often made when computing standard deviations.

Maximum drawdown The maximum drawdown DD measures the worst case loss and is given by

$$DD = \max_{1 \leq u \leq v \leq T} \frac{(V_u - V_v)_+}{V_u} \ ,$$

where V_u is the value of a \$1 investment at time u.

One-way break even transaction cost The return statistics reviewed above do not account for transaction costs, and such costs can play a substantial role in the profitability of a strategy. For a trading strategy, Lo and MacKinlay (1997) define the one-way break even transaction cost measured in percent, with the buy-and-hold as the benchmark strategy as

$$C = \left[1 - \left(\frac{V_T^{\text{bh}}}{V_T^{\text{ts}}} \right)^{1/N} \right] * 100 \ ,$$

where N is total number of one-way transactions. This is a reasonable way to understand the impact of transaction costs on the active strategy since C captures the percentage cost of buying or selling the risky asset such that the total return on a trading strategy equals the total return on a benchmark strategy.

Risk Adjusted Performance Measures

As noted earlier, most of the research literature on filter rules ignores the volatility in the returns series; historically the focus has almost exclusively been on the comparison between the performance of the filter rule and the buy-and-hold strategy. On the other hand, risk adjusted performance measures help us capture the return earned per unit risk for any strategy. We briefly review some of these measures below.

Sharpe Ratio

The annualized Sharpe Ratio SR for a trading strategy is defined by

$$SR = \frac{R - R^f}{S} \ ,$$

where R and S represent the annualized return and annualized standard deviation of the trading strategy and are defined by equations (2.1) and (2.2) respectively. The Sharpe Ratio is probably the most widely used risk adjusted performance measure. It tries to capture "risk" by comparing a trading strategy's excess return relative to the total variability of the trading strategy, but despite its popularity the Sharpe ratio has egregious shortcomings. The annualized standard deviation S is subject to criticism and the Sharpe ratio lacks a rigorous economic interpretation. These points and others suggest the need for additional risk adjusted measures.

Sortino Ratio

The standard deviation takes into account both positive and negative deviations from the mean, and as a consequence the Sharpe ratio penalizes large positive returns as much as it penalizes large negative returns. To address this limitation of the Sharpe ratio, one can consider instead the Sortino ratio which is given by

$$SoR = \frac{R - R^{\text{ref}}}{S^{-}} \; ,$$

where R^{ref} is a pre-specified reference rate of return and where S^{-} is a statistic designed to capture the downside risk. Formally S^{-} is defined by

$$S^{-} = \sqrt{K} * \left(\left[\frac{1}{T_{\text{down}} - 1} \sum_{t=1}^{T} (R_t - \overline{R}^f)^2 * I(R_t < \overline{R}^f) \right]^{1/2} \right) \; ,$$

where the index t denotes weekly or monthly time periods and $T_{\text{down}} = \sum_{t=1}^{T} I(R_t < \overline{R}^f)$. Furthermore, $\overline{R}^f = \frac{1}{T} \sum_{t=1}^{T} R_t^f$ and the indicator variable $I(R_t < \overline{R}^f)$ takes the value one when $R_t < \overline{R}^f$ and is zero otherwise. The pre-specified reference return R^{ref} is typically chosen to accommodate an investor's risk preference. Here we set $R^{\text{ref}} = R^f$, where R^f denotes the annualized return on the risk-free asset.

Here again, the presence of $\sqrt{K}$ in the formula is used to convert the standard deviation of single period (either weekly or monthly) returns to the standard deviation of K-period returns. As defined earlier, for weekly data $K = 52$ and for monthly data $K = 12$.

M^2 AND DIFF-M^2 MEASURES

Bodie, Kane, and Marcus (2002) argue that even though the Sharpe ratio may be a useful measure of performance, but in addition to the limitations addressed by the Sortino ratio; the Sharpe ratio also lacks an economic interpretation of the difference in Sharpe ratios between two competing strategies. For example, what does it mean if the difference between the Sharpe ratios of two competing strategies is 0.50? The M^2 measure is designed to provide a measure of risk adjusted performance that does have a meaningful interpretation.

The M^2 measure, also known as Risk Adjusted Performance or RAP measure, was proposed by Modigliani and Modigliani (1997). Formally, if we assume the buy-and-hold strategy as the benchmark strategy, the RAP measure for a trading strategy is be defined as

$$M^2 = \frac{S^{\text{bh}}}{S^{\text{ts}}} R^{\text{ts}} + (1 - \frac{S^{\text{bh}}}{S^{\text{ts}}}) R^f \ .$$

In essence, the RAP measure is calculated by re-scaling the "risk" (standard deviation) of the active strategy to match the risk of the passive strategy. One could think of this procedure as forming a new portfolio that is a mixture of the risky asset and the risk-free asset, such that the volatility in the new portfolio (here M^2) is the same as the volatility in the benchmark portfolio (here the buy-and-hold strategy).

A simple example that illustrates the process of constructing the new portfolio is the following. Suppose the standard deviation in returns as a result of following a trading strategy is four-thirds the standard deviation of the benchmark strategy. The newly constructed portfolio is formed such that three-fourths of one's wealth is invested in the risky asset and one-fourth in the risk-free asset. If the returns R^{bh} and R^{ts} are assumed to be independent the new portfolio would then have the same standard deviation as the benchmark portfolio. Naturally the independence hypothesis is highly suspect, but one still has at least some hope that this is satisfied.

Given the M^2 measure it is straightforward to define the Diff M^2 measure which is defined as

$$\text{Diff } M^2 = M^2 - R^{\text{bh}} \; .$$

The usefulness of this measure is due to its interpretability as a differential return between the active and passive strategy.

Market Timing Tests

The purest version of a market timing strategy is one that shifts back and forth between a broad market index investment (such as an S&P index fund) and a risk-free asset. Ideally, when the strategy signals a buy, we expect positive returns from holding the risky asset, and when the strategy issues a sell signal we expect negative returns from the risky asset. Market timing tests hope to test if the excess returns that result from following a passive strategy are significantly different when the active strategy signals positive or negative returns.

Here we briefly describe two market timing tests, the Cumby-Modest test and the Pesaran-Timmermann test of the Kuipers score.

Cumby-Modest test

The Cumby-Modest test considers the regression equation,

$$R_t - R_t^f = \alpha + \beta \, I_{\text{in}}(t) + \epsilon_t \;\; , \quad t = 1, 2, \ldots, T, \tag{2.3}$$

and one interprets a significantly positive value for β as an indication of timing ability, while a significantly negative intercept α is interpreted as an indication of over-all superior returns to the active strategy.

Here, in the model (2.3) one posits that the ϵ_t are normally distributed, exhibit constant variance and independence across time. As before there are few reasons to believe in these assumptions but one hopes that they approximately hold.

Kuipers score and Pesaran-Timmermann test

To calculate the Kuipers score and perform the Pesaran-Timmermann test, the observed returns of the asset under investigation are tabulated into a contingency table as follows:

	Observed Returns		
Active Strategy - In/Out	$R_t > 0$	$R_t < 0$	
$I_{\text{out}}(t) = 1$	a	b	r_1
$I_{\text{in}}(t) = 1$	c	d	r_2
	c_1	c_2	T

The cell entries a, b, c, d represent the number of periods for various scenarios. Cell b captures the number of periods where the trading strategy indicated negative returns to the asset ($I_{\text{out}} = 1$) and the asset's return were indeed negative, while cell c represents the number of periods in which the trading strategy suggested positive returns to the asset and the returns observed were also positive. The row and column totals are given by $r_1, r_2, c_1,$ and c_2 respectively.

The Kuipers score defined by

$$KS = \frac{b}{c_2} - \frac{a}{c_1} \ ,$$

measures the difference between the proportion of "bad" events (a fall in the return) that were correctly forecast and the proportion of "good events" (a rise in the return) that were incorrectly forecast. By construction, the Kuipers score takes values between -1 and 1 and has two obvious features:

- A strategy that always correctly predicts the good and bad outcomes, scores a 1, and a strategy that always incorrectly predicts the outcomes scores a -1.
- A completely random strategy, say one based on the results of a coin tossing experiment, will typically result in a Kuipers score with an expected value of zero.

Granger and Pesaran (2000) propose using the test statistic $\frac{T * KS}{\sqrt{\frac{r_1}{c_1 c_2}}}$, to judge the significance of the Kuipers score. For obvious reasons, they call this the Pesaran-Timmermann test and they suggest the use of z-tables to judge its significance.

2.4 Filter Rule Performance for Market Indexes

In this section, we compare the performance of the $\lambda = 0.05$-filter rule to the buy-and-hold strategy using return data from 1962 to 2001 for the CRSP NYSE-AMEX value-weighted index, the CRSP NYSE-AMEX equal-weighted index, the S&P 500 index, the CRSP NASDAQ value-weighted index, and the CRSP NASDAQ equal-weighted index. Before describing our results, there are a few details on the data collection and series construction process that deserve attention.[5]

Data

The CRSP database contains the index values and the return data for the all the CRSP market indexes and the S&P 500 index for both monthly and daily time periods. Also, the CRSP database contains index and return values, adjusted for dividends, for all the indexes except the S&P 500 index. The use of dividend information is crucial given the findings of Fama and Blume (1966) who observe that the performance of the benchmark buy-and-hold strategy, is severely under estimated if the returns fail to include dividends.

The monthly index and return data adjusted for dividends for the period July 1962-December 2001 are directly obtained from the CRSP database. On the other hand, the weekly return series must be constructed, and here we will we follow the same procedure that was outlined in Chapter 1, except for one important difference; here we use dividend adjusted values. For data on the risk-free asset, we use monthly return data on 90-day Treasury bills from the CRSP database. To compute weekly returns for the risk-free asset, we take the monthly return values, scale it to one-week returns and use the same value for all weeks within the given month.

Presentation of Results

Tables 2.1 to 2.5 display the results of applying the $\lambda = 0.05$-filter rule and the buy-and-hold strategy to several market indexes. The tables display results for both weekly and

[5]The data collection process is carried out using SAS programs while the performance measures are computed using Perl programs. All the computation are done in an Unix environment and further details are available from the author.

monthly data, and each table consists of two panels. The first panel lists the performance measures not adjusted for risk, and the second panel displays the risk adjusted performance measures and the results of the market timing tests.

CRSP NYSE-AMEX value-weighted index

Table 2.1 reports the results of the application of $\lambda = 0.05$-filter rule and the buy-and-hold strategy on the CRSP NYSE-AMEX value-weighted index for both weekly and monthly time periods. We begin with a few basic observations, followed by a more detailed look at the results.

- For both weekly and monthly data from 1962-2001, the $\lambda = 0.05$-filter rule does not outperform the buy-and-hold strategy on the basis of those performance measures which are not adjusted for risk.
- After accounting for risk, the $\lambda = 0.05$-filter rule performs slightly better than the buy-and-hold strategy for both weekly and monthly data from 1962-2001.
- On the other hand if one uses the maximum drawdown as the risk measure, then the $\lambda = 0.05$-filter rule has only half the risk of the buy-and-hold strategy. This finding may be of practical significance.

Performance before adjusting for risk

For weekly data from 1962-2001, the annualized return from the $\lambda = 0.05$-filter rule is 10.56%, which is lower than 11.47%, the annualized return of a buy-and-hold strategy. Moreover, the terminal value of a $1 invested on the first trading day in July, 1962 is $53 for the $\lambda = 0.05$-filter rule, while it is $73 for the buy-and-hold strategy. This difference reflects the fact that the filter rule failed to completely capture all the upward movement in the asset. Since the filter rule under performed the buy-and-hold strategy one finds that the one-way transaction cost which is computed on the basis of the terminal values is negative;

this simply reflects the fact that for the filter rule to "catch up" to the buy-and-hold strategy , one would need to be paid to trade.

Performance after adjusting for risk

The annualized standard deviation and the maximum drawdown for the $\lambda = 0.05$-filter rule are 10.68% and 22.16% respectively, while the corresponding values for the buy-and-hold strategy are 14.38% and 45.71%. The lower values to the risk measures for the filter rule when compared to the buy-and-hold strategy underscores the importance of using risk adjusted performance measures to compare the performance of active and passive strategies.

The annualized Sharpe ratios for the $\lambda = 0.05$-filter rule is 0.29 and this is roughly comparable to the value of 0.28 one finds for the buy-and-hold strategy. The small differential RAP measure 0.13% also suggests no difference in performance between the $\lambda = 0.05$-filter rule and the buy-and-hold strategy after matching the risk that results from the two strategies. One might expect the Sortino Ratios to provide a more favorable view of the filter rule, but the observed values are similar to the Sharpe ratio and provides no new information.

Market timing tests

Since the $\lambda = 0.05$-filter rule under performed the buy-and-hold strategy, it is hardly surprising that the market timing test suggests that the filter rule shows no evidence of timing ability. The Cumby-Modest regressions result in a zero estimate for the slope and a zero estimate for the intercept which indicate that there is no evidence of timing ability and there is no evidence of superior returns to the $\lambda = 0.05$-filter rule over the buy-and-hold strategy.

The Kuipers score, which is a measure of forecast accuracy is also close to zero, also confirming the lack of timing ability for the $\lambda = 0.05$-filter rule. The Pesaran-Timmermann test, confirms the lack of statistical evidence in the ability of the $\lambda = 0.05$-filter rule to correctly forecast good events and bad events.

Results for Sub-Periods

Table 2.1: Filter Rule Versus Buy-and-Hold Strategy for CRSP NYSE-AMEX value-weighted index

	Annualized return (%) Buy-and-Hold	Annualized return (%) Filter Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) Filter Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) Filter Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) Filter Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
1962-2001	11.47	10.56	14.38	10.86	73.43	53.12	45.71	22.16	67	1504	-0.23
1962-1971	10.05	9.62	11.71	8.16	2.48	2.39	32.96	12.23	15	347	-0.11
1972-1981	6.91	9.29	15.68	11.75	1.95	2.43	45.71	22.16	20	358	0.55
1982-1991	16.52	15.05	15.77	12.12	4.61	4.06	30.15	14.87	18	372	-0.34
1992-2001	12.36	8.67	13.85	10.55	3.20	2.29	20.68	15.66	15	399	-1.11
Monthly Data											
1962-2001	11.47	10.08	14.81	12.06	72.32	44.07	44.82	23.43	35	366	-0.70
1962-1971	9.96	8.64	13.28	9.98	2.45	2.18	33.30	22.97	9	84	-0.62
1972-1981	6.89	6.61	16.61	12.67	1.94	1.89	44.82	14.44	13	78	-0.09
1982-1991	17.00	15.80	16.29	14.08	4.75	4.28	29.17	23.43	7	95	-0.72
1992-2001	12.59	8.97	12.55	10.80	3.24	2.34	18.00	18.59	8	96	-2.04

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio Filter Rule	Annualized RAP (%) Filter Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio Filter Rule	Cumby-Modest Regressions α	β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
1962-2001	0.28	0.29	11.59	0.13	0.40	0.42	0.00	0.00	-0.33	0.00	-0.13
1962-1971	0.42	0.55	11.57	1.53	0.62	0.80	0.00	0.00	0.08	0.02	0.56
1972-1981	-0.21	-0.08	8.94	2.03	-0.28	-0.11	0.00	0.00	0.09	0.00	-0.24
1982-1991	0.50	0.53	16.98	0.46	0.70	0.80	0.00	0.00	-0.22	0.00	-0.15
1992-2001	0.49	0.29	9.63	-2.72	0.68	0.40	0.00	0.00	-0.60	-0.01	-0.40
Monthly Data											
1962-2001	0.32	0.28	10.84	-0.63	0.47	0.39	0.01	0.00	-0.18	0.03	0.76
1962-1971	0.37	0.36	9.83	-0.12	0.55	0.52	0.01	0.00	-0.22	0.05	0.58
1972-1981	-0.08	-0.13	6.04	-0.84	-0.12	-0.18	0.00	0.00	-0.37	-0.03	-0.42
1982-1991	0.52	0.51	16.94	-0.06	0.76	0.73	0.00	0.01	0.52	0.09	1.14
1992-2001	0.61	0.37	9.63	-2.96	0.90	0.52	0.01	0.00	-0.59	-0.05	-0.81

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

Not surprisingly, the $\lambda = 0.05$-filter rule fails to consistently outperform the buy-and-hold strategy in the sub-periods. But, there are some interesting phenomenon that are observed.

- The sub-period 1972-1981 is the only period where the $\lambda = 0.05$-filter rule significantly outperforms the buy-and-hold strategy. For this sub-period the one-way break even transaction cost is 0.55% and the annualized differential RAP is 2.03%.
- The performance of the $\lambda = 0.05$-filter rule significantly deteriorates over the last two sub-periods 1982-1991 and 1992-2001 with the worst performance occurring in the last sub-period. A look at the annualized differential RAP calculated after adjusting for risk tells the complete story. As we go from sub-period 1972-1981 to sub-period 1992-2001 the annualized differential RAP drops from 2.03% to -2.72%.

Monthly Return Data

From analysis of monthly data in Table 2.1 the $\lambda = 0.05$-filter rule fails to beat the buy-and-hold strategy – both before and after one adjusts for risk. However, we note that the pattern of deteriorating performance from the first sub-period to the last sub-period holds even for monthly data, with the worst performance coming the last sub-period 1992-2001.

CRSP NYSE-AMEX equal-weighted index

Table 2.2 reports the results of the application of $\lambda = 0.05$-filter rule and the buy-and-hold strategy on the CRSP NYSE-AMEX equal-weighted index for both weekly and monthly time periods. There are four significant observations that emerge from the analysis.

- For weekly data from the overall period 1962-2001, the $\lambda = 0.05$-filter rule handily outperforms the buy-and-hold strategy on the basis of performance measures not adjusted for risk.
- Accounting for risk, turns out to magnify the outperformance of the $\lambda = 0.05$-filter rule over the buy-and-hold strategy for weekly data from 1962-2001. Notably, even

the market timing tests show evidence of timing ability for the $\lambda = 0.05$-filter rule.

- For weekly data, for all sub-periods except the last sub-period 1992-2001, the $\lambda = 0.05$-filter rule significantly outperforms the buy-and-hold strategy on a risk unadjusted and risk adjusted basis. However, the performance of the $\lambda = 0.05$-filter rule drops off in the last two sub-periods compared to the first two sub-periods.

- For monthly data, the performance of the $\lambda = 0.05$-filter rule performs as well as the buy-and-hold strategy in the overall period 1962-2001 before adjusting for risk, but outperforms the buy-and-hold strategy on the basis of risk adjusted measures except for the last sub-period 1992-2001.

Performance before adjusting for Risk

As noted above, when one uses the $\lambda = 0.05$-filter rule for weekly data, it handily beats the buy-and-hold strategy based on both simple return measures and risk adjusted measures. This contrasts sharply with the results for the CRSP NYSE-AMEX value-weighted index. We will start by examining the results for the overall period 1962-2001.

The annualized return for the $\lambda = 0.05$-filter rule is 22.25%, which is much higher than 18.77%, the annualized return for the buy-and-hold strategy. Notably, the annualized returns to both the strategies are higher than what we observed for the CRSP NYSE-AMEX value-weighted index. The terminal value of a \$1 invested on the first trading day in July, 1962 is \$2389 for the $\lambda = 0.05$-filter rule which is 2.4 times \$905 the terminal value for the buy-and-hold strategy. Since the filter rule beat the buy-and-hold strategy, the one-way break even transaction cost is positive and equal to 0.96%, which serves to indicate that a transaction cost of about 1% per transaction for the $\lambda = 0.05$-filter rule leads to the same wealth as the buy-and-hold strategy.

Performance after adjusting for Risk

The $\lambda = 0.05$-filter rule is significantly less risky than the buy-and-hold strategy. The annualized standard deviation and the maximum drawdown for the $\lambda = 0.05$-filter rule are 11.18% and 18.16% respectively, while the corresponding values for the buy-and-hold strategy are 15.11% and 49.69%.

The high returns and relatively low risk for the $\lambda = 0.05$-filter rule lead the strategy to a superior performance over the buy-and-hold strategy on a risk adjusted basis. The annualized Sharpe ratios for the $\lambda = 0.05$-filter rule is 1.33, higher than the value of 0.75 which corresponds to the buy-and-hold strategy. Thus, the $\lambda = 0.05$-filter rule yields higher return per unit risk. The differential RAP measure is 8.72%, which also suggests superior performance by the $\lambda = 0.05$-filter rule over the buy-and-hold strategy after matching the risk that result from the two strategies. Here again, the Sortino Ratios give the same information as the Sharpe ratios, but as one would expect are considerable higher for both the strategies.

Market Timing tests

The market timing tests of the $\lambda = 0.05$-filter rule here show significant evidence of timing ability. The Cumby-Modest regressions result in a statistically significant estimate of the slope, the value of the t-test statistic is 4.09. Unlike what we observed for the CRSP NYSE-AMEX value-weighted index there is significant evidence in the ability of the $\lambda = 0.05$-filter rule to time the CRSP NYSE-AMEX equal-weighted index.

Furthermore, the Kuipers score, which is a measure of forecast accuracy, is 0.09, indicating some amount of forecast accuracy for the $\lambda = 0.05$-filter rule. The Pesaran-Timmermann test of the Kuipers score, confirms the presence of significant statistical evidence in the ability of the $\lambda = 0.05$-filter rule to correctly forecast good events and bad events with a z-score of 4.77.

Results for sub-periods

In general, the results for the sub-periods follow a pattern that is similar to what we observed for the CRSP NYSE-AMEX value-weighted index. The first two sub-periods, 1962-1971 and 1972-1981, provide greater evidence to the superiority of the $\lambda = 0.05$-filter rule over the buy-and-hold strategy, while the performance of $\lambda = 0.05$-filter rule in the

Table 2.2: Filter Rule Versus Buy-and-Hold Strategy for CRSP NYSE-AMEX equal-weighted index

	Annualized return (%) Buy-and-Hold	Annualized return (%) Filter Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) Filter Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) Filter Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) Filter Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
1962-2001	18.77	22.25	15.11	11.18	904.43	2839.81	49.69	18.16	59	1520	0.96
1962-1971	18.56	24.14	15.45	10.81	5.04	7.80	47.86	18.16	16	360	1.36
1972-1981	18.24	28.04	17.28	12.91	5.34	11.84	49.69	15.83	17	362	2.32
1982-1991	20.07	21.20	15.49	11.09	6.23	6.84	33.15	11.98	14	374	0.33
1992-2001	17.24	14.39	11.61	9.21	4.89	3.83	26.51	12.97	13	413	-0.94
Monthly Data											
1962-2001	13.51	13.65	19.04	14.55	147.55	154.78	59.50	27.81	35	344	0.07
1962-1971	14.44	20.59	19.49	13.93	3.56	5.83	48.61	8.91	8	76	3.03
1972-1981	12.14	12.35	23.98	16.98	3.12	3.17	55.99	23.06	10	83	0.09
1982-1991	13.88	13.83	18.02	15.41	3.63	3.61	31.72	27.81	8	84	-0.02
1992-2001	11.86	8.15	12.66	9.74	3.04	2.17	24.21	21.32	9	87	-1.86

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio Filter Rule	Annualized RAP (%) Filter Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio Filter Rule	Cumby-Modest Regressions α	Cumby-Modest Regressions β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
1962-2001	0.75	1.33	27.48	8.72	1.10	2.15	0.00	0.00	4.09*	0.09	4.77*
1962-1971	0.87	1.76	32.29	13.72	1.32	2.95	0.00	0.01	2.91*	0.14	3.47*
1972-1981	0.46	1.37	34.04	15.81	0.66	2.26	0.00	0.01	2.97*	0.15	3.71*
1982-1991	0.74	1.13	26.18	6.11	1.04	1.87	0.00	0.00	1.53	0.06	1.39
1992-2001	1.00	0.95	16.69	-0.54	1.43	1.33	0.00	0.00	-0.39	0.02	0.51
Monthly Data											
1962-2001	0.35	0.47	15.77	2.26	0.54	0.71	0.01	0.00	-0.04	0.06	1.50
1962-1971	0.48	1.12	26.80	12.36	0.75	2.27	0.00	0.02	1.33	0.20	2.20*
1972-1981	0.15	0.23	13.96	1.82	0.24	0.32	0.01	0.00	0.00	0.15	1.79
1982-1991	0.29	0.34	14.71	0.83	0.41	0.46	0.00	0.00	0.20	0.10	1.23
1992-2001	0.55	0.33	9.11	-2.73	0.78	0.49	0.01	0.00	-1.28	-0.11	-1.38

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

sub-periods 1982-1991 and 1992-2001 is weaker compared to the first two sub-periods.

The most interesting observation however is that in the last sub-period 1992-2001 the $\lambda = 0.05$-filter rule fails to beat the buy-and-hold strategy both before and after adjusting for risk. In fact, the annualized differential RAP is -0.54%, an indication that after matching the risks of the two strategies the buy-and-hold strategy earns a slightly higher annualized return.

Monthly Return Data

For the monthly data, from Table 2.2, the $\lambda = 0.05$-filter rule performs as well as the buy-and-hold strategy before adjusting for risk. The annualized returns for the two strategies are 13.65 and 13.51% respectively. The one-way break even cost is close to zero indicating similar performance among the two strategies. However, when one accounts for the risk, the $\lambda = 0.05$-filter rule significantly outperforms the buy-and-hold strategy, the annualized differential RAP is 8.72%.

Additionally, we find here that the first two sub-periods 1962-1971 and 1972-1981 show significant evidence in favor of the $\lambda = 0.05$-filter rule over buy-and-hold while the last two sub-periods 1982-1991 and 1992-2001 show evidence against the $\lambda = 0.05$-filter rule. Again, the worst performance occurs in the last sub-period 1992-2001.

The market timing tests for the monthly data show no evidence of timing ability by the $\lambda = 0.05$-filter rule. The only period when the $\lambda = 0.05$-filter rule shows significant timing ability is 1962-1971. Furthermore, for the period 1992-2001 the $\lambda = 0.05$-filter rule shows poor timing ability. The Pesaran-Timmermann test of the Kuipers score has a z-score of -1.38, along with a Kuipers score of -0.11.

Before we move on to examine the next index, we address what appears to be an anomaly in the results above. The annualized return to the CRSP NYSE-AMEX equal-weighted index for a buy-and-hold strategy is 18.77% for weekly data, but rather surprisingly the annualized returns for the same strategy computed with the help of monthly returns is 13.51%. This interesting empirical phenomenon which occurs in equal-weighted indexes is examined in detail in the appendix.

S&P 500 index

Table 2.3 reports the results of the application of $\lambda = 0.05$-filter rule and the buy-and-hold strategy on the S&P 500 index for both weekly and monthly time periods.

Essentially, the results here are similar to what we observed when the $\lambda = 0.05$-filter rule was applied to the CRSP NYSE-AMEX value-weighted index. This is not surprising given the fact that the S&P index consists mainly of large capitalization stocks. Nevertheless, there are some insights to be drawn from the results which we point out below.

- Based on return measures not adjusted for risk, the $\lambda = 0.05$-filter rule fails to outperform the buy-and-hold strategy for the overall period 1962-2001.

- Even on a risk adjusted basis, the $\lambda = 0.05$-filter rule fails to beat the buy-and-hold strategy for 1962-2001. Furthermore, the market timing tests indicate no timing ability for the $\lambda = 0.05$-filter rule in both the overall period and the sub-periods.

- Allen and Karjalainen (1999) find that on a risk unadjusted basis, after accounting for a transaction cost of 0.25%, a genetic algorithm based trading rules fails to beat a buy-and-hold strategy applied to daily return data of the S&P 500 index from 1928-1995. However, we find that for two sub-periods 1962-1971 and 1972-1981, even for return measures not adjusted for risk the $\lambda = 0.05$-filter rule outperforms the buy-and-hold strategy for weekly data. For example, the one-way break even transaction cost, for weekly data, in the two periods are 0.32% and 0.68% respectively.

- For monthly data, the $\lambda = 0.05$-filter rule significantly outperforms the buy-and-hold strategy for the sub-period 1972-1981. The one-way break even transaction cost is 3.19%, a rather large number.

- From the results for the sub-periods, we see that the $\lambda = 0.05$-filter rule outperforms the buy-and-hold strategy in the first two sub-periods, but fails to beat the buy-and-hold strategy in the last two sub-periods 1982-1991 and 1992-2001. Note again that the worst performance comes in the last sub-period 1992-2001.

Table 2.3: Filter Rule Versus Buy-and-Hold Strategy for S&P 500 index

	Annualized return (%) Buy-and-Hold	Annualized return (%) Filter Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) Filter Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) Filter Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) Filter Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
1962-2001	7.90	7.50	14.78	10.99	20.24	17.48	46.99	28.96	73	1433	-0.09
1962-1971	6.26	7.29	11.31	8.04	1.78	1.95	32.47	15.52	14	336	0.32
1972-1981	1.73	4.69	15.61	11.39	1.19	1.58	46.99	28.96	21	331	0.68
1982-1991	13.01	10.20	16.37	12.27	3.40	2.64	30.27	15.73	22	340	-0.56
1992-2001	10.69	8.01	15.14	11.42	2.76	2.16	33.24	25.28	17	398	-0.71
Monthly Data											
1962-2001	7.86	8.04	14.86	11.40	19.72	21.06	46.18	23.65	35	334	0.09
1962-1971	6.14	4.94	12.62	9.18	1.75	1.57	32.90	22.63	10	80	-0.53
1972-1981	1.67	7.84	15.79	10.41	1.18	2.11	46.18	11.09	9	58	3.19
1982-1991	13.35	10.69	16.57	13.76	3.46	2.74	30.17	23.65	9	92	-1.31
1992-2001	10.97	9.22	13.96	11.31	2.81	2.40	31.41	18.05	9	90	-0.87

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio Filter Rule	Annualized RAP (%) Filter Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio Filter Rule	Cumby-Modest Regressions α	Cumby-Modest Regressions β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
1962-2001	0.04	0.01	7.54	-0.34	0.05	0.02	0.00	0.00	-0.65	0.00	-0.33
1962-1971	0.10	0.27	8.17	1.90	0.15	0.38	0.00	0.00	0.33	0.04	1.05
1972-1981	-0.54	-0.48	2.61	0.88	-0.72	-0.64	0.00	0.00	0.12	-0.03	-1.01
1982-1991	0.27	0.13	10.72	-2.27	0.37	0.18	0.00	0.00	-0.50	-0.02	-0.81
1992-2001	0.34	0.21	8.79	-1.89	0.47	0.29	0.00	0.00	-1.18	0.00	-0.17
Monthly Data											
1962-2001	0.07	0.11	8.43	0.57	0.10	0.15	0.00	0.00	0.62	0.07	1.54
1962-1971	0.09	0.00	4.91	-1.23	0.12	0.00	0.00	0.00	-0.43	0.00	-0.12
1972-1981	-0.42	-0.05	7.53	5.86	-0.56	-0.07	0.00	0.01	0.96	0.12	1.27
1982-1991	0.29	0.15	11.11	-2.22	0.41	0.20	0.01	0.00	-0.41	0.01	0.19
1992-2001	0.43	0.38	10.22	-0.74	0.62	0.54	0.00	0.00	0.53	0.00	0.04

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

CRSP NASDAQ value-weighted index

Table 2.4 reports the results of the application of $\lambda = 0.05$-filter rule and the buy-and-hold strategy on the CRSP NASDAQ value-weighted index for both weekly and monthly time periods.[6] The results observed here are in stark contrast to the results observed for the CRSP NYSE-AMEX value-weighted index, and we list four key observations.

- The results of applying the $\lambda = 0.05$-filter rule are impressive. Before adjusting for risk the active strategy outperforms the buy-and-hold strategy on the basis of weekly data for the period 1973-2001.

- The use of risk adjusted measures only serves to magnify the performance of the $\lambda = 0.05$-filter rule over the buy-and-hold strategy. Also, there is moderate evidence of market timing ability in the overall period.

- The superior performance of the $\lambda = 0.05$-filter rule holds in *all* sub-periods as well.

- For monthly data, the $\lambda = 0.05$-filter rule continues to beat the buy-and-hold strategy in both the overall period and all sub-periods except the last sub-period 1992-2001.

Performance measures before adjusting for Risk

For the period 1973-2001 the annualized return for the $\lambda = 0.05$-filter rule is 18.98%, which is much higher than 11.51%, the annualized return to a buy-and-hold strategy. Naturally, the terminal value of a \$1 invested on the first trading day in Jan, 1973 for the $\lambda = 0.05$-filter rule is \$155 and significantly higher than \$24, the corresponding value for the buy-and-hold strategy. Given the superior performance of the filter rule, the one-way transaction cost computed on the basis of the terminal values is positive and equal to 0.80%, which indicates that we could afford a per transaction cost of 0.80% and still equal the performance of the buy-and-hold strategy.

Performance measures after adjusting for Risk

[6] As we pointed out in Chapter 1, the overall time period under investigation here is from 1973-2001.

From the risk measures, the $\lambda = 0.05$-filter rule appears to be less risky than the buy-and-hold strategy. The annualized standard deviation and the maximum drawdown for the $\lambda = 0.05$-filter rule are 14.23% and 32.74% respectively, while the corresponding values for the buy-and-hold strategy are 20.45% and 70.40%. Notably, under both the strategies, the CRSP NASDAQ value-weighted index has higher risk than both the CRSP NYSE-AMEX value-weighted index and the CRSP NYSE-AMEX equal-weighted index.

On risk adjusted basis, the $\lambda = 0.05$-filter rule significantly outperforms the buy-and-hold strategy. The annualized Sharpe ratios are higher for the $\lambda = 0.05$-filter rule taking a value of 0.76, compared to a value of 0.16 for the buy-and-hold strategy. In addition, the annualized differential RAP measure is 12.18%, suggesting superior performance by the $\lambda = 0.05$-filter rule over the buy-and-hold strategy after matching the risk that result from the two strategies.

Market Timing tests

The market timing tests of the $\lambda = 0.05$-filter rule show significant evidence of timing ability at least in the overall period. The Cumby-Modest regressions yield a positive and significant estimate of the slope ($t_\beta = 3.33$). Also, the Kuipers score is positive, taking a value of 0.08 and the Pesaran-Timmermann test of the Kuipers score, confirms the significant statistical evidence in the ability of the $\lambda = 0.05$-filter rule to correctly forecast good events and bad events by taking a z-score of 3.50.

Results sub-periods

The results for the sub-periods in essence are similar to what we observed for the CRSP NYSE-AMEX value-weighted index and the CRSP NYSE-AMEX equal-weighted index. The first sub-period 1973-1981 provides the greatest evidence to the superiority of the $\lambda = 0.05$-filter rule over the buy-and-hold strategy, while the performance of $\lambda = 0.05$-filter rule in the sub-periods 1982-1991 and 1992-2001 is weaker compared to the first sub-period. Also as before, the worst performance occurs in the last sub-period 1992-2001.

Table 2.4: Filter Rule Versus Buy-and-Hold Strategy for CRSP NASDAQ value-weighted index

	Annualized return (%) Buy-and-Hold	Annualized return (%) Filter Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) Filter Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) Filter Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) Filter Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
1973-2001	11.51	18.98	20.45	14.23	23.63	155.49	70.40	32.74	55	1047	1.70
1973-1981	7.42	19.65	15.84	11.09	1.90	5.02	57.43	16.84	13	329	3.66
1982-1991	13.48	18.01	17.40	11.46	3.54	5.24	35.63	13.53	18	347	1.08
1992-2001	13.10	18.70	26.15	18.47	3.42	5.53	70.40	32.74	25	365	0.96
Monthly Data											
1973-2001	11.57	13.11	22.79	17.98	23.71	35.26	68.11	46.98	31	250	0.64
1973-1981	8.06	13.00	20.35	15.38	2.00	2.97	54.52	17.68	9	77	2.19
1982-1991	14.14	15.10	19.78	16.88	3.71	4.03	32.56	28.70	9	86	0.46
1992-2001	12.21	12.15	27.30	20.83	3.13	3.12	68.11	46.98	13	82	-0.01

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio Filter Rule	Annualized RAP (%) Filter Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio Filter Rule	Cumby-Modest Regressions α	Cumby-Modest Regressions β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
1973-2001	0.16	0.76	23.69	12.18	0.22	1.13	0.00	0.01	3.33*	0.08	3.50*
1973-1981	-0.22	0.78	23.36	15.94	-0.28	1.10	0.00	0.01	3.38*	0.16	3.78*
1982-1991	0.28	0.82	22.87	9.39	0.37	1.26	0.00	0.00	1.65	0.07	1.56
1992-2001	0.29	0.71	24.15	11.05	0.40	1.07	0.00	0.01	1.49	0.04	0.88
Monthly Data											
1973-2001	0.18	0.32	14.64	3.07	0.26	0.45	0.00	0.01	0.86	0.10	1.94
1973-1981	-0.03	0.26	14.32	6.26	-0.05	0.36	0.00	0.01	0.71	0.15	1.70
1982-1991	0.28	0.39	16.22	2.08	0.39	0.53	0.00	0.00	0.37	0.14	1.70
1992-2001	0.27	0.35	14.39	2.18	0.38	0.52	0.00	0.01	0.71	0.04	0.46

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

The most interesting observation though is that among the four indexes examined so far, the CRSP NASDAQ value-weighted index is the only one where the $\lambda = 0.05$-filter rule outperforms the buy-and-hold strategy using return measures not adjusted for risk in all the sub-periods including 1992-2001. In fact, the one-way break-even cost during the 1992-2001 period is 0.96%, and the terminal value of $1 investment beginning the first trading day in January, 1992 is $6 compared to a buy-and-hold strategy that yields $3.

MONTHLY RETURN DATA

The $\lambda = 0.05$-filter rule outperforms the buy-and-hold strategy in the overall period and all sub-periods except the 1992-2001 period both before and after adjusting for risk. The one-way break even transaction cost is 0.64% for the overall period and the annualized differential RAP is 3.07%.

CRSP NASDAQ equal-weighted index

Table 2.5 reports the results of the application of $\lambda = 0.05$-filter rule and the buy-and-hold strategy on the CRSP NASDAQ equal-weighted index for both weekly and monthly time periods. Most of the results observed here coincide with our observations for the CRSP NASDAQ value-weighted index and hence we highlight only the most interesting observations.

- The values of all the performance measures for the CRSP NASDAQ equal-weighted index are larger in magnitude than what we observed for the CRSP NASDAQ value-weighted index.

- For weekly data, the $\lambda = 0.05$-filter rule outperforms the buy-and-hold strategy for the overall period and all the sub-periods both before and after adjusting for risk.

- For weekly data, the market timing tests show evidence of significant timing ability for the $\lambda = 0.05$-filter rule in the overall period and *all* the sub-periods.

- The one-way transaction cost for the overall period using weekly data is 2.71%. In fact, this is the best performance by the $\lambda = 0.05$-filter rule in the overall period for all the indexes examined here.

- The empirical phenomenon that we observed when working with the CRSP NYSE-AMEX equal-weighted index is present here as well, and in fact more severe. The annualized return calculated using weekly data for the period 1973-2001 is 27.18%, while the annualized return calculated using monthly data is 14.33%.

- Overall, similar to the other indexes examined so far, the first sub-period 1973-1981 provides greater evidence to superiority of the $\lambda = 0.05$-filter rule over the buy-and-hold strategy than the other two sub-periods 1982-1991 and 1992-2001.

2.5 Concluding Remarks

The central aim of this chapter was to examine the risk adjusted returns and the profitability of the filter rule. We began with the definition of the filter rule along with a review of the earlier work on the filter rule. This set the stage for us to specify the assumptions behind the implementation of the filter rule as a trading strategy. We then made explicit the choice of the parameter for the filter rule, and in the process understood the source of data-snooping biases in empirical studies and ways to limit them.

Before turning our attention to the results of applying the filter rule, we also reviewed the various performance measures that we use to assess the filter rule and the buy-and-hold strategy (the benchmark strategy). Three types of performance measures were presented, measures that do not account for risk, risk adjusted measures, and, market timing tests.

The performance of the $\lambda = 0.05$-filter rule for the period 1962-2001 and four sub-periods 1962-1971, 1972-1981, 1982-1991, 1992-2001, was compared to the performance of the buy-and-hold strategy with the help of weekly and monthly return data obtained from the CRSP NYSE-AMEX equal-weighted index, the CRSP NYSE-AMEX value-weighted index, the S&P 500 index, the CRSP NASDAQ equal-weighted index, and the CRSP NASDAQ value-weighted index. In short, eight noteworthy observations emerged from our results.

Table 2.5: Filter Rule Versus Buy-and-Hold Strategy for CRSP NASDAQ equal-weighted index

	Annualized return (%) Buy-and-Hold	Annualized return (%) Filter Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) Filter Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) Filter Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) Filter Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
1973-2001	27.18	36.16	15.77	11.64	1075.97	7800.82	55.13	23.17	36	1117	2.71
1973-1981	17.03	31.54	14.04	9.92	4.12	11.79	55.13	11.23	11	330	4.67
1982-1991	18.75	25.24	13.75	10.57	5.58	9.49	31.22	23.17	11	374	2.39
1992-2001	46.50	51.33	18.66	13.58	45.19	62.50	37.55	20.81	15	407	1.08
Monthly Data											
1973-2001	14.33	15.35	21.89	16.57	48.09	62.19	52.09	28.68	31	240	0.41
1973-1981	17.51	17.35	22.51	17.05	4.21	4.17	52.09	24.16	9	80	-0.06
1982-1991	10.58	13.12	18.53	15.45	2.71	3.39	32.36	28.68	10	75	1.12
1992-2001	13.92	14.52	23.89	16.36	3.64	3.84	43.04	26.18	13	81	0.20

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio Filter Rule	Annualized RAP (%) Filter Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio Filter Rule	Cumby-Modest Regressions α	Cumby-Modest Regressions β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
1973-2001	1.20	2.40	46.05	18.88	1.72	4.02	0.00	0.01	7.16*	0.22	9.01*
1973-1981	0.43	2.07	40.09	23.07	0.58	3.31	0.00	0.01	5.41*	0.26	5.82*
1982-1991	0.74	1.57	30.21	11.46	1.01	2.38	0.00	0.01	3.27*	0.19	4.75*
1992-2001	2.19	3.37	68.45	21.95	3.31	6.05	0.00	0.01	3.23*	0.19	4.81*
Monthly Data											
1973-2001	0.32	0.48	17.90	3.57	0.47	0.72	0.01	0.00	0.33	0.09	1.69
1973-1981	0.38	0.49	20.05	2.55	0.56	0.68	0.01	0.00	0.13	0.14	1.54
1982-1991	0.11	0.29	14.01	3.44	0.15	0.40	0.00	0.00	-0.18	0.13	1.46
1992-2001	0.38	0.59	18.94	5.01	0.58	1.02	0.01	0.01	0.43	0.00	0.05

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

- For weekly data from 1962-2001 obtained from the CRSP NYSE-AMEX equal-weighted index, the CRSP NASDAQ value-weighted index, and the CRSP NASDAQ equal-weighted index, the $\lambda = 0.05$-filter rule outperforms the buy-and-hold strategy even on the basis of performance measures not adjusted for risk.

- After accounting for risk, the $\lambda = 0.05$-filter rule performs at least as well as the buy-and-hold strategy for weekly data from 1962-2001 for all the indexes except the S&P 500 index. In fact if one uses the maximum drawdown as the risk measure, then the $\lambda = 0.05$-filter rule has significantly lower risk than the buy-and-hold strategy for all the indexes.

- Only for weekly data only from the NASDAQ indexes, the $\lambda = 0.05$-filter rule significantly outperforms the buy-and-hold strategy in the sub-period 1992-2001 before adjusting for risk.

- The market timing tests show evidence of timing ability for the $\lambda = 0.05$-filter rule for weekly data from the CRSP NASDAQ value-weighted index and the equal-weighted indexes.

- Notably for the S&P 500 index, we find that for two sub-periods 1962-1971 and 1972-1981, even for return measures not adjusted for risk the $\lambda = 0.05$-filter rule outperforms the buy-and-hold strategy for weekly data.

- An interesting empirical phenomenon manifests itself in the annualized returns of the equal-weighted indexes. The annualized return for an equal-weighted index calculated using weekly data is at least 5% higher than the annualized return calculated using monthly data from the same index under a buy-and-hold strategy.

- Overall, similar to our observations in Chapter 1, the first set of sub-periods 1962-1971, and 1972-1981, provide greater evidence to superiority of the $\lambda = 0.05$-filter rule over the buy-and-hold strategy, irrespective of the performance measure, than the other two sub-periods 1982-1991 and 1992-2001.

- For all indexes considered here, the worst performance of the $\lambda = 0.05$-filter rule consistently occurred in the last sub-period 1992-2001.

A common theme that emerges from the results is the decline in performance of the trading strategy from the 1962-1985 period to the 1986-2001 period. This coincides with our observation in Chapter 1, wherein for all assets examined there was a considerable drop-off in the evidence against RWH-LM between 1962-1985 and 1986-2001. Interestingly, the existence of the decline in profits and decline in evidence against RWH-LM confirms the observations of Corrado and Lee (1992), who found a significant relationship between autocorrelation in returns and filter rule returns. We will discuss this association in greater detail in Chapter 3 after discussing the results to decile and sector portfolios

Similar to observations in Chapter 1 one wonders if there is a size story here since the equal-weighted indexes are more profitable under the $\lambda = 0.05$-filter rule than the value-weighted indexes. This issue requires further examination and we examine this issue in detail in the following chapter with the help of decile portfolios. Also, continuing with our theme of gleaning information from the various industry groups, we focus on sector based portfolios as well.

In summary, given the overall skepticism towards the usefulness of trading strategies, there is one startling piece of information, and that is the performance of the $\lambda = 0.05$-filter rule on the CRSP NASDAQ value-weighted index. To clarify, this is startling since this index is relatively well-behaved and is not clouded by any size effects. The terminal value of a \$1 investment as a result of following the filter rule as opposed to using the buy-and-hold strategy yields approximately an additional \$131 at a lower risk. For people who are concerned with transaction costs, the one-way break even transaction cost here is 1.70%, which is considerably large. Also, the performance of the $\lambda = 0.05$-filter rule is consistent across all time periods.

Chapter 3

Risk Adjusted Returns and Profitability of the Filter Rule for Decile and Sector Data

In this chapter we continue our evaluation of the $\lambda = 0.05$-filter rule with the help of data from size-sorted portfolios and sector-based portfolios from July 1962 to December 2001. Given the superior performance of the filter rule on equal-weighted indexes in Chapter 2 the next sensible step is to understand the performance of the filter rule on size-sorted portfolios. To clarify, the use of size-sorted portfolios help us discern if the superior performance of the filter rule is restricted only to *small* stocks or more widespread.

Given our path of analysis of the RWH-LM, the next step is more familiar and involves evaluating the performance of the filter rule on sector-based portfolios. To our knowledge there has been no investigation of filter rules on sector-based portfolios, however, Chelley-Steeley and Steeley (2000) applied filter rules to decile data.

Our continuing investigation of the filter rule begins with a brief review of Chelley-Steeley and Steeley (2000). Following this, in sections one and two, we carefully detail the portfolio construction process and the results of applying the filter rule to size-sorted and sector-based portfolios. In section three, we discuss the apparent association between returns to the filter rule and the autocorrelation in the assets. Finally, in section four we conclude.

Review of Chelley-Steeley and Steeley

Chelley-Steeley and Steeley (2000) apply filter rules with values of λ ranging from 0.001 to 0.05 to five size-sorted portfolios, where the five size-sorted portfolios are constructed based on monthly return data from January, 1976 to December, 1991 of 250 companies that trade in the United Kingdom. Although the authors primarily focus on how interrelationships among securities within a portfolio affect the profitability of the filter rule, in the process they find that for a well diversified portfolio of small (as measured by size) firms, filter rules with small values of λ outperform a buy-and-hold strategy even after accounting for transaction costs.

3.1 Results of Filter rule on Decile Data

Using stock return data adjusted for dividends on individual securities, we construct a 10-asset group of size-sorted portfolios. To construct these size-sorted portfolios all NYSE stocks are sorted by size(shares outstanding times price per share) at the end of each month (or week for weekly data) to determine the NYSE decile breakpoints. All NYSE, AMEX, and NASDAQ stocks on the basis of their size are then allocated to the 10 size portfolios formed using the NYSE breakpoints. Decile 1 represents the portfolio of the smallest of firms while Decile 10 represents the portfolio of the largest of firms. The index values adjusted for dividends for each decile portfolio are constructed by value-weighting the individual assets that fall within each decile and are continuously updated every week or month.

Tables 3.1 through 3.3 reports the results of the application of $\lambda = 0.05$-filter rule and the buy-and-hold strategy on the size-sorted portfolios for both weekly and monthly time periods. Here, as in Chapter 1 we look at three periods the overall period 1962-2001, and two sub-periods 1962-1985 and 1986-2001. From the tables, the following four observations seem noteworthy.

- For weekly data, the $\lambda = 0.05$-filter rule significantly outperforms the buy-and-hold strategy for all decile portfolios except Decile 10, the portfolio of the largest firms before adjusting for risk.

- Accounting for risk only serves to magnify the superior performance of the $\lambda = 0.05$-filter rule. Furthermore, the market timing tests show evidence of timing ability for the filter rule for all deciles except the largest two decile portfolios.

- For monthly data, before adjusting for risk, the $\lambda = 0.05$-filter rule outperforms the buy-and-hold strategy for Deciles 1–5 but, on a risk adjusted basis, the filter rule outperforms the buy-and-hold strategy for all decile portfolios except Decile 9.

- Results for the sub-periods essentially confirm the superior performance of the $\lambda = 0.05$-filter rule except for the now familiar decline in performance in the latter sub-period 1986-2001.

Performance before adjusting for risk

From Table 3.1 we see that for weekly data from 1962-2001 the $\lambda = 0.05$-filter rule significantly outperforms the buy-and-hold strategy for almost all decile portfolios before adjusting for risk. The annualized returns for the $\lambda = 0.05$-filter rule are 24.71% and 10.06% for Decile 1 and Decile 10 respectively; and are 14.28% and 10.90% respectively for the buy-and-hold strategy. Decile 10 is the only portfolio where the annualized return to the filter rule is smaller than that of the buy-and-hold strategy.

Given these values for the annualized returns, we naturally expect the terminal values of a \$1 investment for the filter rules to be higher for the filter rule for almost all decile portfolios. The difference in the terminal values to the two strategies, the filter rule and the buy-and-hold strategy is largest for Decile 1, a value of \$6043, and progressively declines as we move to Decile 10, a value of -\$16. Not surprisingly, the one-way break even costs also monotonically decline as we move from Decile 1 to Decile 10. The one-way break even cost is a whopping 3.09% for Decile 1 and falls to -0.22% for Decile 10. Consistent with our results for the CRSP value-weighted index and the S&P 500 index which are driven by large capitalization stocks, we see here that for Decile 10 which consists of large firms, we need to get paid for each transaction to break even with the buy-and-hold strategy.

Performance after adjusting for risk

Here, similar to results obtained in Chapter 2, we see that the $\lambda = 0.05$-filter rule is less risky than the buy-and-hold strategy for all the size-sorted portfolios for weekly data from 1962-2001. For Decile 1, the annualized standard deviation and the maximum drawdown for the $\lambda = 0.05$-filter rule are 11.31% and 24.90% respectively, while the corresponding values for the buy-and-hold strategy are 16.11% and 62.75%. For Decile 10, the annualized standard deviation and the maximum drawdown for the $\lambda = 0.05$-filter rule are 11.23% and 26.55% respectively, while the corresponding values for the buy-and-hold strategy are 14.57% and 44.14%.

Given the high returns and low risk associated with the $\lambda = 0.05$-filter rule, not surprisingly, on a risk adjusted basis the $\lambda = 0.05$-filter rule significantly outperforms the buy-and-hold strategy for all size-sorted portfolios except Decile 10. The annualized Sharpe ratio under the $\lambda = 0.05$-filter rule for Decile 1 and Decile 10 are 1.53 and 0.24 respectively, while the corresponding values under the buy-and-hold strategy are 0.43 and 0.24. Furthermore, the annualized differential RAP measure is positive for Deciles 1–9, with a value of 17.78% for Decile 1 and a value of -0.04% for Decile 10. Similar to our observations in Chapter 2, the Sortino Ratio provides the same information as the Sharpe ratio.

Market Timing Tests

The market timing tests of the $\lambda = 0.05$-filter rule show significant evidence of timing ability for all size-sorted portfolios except Decile 9 and Decile 10. The Cumby-Modest regressions result in a positive and statistically significant estimate for the slope for Deciles 1–7. For Decile 1, the estimate of the slope is 0.01, with a corresponding statistically significant t-value of 7.11. Furthermore, the Kuipers score, which is a measure of forecast accuracy ranges from 0.19 to 0.07 for Decile 1 to Decile 8. The Pesaran-Timmermann test of the Kuipers score confirms the presence of significant statistical evidence in the ability of the $\lambda = 0.05$-filter rule to correctly forecast good events and bad events with a significant

Table 3.1: Filter Rule Versus Buy-and-Hold Strategy for Decile Data from 1962-2001

	Annualized return (%) Buy-and-Hold	Annualized return (%) Filter Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) Filter Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) Filter Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) Filter Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
Decile 1	14.28	24.71	16.11	11.31	196.60	6240.34	62.75	24.90	55	1362	3.09
Decile 2	12.37	21.53	16.16	11.18	101.20	2247.45	65.49	18.87	59	1420	2.59
Decile 3	13.20	21.02	16.60	11.50	135.19	1901.30	63.09	16.51	64	1416	2.04
Decile 4	13.53	20.12	16.38	11.73	151.54	1417.85	59.27	18.87	63	1494	1.76
Decile 5	13.70	19.97	16.35	11.53	160.99	1347.24	53.97	18.39	60	1468	1.75
Decile 6	13.14	18.15	16.23	11.43	132.53	736.89	53.60	18.27	63	1459	1.35
Decile 7	12.37	15.78	16.02	11.51	101.19	329.96	51.96	22.88	68	1467	0.87
Decile 8	13.04	15.53	15.74	11.55	127.95	302.66	44.38	26.03	64	1453	0.67
Decile 9	11.89	12.92	15.52	11.55	85.24	122.53	47.87	21.47	69	1483	0.26
Decile 10	10.90	10.06	14.57	11.23	59.96	44.35	44.14	26.55	65	1524	-0.22
Monthly Data											
Decile 1	13.80	16.48	22.32	16.45	163.43	408.31	67.54	32.31	40	313	1.14
Decile 2	14.08	14.25	20.85	15.80	180.09	190.46	63.96	33.72	41	336	0.07
Decile 3	14.79	15.03	20.62	15.65	230.06	249.21	60.60	36.00	40	340	0.10
Decile 4	15.24	16.21	19.98	15.50	267.78	373.41	55.42	30.07	37	354	0.45
Decile 5	15.93	16.13	19.26	15.09	338.71	363.40	50.05	30.83	36	349	0.10
Decile 6	14.26	12.88	18.67	14.76	191.25	118.40	50.49	29.91	39	360	-0.61
Decile 7	16.06	15.22	19.20	15.71	354.76	266.13	48.49	26.66	38	361	-0.37
Decile 8	15.05	13.92	17.58	13.88	251.37	170.17	45.90	25.97	37	361	-0.52
Decile 9	13.34	11.97	16.53	13.23	139.00	86.14	46.26	24.58	37	354	-0.64
Decile 10	13.94	13.86	17.81	15.65	171.39	166.82	44.96	27.23	30	360	-0.04

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio Filter Rule	Annualized RAP (%) Filter Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio Filter Rule	Cumby-Modest Regressions α	β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
Decile 1	0.43	1.53	32.05	17.78	0.61	2.57	0.00	0.01	7.11*	0.19	9.04*
Decile 2	0.31	1.26	27.82	15.45	0.42	2.03	0.00	0.01	6.29*	0.15	7.27*
Decile 3	0.35	1.19	27.08	13.88	0.48	1.87	0.00	0.01	5.12*	0.12	5.70*
Decile 4	0.37	1.09	25.17	11.64	0.52	1.66	0.00	0.01	4.45*	0.11	5.42*
Decile 5	0.39	1.09	25.23	11.53	0.53	1.67	0.00	0.01	4.49*	0.11	5.44*
Decile 6	0.35	0.94	22.68	9.54	0.49	1.44	0.00	0.00	3.61*	0.11	5.38*
Decile 7	0.31	0.73	19.06	6.69	0.43	1.08	0.00	0.00	2.50*	0.06	2.84*
Decile 8	0.36	0.70	18.48	5.44	0.50	1.05	0.00	0.00	1.91	0.07	3.29*
Decile 9	0.29	0.48	14.82	2.93	0.41	0.70	0.00	0.00	1.10	0.03	1.56
Decile 10	0.24	0.24	10.85	-0.04	0.34	0.34	0.00	0.00	-0.06	0.01	0.73
Monthly Data											
Decile 1	0.32	0.59	19.95	6.14	0.50	0.95	0.01	0.00	0.60	0.14	3.26*
Decile 2	0.35	0.47	16.64	2.56	0.53	0.71	0.01	0.00	0.32	0.08	1.94
Decile 3	0.39	0.53	17.66	2.86	0.59	0.80	0.01	0.00	0.17	0.10	2.38*
Decile 4	0.42	0.61	18.95	3.71	0.63	0.93	0.01	0.01	0.91	0.08	1.86
Decile 5	0.48	0.62	18.72	2.80	0.71	0.94	0.01	0.00	0.27	0.12	2.93*
Decile 6	0.40	0.41	14.49	0.24	0.60	0.61	0.01	0.00	-0.88	0.04	0.97
Decile 7	0.48	0.54	17.10	1.03	0.77	0.89	0.01	0.00	0.29	0.05	1.21
Decile 8	0.47	0.52	15.83	0.78	0.72	0.79	0.01	0.00	-0.23	0.04	1.00
Decile 9	0.40	0.39	13.27	-0.06	0.60	0.59	0.01	0.00	-0.10	0.04	1.09
Decile 10	0.40	0.45	14.84	0.90	0.73	0.90	0.00	0.01	0.94	0.06	1.46

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

z-score for Deciles 1–8.

Monthly Return Data

The results for monthly data for the period 1962-2001 are also shown in Table 3.1. The $\lambda = 0.05$-filter rule outperforms the buy-and-hold strategy before adjusting for risk for Deciles 1–5. For two decile portfolios Decile 1 and Decile 4, the one-way break even transaction costs are much larger than zero, for Decile 1 the value is 1.14% and for Decile 4 the value is 0.45%. However, for larger deciles the one-way break even costs go negative, for example the one-way break even transaction cost for Decile 9 is -0.64%.

The risk measures continue to indicate a lower risk for the $\lambda = 0.05$-filter rule compared to the buy-and-hold strategy. As we move from Decile 1 to Decile 10, the difference between the values of the annualized standard deviation for both the strategies declines, but, the values of the maximum drawdown for the $\lambda = 0.05$-filter rule continue to be one half of the corresponding value for the buy-and-hold strategy. For example, even for Decile 10 the maximum drawdown for the $\lambda = 0.05$-filter rule is 26.55%, while the maximum drawdown under a buy-and-hold strategy is 44.14%.

On a risk adjusted basis, the $\lambda = 0.05$-filter rule does moderately outperform the buy-and-hold strategy. The Sharpe ratios for all deciles are higher for the $\lambda = 0.05$-filter rule, except for Decile 9. Also, the annualized differential RAP measures are all positive (except for Decile 9), ranging from a high of 6.14% for Decile 1 to a value of 0.90% for Decile 10. The only decile portfolios where the market timing tests show evidence of timing ability are Decile 1, Decile 3, and Decile 5.

Results for the sub-periods

The results for the sub-periods 1962-1985 and 1986-2001, are in essence similar to what we observed in Chapter 2. The first sub-period 1962-1985 provides greater evidence to the superiority of the $\lambda = 0.05$-filter rule over the buy-and-hold strategy, while the performance of $\lambda = 0.05$-filter rule in the sub-period 1986-2001 is weaker compared to the first sub-period. Furthermore, these results are consistent with our conclusions from Chapter 1, namely that

Table 3.2: Filter Rule Versus Buy-and-Hold Strategy for Decile Data from 1962-1985

	Annualized return (%) Buy-and-Hold	Annualized return (%) Filter Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) Filter Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) Filter Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) Filter Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
Decile 1	17.71	29.45	16.80	11.89	46.40	435.41	62.75	19.84	35	811	3.15
Decile 2	14.96	25.09	16.46	11.82	26.64	194.29	65.49	18.87	36	851	2.72
Decile 3	14.92	23.52	16.68	12.02	26.40	144.20	63.09	16.51	40	848	2.10
Decile 4	14.59	21.76	16.03	11.76	24.68	103.01	59.27	18.87	40	867	1.77
Decile 5	14.96	22.47	15.56	11.26	26.62	118.15	53.97	16.58	35	866	2.11
Decile 6	12.86	18.95	15.39	11.16	17.25	59.48	53.60	18.18	38	853	1.62
Decile 7	12.50	17.10	15.18	11.11	16.01	41.06	51.96	18.58	41	852	1.14
Decile 8	13.46	17.63	14.73	11.03	19.55	45.74	44.38	15.16	36	862	1.17
Decile 9	10.80	13.34	14.28	10.68	11.17	19.05	47.87	14.45	40	865	0.67
Decile 10	8.95	9.41	13.41	10.12	7.51	8.31	44.14	26.55	37	865	0.14
Monthly Data											
Decile 1	17.20	20.92	23.69	17.38	41.10	85.48	67.54	32.31	24	187	1.51
Decile 2	16.33	17.74	22.00	16.30	34.55	45.77	63.96	33.72	24	199	0.58
Decile 3	16.30	17.28	21.45	16.08	34.32	41.82	60.60	36.00	24	199	0.41
Decile 4	16.86	18.53	20.39	15.64	38.39	53.52	55.42	27.50	22	210	0.75
Decile 5	17.32	18.53	19.36	14.82	42.15	53.53	50.05	30.83	20	202	0.60
Decile 6	14.50	13.88	18.77	14.74	23.82	20.97	50.49	29.91	22	214	-0.28
Decile 7	17.90	16.81	20.13	16.49	47.27	38.05	48.49	25.63	24	206	-0.44
Decile 8	15.49	14.68	17.71	13.64	29.12	24.70	45.90	22.75	22	206	-0.36
Decile 9	11.53	11.04	15.86	12.37	12.87	11.61	46.26	23.82	22	200	-0.22
Decile 10	10.69	11.30	13.83	10.29	10.78	12.28	44.96	27.23	18	200	0.36

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio Filter Rule	Annualized RAP (%) Filter Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio Filter Rule	Cumby-Modest Regressions α	β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
Decile 1	0.56	1.78	38.22	20.51	0.83	3.17	0.00	0.01	6.34*	0.21	7.67*
Decile 2	0.41	1.42	31.70	16.73	0.58	2.32	0.00	0.01	5.54*	0.17	6.44*
Decile 3	0.40	1.27	29.43	14.51	0.57	2.02	0.00	0.01	4.44*	0.15	5.45*
Decile 4	0.40	1.15	26.67	12.08	0.56	1.78	0.00	0.01	3.88*	0.13	4.82*
Decile 5	0.43	1.26	27.91	12.95	0.62	1.99	0.00	0.01	4.48*	0.14	5.36*
Decile 6	0.30	0.96	23.00	10.14	0.43	1.48	0.00	0.00	3.29*	0.14	5.17*
Decile 7	0.28	0.80	20.34	7.84	0.40	1.21	0.00	0.00	2.47*	0.08	3.18*
Decile 8	0.35	0.85	20.78	7.31	0.52	1.32	0.00	0.00	2.24*	0.11	4.01*
Decile 9	0.18	0.48	15.06	4.26	0.26	0.71	0.00	0.00	1.17	0.06	2.28*
Decile 10	0.05	0.12	9.79	0.85	0.07	0.17	0.00	0.00	0.67	0.03	1.22
Monthly Data											
Decile 1	0.41	0.78	25.83	8.63	0.67	1.33	0.01	0.01	0.95	0.20	3.49*
Decile 2	0.41	0.63	21.36	5.02	0.65	1.02	0.01	0.01	0.85	0.12	2.23*
Decile 3	0.42	0.61	20.58	4.28	0.66	0.99	0.01	0.01	0.72	0.11	2.07*
Decile 4	0.46	0.71	21.91	5.05	0.73	1.16	0.00	0.01	1.49	0.08	1.47
Decile 5	0.51	0.75	21.94	4.61	0.81	1.20	0.00	0.01	1.21	0.17	3.07*
Decile 6	0.38	0.44	15.65	1.15	0.59	0.67	0.01	0.00	-0.11	0.07	1.34
Decile 7	0.52	0.57	18.89	0.99	0.90	1.03	0.01	0.01	0.79	0.05	0.96
Decile 8	0.46	0.53	16.85	1.36	0.74	0.85	0.01	0.00	0.20	0.07	1.33
Decile 9	0.26	0.29	12.07	0.54	0.40	0.44	0.00	0.00	0.15	0.08	1.39
Decile 10	0.24	0.38	12.65	1.96	0.36	0.58	0.00	0.00	0.62	0.10	1.75

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

Table 3.3: Filter Rule Versus Buy-and-Hold Strategy for Decile Data from 1986-2001

	Annualized return (%) Buy-and-Hold	Annualized return (%) Filter Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) Filter Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) Filter Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) Filter Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
Decile 1	9.27	17.60	15.01	10.34	4.14	13.42	41.62	24.90	21	544	2.76
Decile 2	8.55	16.01	15.69	10.11	3.72	10.80	36.15	14.90	24	561	2.19
Decile 3	10.64	17.10	16.50	10.64	5.05	12.54	36.44	13.99	25	560	1.80
Decile 4	11.89	17.35	16.90	11.67	6.05	12.98	36.21	16.78	24	620	1.58
Decile 5	11.80	15.95	17.45	11.89	5.97	10.71	37.28	18.39	26	594	1.12
Decile 6	13.48	16.58	17.40	11.78	7.58	11.67	34.18	18.27	26	598	0.83
Decile 7	12.12	13.55	17.18	12.06	6.25	7.66	34.53	22.88	28	608	0.36
Decile 8	12.38	12.06	17.14	12.24	6.49	6.20	33.27	26.03	29	584	-0.07
Decile 9	13.46	11.90	17.18	12.69	7.56	6.05	32.21	21.47	30	611	-0.36
Decile 10	13.78	10.83	16.12	12.62	7.90	5.20	38.24	19.12	29	652	-0.72
Monthly Data											
Decile 1	8.68	9.59	20.09	14.77	3.76	4.29	40.12	29.11	17	124	0.39
Decile 2	10.75	8.81	19.05	14.92	5.08	3.84	33.73	30.11	18	135	-0.77
Decile 3	12.59	11.38	19.39	14.93	6.60	5.56	32.62	29.57	17	139	-0.50
Decile 4	12.79	12.26	19.40	15.17	6.80	6.30	33.11	30.07	16	142	-0.23
Decile 5	13.82	12.15	19.15	15.39	7.85	6.20	32.84	29.42	17	145	-0.69
Decile 6	13.84	10.89	18.57	14.74	7.88	5.18	30.17	27.66	18	144	-1.16
Decile 7	13.38	12.46	17.78	14.45	7.38	6.48	29.01	26.66	15	153	-0.43
Decile 8	14.30	12.22	17.43	14.17	8.39	6.27	30.34	25.97	16	153	-0.91
Decile 9	15.92	12.50	17.48	14.19	10.50	6.51	27.77	24.58	16	152	-1.49
Decile 10	19.01	17.39	22.37	21.13	15.96	12.83	34.72	21.58	13	158	-0.83

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio Filter Rule	Annualized RAP (%) Filter Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio Filter Rule	Cumby-Modest Regressions α	Cumby-Modest Regressions β	Cumby-Modest Regressions t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
Decile 1	0.21	1.11	22.77	13.50	0.28	1.69	0.00	0.01	3.20*	0.16	4.80*
Decile 2	0.15	0.97	21.44	12.89	0.20	1.51	0.00	0.01	2.91*	0.12	3.54*
Decile 3	0.27	1.03	23.12	12.48	0.36	1.61	0.00	0.00	2.51*	0.07	2.11*
Decile 4	0.34	0.96	22.37	10.48	0.45	1.43	0.00	0.00	2.11*	0.08	2.48*
Decile 5	0.32	0.82	20.54	8.75	0.43	1.21	0.00	0.00	1.58	0.06	1.86
Decile 6	0.42	0.88	21.54	8.06	0.57	1.33	0.00	0.00	1.53	0.06	1.96
Decile 7	0.35	0.61	16.70	4.58	0.47	0.88	0.00	0.00	0.84	0.01	0.42
Decile 8	0.36	0.48	14.42	2.04	0.49	0.68	0.00	0.00	0.22	0.00	0.06
Decile 9	0.43	0.45	13.93	0.47	0.58	0.64	0.00	0.00	0.14	-0.01	-0.67
Decile 10	0.47	0.37	12.13	-1.63	0.65	0.53	0.00	0.00	-1.10	-0.01	-0.77
Monthly Data											
Decile 1	0.14	0.26	10.94	2.26	0.21	0.36	0.01	0.00	-0.58	0.05	0.77
Decile 2	0.26	0.20	9.64	-1.10	0.36	0.27	0.01	0.00	-0.87	0.01	0.19
Decile 3	0.35	0.37	13.03	0.44	0.49	0.51	0.01	0.00	-0.91	0.07	1.02
Decile 4	0.36	0.42	14.05	1.26	0.50	0.58	0.01	0.00	-0.70	0.07	1.01
Decile 5	0.42	0.41	13.69	-0.12	0.58	0.57	0.02	0.00	-1.29	0.04	0.60
Decile 6	0.43	0.34	12.20	-1.63	0.60	0.47	0.02	0.00	-1.55	0.00	-0.22
Decile 7	0.43	0.46	13.99	0.60	0.59	0.65	0.01	0.00	-0.86	0.03	0.43
Decile 8	0.49	0.45	13.70	-0.59	0.69	0.66	0.01	0.00	-0.99	-0.02	-0.47
Decile 9	0.58	0.47	14.04	-1.87	0.84	0.69	0.01	0.00	-0.91	-0.02	-0.52
Decile 10	0.59	0.55	18.07	-0.94	1.22	1.24	0.01	0.00	0.20	-0.02	-0.53

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

the first sub-period exhibits greater evidence against RWH-LM than the second sub-period. We now list five key observations that emerge from the analysis of weekly data.[1]

- For the first sub-period 1962-1985, the $\lambda = 0.05$-filter rule beats the buy-and-hold strategy for all decile portfolios both before and after adjusting for risk.
- The one-way break even transaction cost for Decile 1 is 3.15% and progressively declines to 0.14% for Decile 10.
- The annualized differential RAP measure is positive for all decile portfolios, and the market timing tests suggest the presence of timing ability for the $\lambda = 0.05$-filter rule for Deciles 1–9.
- For the second sub-period 1986-2001, the $\lambda = 0.05$-filter rule beats the buy-and-hold strategy for Deciles 1–7 before adjusting for risk. Notably, for Deciles 1–7, the one-way transaction costs are lower than what was observed in 1962-1985 sub-period.
- On a risk adjusted basis, the $\lambda = 0.05$-filter rule beats the buy-and-hold strategy for all deciles except Decile 10. Furthermore, the $\lambda = 0.05$-filter rule appears to have significant ability to time the market for Deciles 1–4.

3.2 Results of Filter rule on Sector Data

Using the Standard Industrial Classification (or SIC) codes we form 10 sector-based portfolios where the 10 sectors are, Basic Industries, Construction (includes Mining), Durables, NonDurables, Transportation (includes Communication), Utilities, Trade, Finance (including Real Estate and Insurance), Oil and Coal, and Services. As with decile portfolios, we use weekly and monthly return data (adjusted for dividends) to construct index values for each sector. Note that, within each sector we construct value-weighted portfolios and similar to decile portfolios, the sector-based portfolios are continuously changing and are updated every month (or week for weekly data).

[1] We do not report the results for monthly data since the results in both the sub-periods are similar to the results we observed in the overall period.

Tables 3.4 through 3.6 reports the results of the application of $\lambda = 0.05$-filter rule and the buy-and-hold strategy on the sector-based portfolios for both weekly and monthly time periods. Table 3.4 contains the results for the period 1962-2001 while Tables 3.5 and 3.6, contain the results for the sub-periods 1962-1985 and 1986-2001 respectively. We focus primarily on the results to weekly data from 1962-2001 and begin with four noteworthy observations.

- Before adjusting for risk, the $\lambda = 0.05$-filter rule does at least as well as the buy-and-hold strategy for data from the following sector-based portfolios, Basic Industries, Construction, Durables, Utilities, Trade, Finance, Oil and Coal, and Services. The best performance of the $\lambda = 0.05$-filter rule occurs in the Basic Industries sector (a one-way break even transaction cost of 1.88%), while the worst performance occurs in the NonDurables sector (a one-way break even transaction cost of -0.21%).

- After adjusting for risk, the $\lambda = 0.05$-filter rule beats the buy-and-hold strategy for all sectors. The lowest annualized differential RAP is 0.67% which is association with the NonDurables sector. Furthermore, the $\lambda = 0.05$-filter rule shows evidence of market timing as well for the Basic Industries, Utilities, Finance, Oil and Coal, and Services sectors.

- The performance of the $\lambda = 0.05$-filter rule for monthly data is much weaker. The filter rule outperforms the buy-and-hold strategy for only the Basic Industries sector and the Oil and Coal sector before adjusting for risk. After adjusting for risk, the filter rule outperforms the buy-and-hold strategy for five out of the ten sectors.

- The results to the filter rule in the sub-periods are similar to what we observed for the decile portfolios. In the first sub-period 1962-1985, the $\lambda = 0.05$-filter rule beats the buy-and-hold strategy, before adjusting for risk in all sectors, whereas in the second sub-period 1986-2001, the filter rule beats the buy-and-hold strategy, before adjusting for risk only in four out of the ten sectors.

Performance before adjusting for risk

As we noted above, from Table 3.4 we see that the $\lambda = 0.05$-filter rule significantly outperforms the buy-and-hold strategy for the period 1962-2001 before adjusting for risk for data from the Basic Industries, Construction, Durables, Utilities, Trade, Finance, Oil and Coal, and Services portfolios. To understand the superior performance we use the one-way break even transaction cost which captures the per transaction cost at which the wealth earned from following the filter rule equals the wealth earned from following the buy-and-hold strategy. The best performance of the filter rule is for the Basic Industries sector which has a one-way break even transaction cost of 1.88%, while the NonDurables sector is the worst performing under the filter rule and has a one-way break even transaction cost of 0.21%. In total there are three sectors that have one-way break even transaction costs close to (or larger than) one percent, they are the Basic Industries sector, Construction and Mining sector, and the Services sector.

Performance after adjusting for risk

As we have seen repeatedly, the $\lambda = 0.05$-filter rule has lower risk than the buy-and-hold strategy for all sector-based portfolios. In fact, the maximum drawdowns in each sector for the filter rule is approximately half of those for the buy-and-hold strategy. For example, the maximum drawdown in the Services sector under a buy-and-hold strategy is 74.61%, while the maximum drawdown under the $\lambda = 0.05$-filter rule is only 38.99%.

Given the values of the risk measures and annualized returns, on a risk adjusted basis the $\lambda = 0.05$-filter rule significantly outperforms the buy-and-hold strategy for almost all sector-based portfolios. The annualized Sharpe ratios even for the sectors that had better performance to the buy-and-hold strategy before adjusting for risk are lower than the corresponding values for the $\lambda = 0.05$-filter rule. After adjusting for risk, the performance of the filter rule is almost the same in the Basic Industries sector and the Services sector where the annualized Sharpe ratios are 0.69 and 0.66 respectively. Furthermore, the annualized differential RAP measure is positive for all sectors, with a value of 12.31% for the Basic

Table 3.4: Filter Rule Versus Buy-and-Hold Strategy for Sector (Value-Weighted) Data from 1962-2001

	Annualized return (%) Buy-and-Hold	Annualized return (%) Filter Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) Filter Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) Filter Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) Filter Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
Basic Industries	7.94	16.45	18.64	13.13	20.59	414.24	79.76	27.32	79	1330	1.88
Construction	8.53	11.91	19.45	14.36	25.54	85.89	59.43	31.19	95	1307	0.64
Durables	10.76	11.56	18.45	13.36	57.05	75.77	60.91	35.51	89	1378	0.16
NonDurables	13.17	12.38	14.30	11.05	133.75	101.28	39.93	23.20	63	1496	-0.21
Transportation	10.70	10.50	15.22	11.65	55.94	51.96	55.07	31.86	70	1434	-0.04
Utilities	9.45	10.99	12.11	9.23	35.71	62.00	44.02	16.77	50	1428	0.55
Trade	12.20	12.14	17.75	13.30	95.03	93.22	58.19	41.26	87	1403	0.00
Fin, RE, Ins	11.38	11.77	15.58	11.39	71.16	81.80	54.36	21.05	76	1422	0.09
Oil and Coal	10.23	12.39	20.00	14.21	47.25	101.74	58.29	28.51	99	1329	0.39
Services	13.03	17.73	22.04	15.64	127.35	639.52	74.61	38.99	104	1383	0.77
Monthly Data											
Basic Industries	7.56	10.19	21.93	16.42	17.67	45.80	80.67	51.66	43	305	1.10
Construction	9.14	7.69	22.29	17.26	31.42	18.56	55.66	35.66	54	319	-0.48
Durables	10.96	9.57	19.21	15.47	60.34	36.71	60.31	34.99	46	335	-0.53
NonDurables	17.88	16.67	25.77	24.46	653.78	435.11	39.10	22.72	29	366	-0.69
Transportation	17.04	15.45	17.06	14.60	494.37	288.36	40.94	28.01	36	362	-0.74
Utilities	10.02	8.73	14.39	11.81	43.17	27.06	42.25	26.59	35	331	-0.66
Trade	12.71	12.34	18.70	14.24	111.82	98.01	57.83	33.60	41	327	-0.15
Fin, RE, Ins	15.24	14.01	16.38	13.51	267.68	175.61	53.38	28.57	31	372	-0.67
Oil and Coal	13.46	13.66	24.97	19.85	144.99	155.57	60.94	34.13	47	326	0.07
Services	15.77	15.36	25.06	18.80	320.74	279.69	74.24	45.54	47	319	-0.14

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio Filter Rule	Annualized RAP (%) Filter Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio Filter Rule	Cumby-Modest Regressions α	β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
Basic Industries	0.03	0.69	20.25	12.31	0.04	1.06	0.00	0.01	4.72*	0.09	4.18*
Construction	0.06	0.31	13.51	4.98	0.08	0.47	0.00	0.00	1.43	0.03	1.54
Durables	0.18	0.31	13.14	2.39	0.26	0.46	0.00	0.00	0.60	0.01	0.30
NonDurables	0.40	0.45	13.84	0.67	0.57	0.65	0.00	0.00	0.07	0.03	1.46
Transportation	0.22	0.27	11.45	0.74	0.31	0.37	0.00	0.00	0.65	0.02	1.09
Utilities	0.17	0.39	12.11	2.66	0.25	0.59	0.00	0.00	1.75	0.06	3.13*
Trade	0.27	0.36	13.73	1.54	0.39	0.53	0.00	0.00	0.32	0.01	0.46
Fin, RE, Ins	0.26	0.38	13.38	2.00	0.36	0.56	0.00	0.00	0.35	0.05	2.33*
Oil and Coal	0.14	0.35	14.43	4.20	0.21	0.52	0.00	0.00	2.23*	0.07	3.37*
Services	0.26	0.66	21.96	8.93	0.36	0.97	0.00	0.00	2.44*	0.08	3.75*
Monthly Data											
Basic Industries	0.04	0.21	11.34	3.78	0.05	0.30	0.00	0.01	0.79	0.11	2.58*
Construction	0.11	0.05	7.96	-1.17	0.15	0.08	0.01	0.00	-0.89	0.00	-0.25
Durables	0.22	0.18	10.25	-0.70	0.32	0.26	0.01	0.00	-0.13	-0.03	-0.89
NonDurables	0.43	0.41	17.20	-0.67	1.18	1.24	0.01	0.00	0.51	0.09	2.26*
Transportation	0.60	0.60	16.92	-0.12	0.99	1.00	0.01	0.00	0.29	0.03	0.77
Utilities	0.23	0.17	9.16	-0.85	0.36	0.27	0.01	0.00	-0.92	0.06	1.45
Trade	0.32	0.39	14.08	1.37	0.48	0.61	0.00	0.00	0.50	0.05	1.25
Fin, RE, Ins	0.52	0.54	15.55	0.32	0.80	0.82	0.01	0.00	0.20	0.07	1.82
Oil and Coal	0.27	0.35	15.44	1.98	0.46	0.65	0.00	0.01	0.77	0.09	1.98*
Services	0.36	0.46	18.23	2.46	0.55	0.73	0.01	0.01	0.72	0.04	0.85

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

Industries sector and a value of 8.93% for the Services sector.

Market Timing Tests

The market timing tests of the $\lambda = 0.05$-filter rule here, show significant evidence (statistically significant values from both the Cumby-Modest regression and the Kuipers score) of timing ability for the Basic Industries sector, the Oil and Coal sector, and the Services sector. For example, for the Oil and Coal sector, the Cumby-Modest regressions result in a statistically significant t-value of 2.24 for the slope, and the Kuipers score is 0.09 with a statistically significant z-score of 3.29.

Monthly Return Data

The results for the monthly data for the period 1962-2001 indicate a much weaker performance before adjusting for risk by the $\lambda = 0.05$-filter rule compared to the buy-and-hold strategy. The Basic Industries sector and the Oil and Coal sector are the only industry groups where the $\lambda = 0.05$-filter rule performs better than the buy-and-hold strategy with one-way break even transaction cost of 1.10% and 0.07% respectively.

However, on a risk adjusted basis, the $\lambda = 0.05$-filter rule moderately outperforms the buy-and-hold strategy for five out of the ten sectors. Interestingly, the Construction sector is the one where the performance of the filter rule has swung from good on the basis of weekly data to the worst on the basis of monthly data.

Results for the sub-periods

The results for the sub-periods 1962-1985 and 1962-2001, are in essence similar to what we observed for Decile data and Chapter 2. The first sub-period 1962-1985 provides greater evidence to the superiority of the $\lambda = 0.05$-filter rule over the buy-and-hold strategy, while the performance of $\lambda = 0.05$-filter rule in the sub-period 1986-2001 is significantly weaker compared to the first sub-period.

The most interesting observation though is that, before adjusting for risk the $\lambda = 0.05$-filter rule outperforms the buy-and-hold strategy in all sectors in the first sub-period 1962-1985, but only four out of the ten sectors in the second sub-period 1986-2001.

Table 3.5: Filter Rule Versus Buy-and-Hold Strategy for Sector Data (Value-Weighted) from 1962-1985

	Annualized return (%) Buy-and-Hold	Annualized return (%) Filter Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) Filter Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) Filter Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) Filter Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
Basic Industries	9.38	20.55	18.38	13.19	8.25	81.39	79.76	27.32	45	815	2.51
Construction	8.64	12.46	18.85	13.90	7.04	15.85	59.43	31.19	58	758	0.70
Durables	9.92	11.42	16.17	12.02	9.27	12.74	50.69	35.51	48	793	0.33
NonDurables	11.34	11.82	14.09	10.77	12.53	13.88	39.93	23.20	38	870	0.13
Transportation	9.71	11.16	12.55	9.45	8.86	12.07	33.30	17.07	34	825	0.45
Utilities	8.85	11.36	11.58	8.70	7.36	12.59	44.02	16.77	30	812	0.89
Trade	10.92	14.20	16.43	12.28	11.47	22.75	58.19	17.18	45	807	0.76
Fin, RE, Ins	9.52	12.80	14.88	10.69	8.51	17.03	54.36	19.58	42	817	0.82
Oil and Coal	12.38	14.78	19.26	13.82	15.60	25.65	58.29	28.51	55	794	0.45
Services	12.86	19.59	20.70	14.47	17.24	67.42	74.61	22.44	62	777	1.09
Monthly Data											
Basic Industries	9.55	13.68	22.43	16.47	8.47	20.14	80.67	51.66	24	182	1.79
Construction	9.80	9.40	22.48	17.04	8.93	8.20	55.66	32.59	32	194	-0.12
Durables	9.65	9.27	17.30	13.16	8.64	7.96	50.74	20.85	27	189	-0.14
NonDurables	13.32	13.78	14.90	11.38	18.70	20.54	39.10	22.12	18	204	0.26
Transportation	17.74	16.38	15.68	13.55	45.78	34.92	27.51	13.96	20	213	-0.67
Utilities	9.75	8.07	14.85	12.04	8.84	6.15	42.25	26.59	22	192	-0.82
Trade	11.22	12.50	18.39	13.92	12.07	15.76	57.83	33.60	22	187	0.60
Fin, RE, Ins	15.03	15.57	16.55	13.18	26.53	29.65	53.38	28.57	18	215	0.31
Oil and Coal	17.47	21.54	26.48	22.14	43.36	96.32	60.94	22.27	24	200	1.65
Services	16.61	17.77	24.84	17.28	36.54	46.06	74.24	21.91	26	180	0.44

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio Filter Rule	Annualized RAP (%) Filter Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio Filter Rule	Cumby-Modest Regressions α	Cumby-Modest Regressions β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
Basic Industries	0.06	0.93	25.39	16.01	0.09	1.48	0.00	0.01	5.07*	0.12	4.60*
Construction	0.02	0.30	13.96	5.31	0.03	0.45	0.00	0.00	1.51	0.02	0.89
Durables	0.10	0.26	12.51	2.59	0.15	0.39	0.00	0.00	0.40	0.03	0.96
NonDurables	0.22	0.33	12.92	1.58	0.32	0.48	0.00	0.00	0.56	0.05	1.75
Transportation	0.12	0.31	12.12	2.41	0.17	0.47	0.00	0.00	1.47	0.04	1.47
Utilities	0.05	0.36	12.39	3.54	0.08	0.56	0.00	0.00	1.61	0.06	2.34*
Trade	0.16	0.48	16.20	5.28	0.24	0.77	0.00	0.00	1.26	0.04	1.59
Fin, RE, Ins	0.09	0.43	14.58	5.06	0.12	0.64	0.00	0.00	1.53	0.08	3.08*
Oil and Coal	0.21	0.47	17.35	4.97	0.31	0.69	0.00	0.00	2.24*	0.09	3.29*
Services	0.22	0.78	24.48	11.62	0.32	1.20	0.00	0.00	2.45*	0.11	4.03*
Monthly Data											
Basic Industries	0.10	0.38	15.96	6.41	0.14	0.59	0.00	0.01	1.21	0.17	2.88*
Construction	0.11	0.12	10.04	0.24	0.16	0.17	0.01	0.00	-0.46	0.02	0.34
Durables	0.13	0.14	9.86	0.21	0.19	0.21	0.00	0.00	-0.23	-0.01	-0.27
NonDurables	0.40	0.56	15.75	2.43	0.63	0.88	0.00	0.00	0.71	0.15	2.77*
Transportation	0.66	0.66	17.80	0.06	1.25	1.35	0.01	0.00	0.40	0.07	1.35
Utilities	0.16	0.06	8.23	-1.52	0.26	0.09	0.01	0.00	-1.25	0.06	1.00
Trade	0.21	0.37	14.14	2.91	0.32	0.57	0.00	0.01	1.16	0.13	2.30*
Fin, RE, Ins	0.46	0.62	17.66	2.64	0.74	1.05	0.00	0.01	0.98	0.11	2.16*
Oil and Coal	0.38	0.64	24.31	6.85	0.72	1.48	0.00	0.02	2.20*	0.13	2.43*
Services	0.37	0.60	22.31	5.70	0.59	1.03	0.01	0.01	0.88	0.06	1.03

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

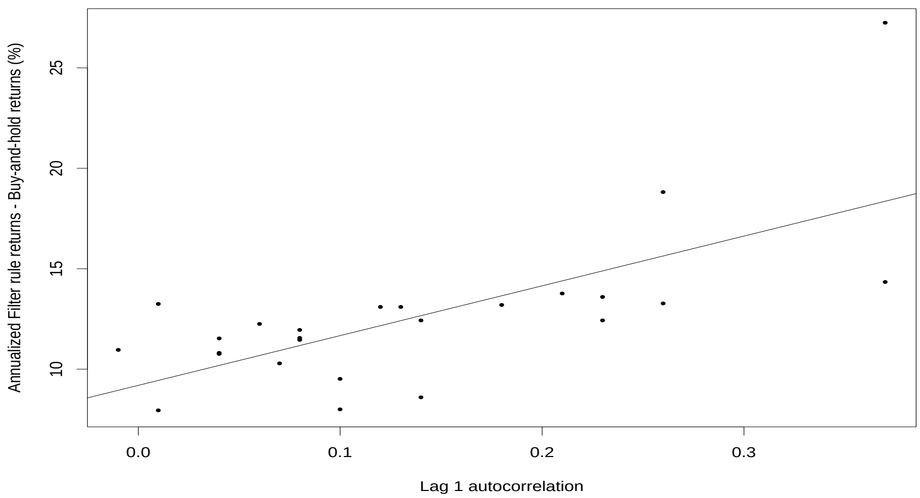
Table 3.6: Filter Rule Versus Buy-and-Hold Strategy for Sector Data (Value-Weighted) from 1986-2001

	Annualized return (%) Buy-and-Hold	Annualized return (%) Filter Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) Filter Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) Filter Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) Filter Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
Basic Industries	5.78	10.14	19.03	12.97	2.46	4.70	45.50	21.41	35	509	0.92
Construction	8.22	10.52	20.30	14.96	3.54	4.96	37.42	18.55	38	546	0.44
Durables	11.93	11.51	21.36	15.07	6.08	5.72	60.91	20.75	42	579	-0.06
NonDurables	15.89	13.05	14.61	11.41	10.61	7.13	29.91	13.55	26	619	-0.76
Transportation	12.13	9.39	18.46	14.26	6.26	4.21	55.07	31.86	37	601	-0.53
Utilities	10.27	10.04	12.86	9.91	4.79	4.63	22.07	11.88	21	609	-0.07
Trade	14.04	8.89	19.54	14.62	8.20	3.92	40.34	41.26	43	590	-0.85
Fin, RE, Ins	14.07	9.88	16.55	12.30	8.24	4.52	28.40	21.05	35	598	-0.85
Oil and Coal	7.06	8.98	21.04	14.75	2.98	3.96	48.09	19.12	44	535	0.32
Services	13.24	14.73	23.88	17.21	7.32	9.03	63.83	38.99	43	599	0.24
Monthly Data											
Basic Industries	4.31	4.32	21.14	16.09	1.96	1.96	43.70	42.42	20	121	0.01
Construction	7.89	4.54	22.05	17.52	3.35	2.03	39.76	35.66	23	122	-1.09
Durables	12.90	9.54	21.73	18.31	6.90	4.27	60.31	34.99	20	144	-1.20
NonDurables	25.06	20.52	36.19	35.82	35.14	19.49	28.70	22.72	12	160	-2.48
Transportation	16.23	13.86	18.94	15.99	10.95	7.90	40.94	28.01	17	147	-0.96
Utilities	10.22	9.09	13.70	11.37	4.71	3.99	19.58	19.67	14	137	-0.58
Trade	14.84	11.50	19.18	14.64	9.05	5.66	39.13	19.77	20	138	-1.17
Fin, RE, Ins	15.42	11.11	16.18	13.87	9.80	5.35	25.91	21.35	14	155	-2.18
Oil and Coal	8.25	3.41	22.48	15.42	3.53	1.71	45.04	34.13	23	125	-1.58
Services	14.55	11.44	25.44	20.79	8.69	5.61	60.15	45.54	22	137	-0.99

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio Filter Rule	Annualized RAP (%) Filter Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio Filter Rule	Cumby-Modest Regressions α	Cumby-Modest Regressions β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
Basic Industries	-0.01	0.31	12.00	6.22	-0.02	0.45	0.00	0.00	1.13	0.03	0.89
Construction	0.10	0.29	12.07	3.86	0.14	0.43	0.00	0.00	0.31	0.04	1.23
Durables	0.27	0.36	13.74	1.81	0.37	0.51	0.00	0.00	0.29	-0.02	-0.83
NonDurables	0.67	0.60	14.98	-0.89	0.92	0.86	0.00	0.00	-0.73	0.00	-0.10
Transportation	0.32	0.23	10.34	-1.78	0.45	0.31	0.00	0.00	-0.49	0.00	-0.13
Utilities	0.32	0.39	11.20	0.93	0.45	0.56	0.00	0.00	0.42	0.05	1.74
Trade	0.40	0.19	9.81	-4.21	0.56	0.26	0.00	0.00	-0.98	-0.03	-1.40
Fin, RE, Ins	0.48	0.30	11.17	-2.90	0.67	0.43	0.00	0.00	-1.48	-0.01	-0.59
Oil and Coal	0.04	0.19	10.18	3.12	0.06	0.29	0.00	0.00	0.87	0.05	1.36
Services	0.30	0.50	18.05	4.82	0.40	0.71	0.00	0.00	0.79	0.02	0.66
Monthly Data											
Basic Industries	-0.06	-0.08	3.86	-0.44	-0.08	-0.11	0.00	0.00	-0.64	0.03	0.45
Construction	0.09	-0.06	4.20	-3.68	0.13	-0.09	0.01	0.00	-0.88	-0.06	-1.02
Durables	0.33	0.20	10.24	-2.65	0.46	0.28	0.01	0.00	-0.26	-0.09	-1.49
NonDurables	0.53	0.41	20.67	-4.38	2.03	1.63	0.02	0.00	-0.25	-0.01	-0.41
Transportation	0.55	0.50	15.35	-0.87	0.80	0.73	0.01	0.00	-0.17	-0.02	-0.52
Utilities	0.32	0.29	9.76	-0.46	0.48	0.44	0.01	0.00	-0.26	0.06	0.91
Trade	0.47	0.39	13.27	-1.57	0.69	0.61	0.01	0.00	-1.03	-0.07	-1.13
Fin, RE, Ins	0.59	0.38	11.99	-3.42	0.88	0.52	0.02	0.00	-1.36	0.00	-0.06
Oil and Coal	0.11	-0.15	2.31	-5.93	0.16	-0.19	0.01	-0.01	-1.79	0.02	0.24
Services	0.34	0.27	12.70	-1.84	0.50	0.40	0.01	0.00	-0.11	0.00	-0.17

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

Figure 3.1: Scatterplot of Annualized Filter rule returns – Buy-and-hold returns Versus Lag 1 autocorrelation



Regression of Excess Returns on Weekly Lag 1 Autocorrelation

```
Residuals:

    Min     1Q Median      3Q    Max

 -4.134 -1.54 0.2038 0.8617 8.811


Coefficients:

              Value Std. Error t value Pr(>|t|)

(Intercept)            9.1921  0.9183    10.0097  0.0000

Lag 1 autocorrelation 24.8014  5.4317     4.5661  0.0001

Residual standard error: 2.814 on 23 degrees of freedom

Multiple R-Squared: 0.4755

F-statistic: 20.85 on 1 and 23 degrees of freedom, the p-value is 0.0001373
```

Excess returns = Annualized Filter rule - Annualized Buy-and-hold returns

3.3 Relationship between filter rule profits and RWH

The values of the simple return measures and the risk adjusted measures for the sub-periods tell a story that is similar to the one we saw in Chapter 1. Specifically, in Chapter 1 we saw that the evidence against RWH-LM was strong in the period 1962-1985 and weak during 1986-2001 and the results from Chapter 2 and 3 exhibit a similar pattern. To be precise, the results from applying the $\lambda = 0.05$-filter rule indicate stronger performance (say as measured by one-way break even transaction costs) over the buy-and-hold strategy, in the first sub-period 1962-1985 than the second sub-period 1986-2001. [2]

This apparent association that we have observed between the autocorrelation in the return series and the $\lambda = 0.05$-filter rule returns coincides with the observations of Corrado and Lee (1992) that we highlighted earlier. Although Corrado and Lee observed the association for daily returns using individual stocks, the phenomenon appears to exist for weekly return data of market indexes, decile portfolios, and sector-based portfolios as well.

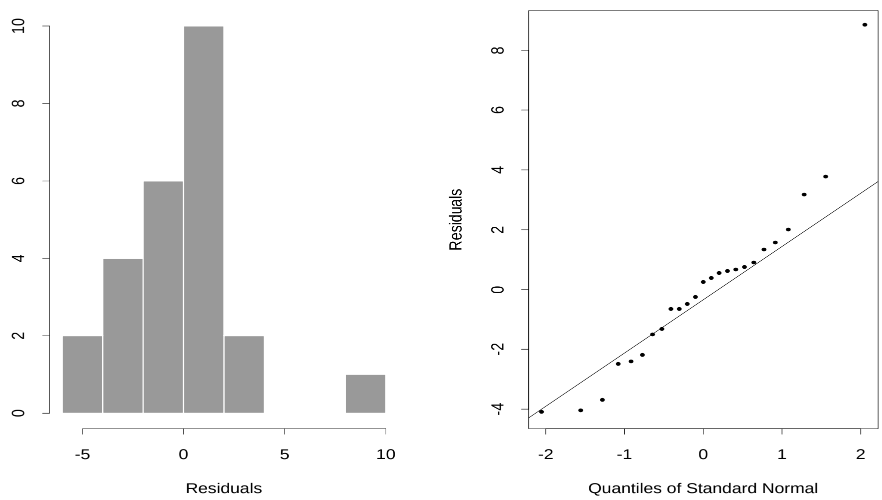
In order to quantify this relationship, we regress the excess returns (defined as the difference between annualized returns to the $\lambda = 0.05$-filter rule and the annualized returns to the buy-and-hold strategy) on the lag one autocorrelation of weekly returns. The scatterplot and residual plots along with the regression output are given above (Figures 3.1 through 3.3). From the scatterplot one sees the presence of a strong linear relationship between excess returns and weekly lag one autocorrelation. This is confirmed by the significant F-statistic (= 20.85 , p-value = 0) and the moderately high value of the coefficient of determination ($R^2 = 0.48$).

The most interesting finding though is that from the regression equation we can infer that a 10% increase in the weekly lag one return autocorrelation leads to an estimated 2.48% increase, on average, in excess returns.

As a sidenote, we check to see if the assumptions for the regression model are satisfied by examining the residuals. The normal quantile plot and the plot of the fitted values against

[2] Note that, in Chapter 2 we assume that the sub-period 1962-1985 is well captured by the two sub-periods 1962-1971 and 1972-1981, and similarly the sub-period 1986-2001 is well captured by 1982-1991 and 1992-2001.

Figure 3.2: Histogram and Normal Quantile Plot of Residuals



the residuals indicate that the residuals are fairly well-behaved. Not surprisingly, given the type of portfolios considered here (high correlation between them), the plot of residuals by portfolios type does indicate possible violation of the independence of residuals assumption.

3.4 Concluding Remarks

The central aim of this chapter was to continue our examination of the profitability of the filter rule on size-sorted and sector-based portfolios. In short, six noteworthy observations emerged from our results.

- For weekly data, the $\lambda = 0.05$-filter rule significantly outperforms the buy-and-hold strategy for all decile portfolios except Decile 10 the portfolio of the largest firms before adjusting for risk and accounting for risk only serves to magnify the superior performance of the $\lambda = 0.05$-filter rule.

- For monthly data, before adjusting for risk, the $\lambda = 0.05$-filter rule outperforms the buy-and-hold strategy for Deciles 1–5 but, on a risk adjusted basis, the filter rule

Figure 3.3: Plot of Residuals versus Fitted values

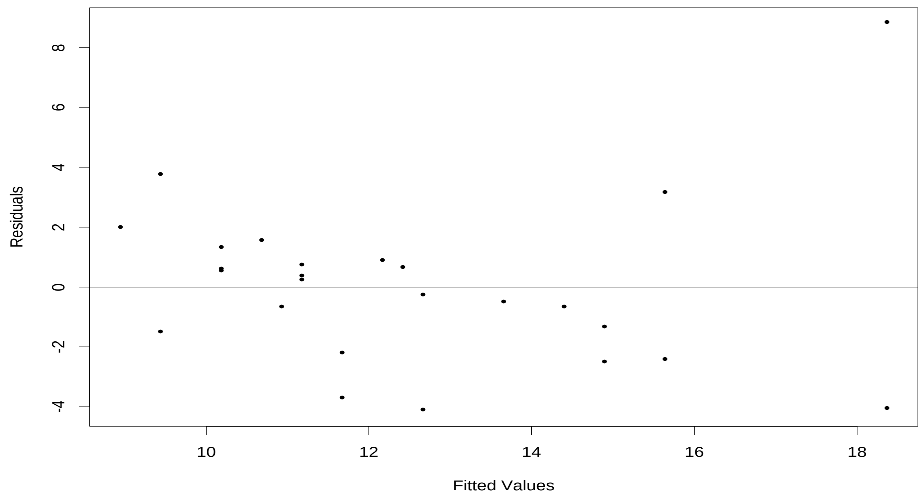
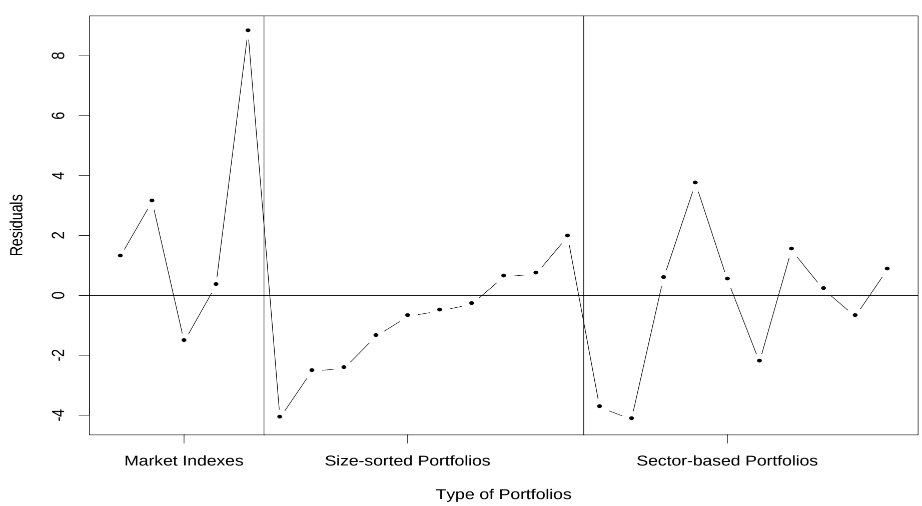


Figure 3.4: Plot of Residuals By Portfolio type



outperforms the buy-and-hold strategy for all decile portfolios except Decile 9.

- Results for the sub-periods essentially confirm the superior performance of the $\lambda = 0.05$-filter rule except for the now familiar decline in performance in the latter sub-period 1986-2001.

- Before adjusting for risk, the $\lambda = 0.05$-filter rule does at least as well as the buy-and-hold strategy for data from Basic Industries, Construction, Durables, Utilities, Trade, Finance, Oil and Coal, and Services. After adjusting for risk, the $\lambda = 0.05$-filter rule beats the buy-and-hold strategy for all sectors.

- The performance of the $\lambda = 0.05$-filter rule for monthly data is much weaker. The filter rule outperforms the buy-and-hold strategy for only the Basic Industries sector and the Oil and Coal sector before adjusting for risk. After adjusting for risk, the filter rule outperforms the buy-and-hold strategy for five out of the ten sectors.

- The results to the filter rule in the sub-periods are similar to what we observed for the decile portfolios. In the first sub-period 1962-1985, the $\lambda = 0.05$-filter rule beats the buy-and-hold strategy, before adjusting for risk, in all sectors, whereas in the second sub-period 1986-2001, the filter rule beats the buy-and-hold strategy, before adjusting for risk, only in four out of the ten sectors.

As in the results to the filter rule applied to returns from market indexes, there is a decline in performance of the filter rule from the 1962-1985 period to the 1986-2001 period for size-sorted and sector-based portfolios as well. Since we now we have the filter rule returns to all the assets as well as the weekly lag one autocorrelations we ran a regression of excess returns (difference between annualized returns to the filter rule and the annualized returns to the buy-and-hold strategy) on the lag one autocorrelation. From the regression model we see that for a 10% increase in lag one autocorrelation there is a 2.39% increase in the excess returns. Interestingly, this piece of evidence coincides with the observations of Corrado and Lee (1992), which finds a significant relationship between autocorrelation in returns and filter rule returns in individual stocks.

In summary, the results to the decile portfolios and the sector-based portfolios strategy provide valuable information for sector rotation and size-based rotation strategies. In addition to the success of the filter rule, the relationship between the annualized returns to the filter rule and the lag one autocorrelations does add a new dimension to the usefulness of the filter rule as a trading strategy.

Chapter 4

Risk Adjusted Returns and Profitability of the MACD and MA Strategies

This chapter continues the investigation of momentum strategies; in particular it engages the analysis of the moving average convergence divergence indicator and the analysis of a moving average strategy. As before, we use data on market indexes, size-sorted portfolios, and sector based portfolios for the time period July 1962 to December 2001.

Given the experience with the filter rule in the preceding chapter, there is no need to recall the performance measures and the data construction process; here we will use exactly the same framework. Nevertheless, before we take up the analysis of the two strategies, there are some issues that deserve attention. Specifically, we need to address three topics:

1. the formal definition of the two strategies,
2. a review of earlier work on similar momentum based rules, and
3. the choice of parameter values for the two strategies.

4.1 The Two Strategies – MACD and MA

Two popular short-term strategies that have substantial professional following are the Moving Average strategy (or the MA) and the Moving Average Convergence Divergence strategy (or the MACD). We now formally define the two strategies. Let $P_t,\ t = 1, 2, \ldots$, denote a sequence of prices of a financial asset and let $\mathrm{MA}^n(\cdot)$ denote the n-period simple moving average, and let $\mathrm{EMA}^n(\cdot)$ denote the n-period exponential moving average. Recall that

1. the n-period moving average of a process $\{X_t : \ t \geq 1\}$ at time t is given by

$$\mathrm{MA}^n(X_t) = \frac{\sum_{i=1}^{n} X_{t-i+1}}{n}, \quad \text{and} \tag{4.1}$$

2. the n-period exponential moving average of a process $\{X_t : \ t \geq 1\}$ at time t is defined recursively by the formula

$$\mathrm{EMA}^n(X_t) = \frac{2}{n+1} * X_t + (1 - \frac{2}{n+1}) * \mathrm{EMA}^n(X_{t-1}) \ \ , \tag{4.2}$$

where the recursion is begun by setting $\mathrm{EMA}^n(X_1) = X_1$.

Moving Average Strategy

The n-period Moving Average (or MA^n) strategy generates *buy* and *sell* signals by a simple recipe. The time B_1 of the first buy signal is given by

$$B_1 = \min\{t \geq 1 : P_t > \mathrm{MA}^n(P_t)\}\,,$$

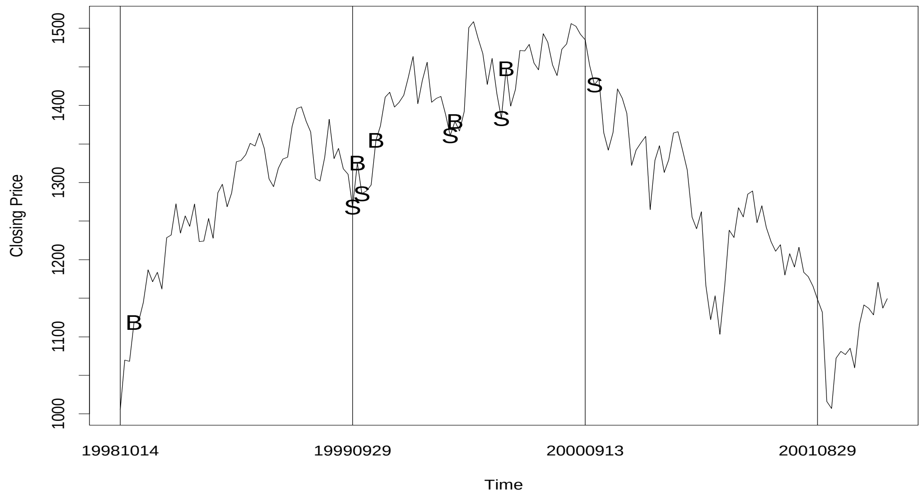
where the operator MA^n defined in equation (4.1) is now applied to the price process $\{P_t\}$. The time S_1 of the first sell signal following the first buy signal is then given by

$$S_1 = \min\{t \geq B_1 : P_t \leq \mathrm{MA}^n(P_t)\}\,.$$

All of the subsequent buy and sell signals are then defined analogously by recursion. That is, for $v \geq 2$ the time B_v of the v^{th} buy signal is given by

$$B_v = \min\{t \geq S_{v-1} : P_t > \mathrm{MA}^n(P_t)\}\,,$$

Figure 4.1: Plot of MA^{40} strategy applied to Closing Prices of S&P 500 Index



and the time S_v of the v^{th} sell signal is given by

$$S_v = \min\{t \geq B_v : P_t \leq \mathrm{MA}^n(P_t)\}\,.$$

Figure 4.1 illustrates the buy and sell signals which are generated by the MA^{40} strategy when it is applied to the weekly closing prices of the S&P 500 index for the time period 1998 to 2001.

MACD

The Moving Average Convergence Divergence (or MACD) indicator was invented by Gerald Appel in 1979 (Murphy (1999, pp. 200)), and it is representative of the large class of *oscillator strategies*. To specify a particular instance of the MACD strategy we need three parameters n_1, n_2, and n_3 with $n_1 < n_2$. The MACD strategy uses three kinds of exponential moving averages: a short or fast average, captured by n_1, a long or slow average, captured by n_2 (note $n_1 < n_2$), and the average of the difference between the short and long averages which is smoothed over n_3 periods.[1] The MACD(n_1, n_2, n_3) strategy is like the MA strategy and generates *buy* and *sell* signals at various time points by a recursive recipe. For the MACD(n_1, n_2, n_3) the time B_1 of the first buy signal is given by the formula

$$B_1 = \min\{t \geq 1 : \text{EMA}^{n_1}(P_t) - \text{EMA}^{n_2}(P_t) > \text{EMA}^{n_3}(\text{EMA}^{n_1}(P_t) - \text{EMA}^{n_2}(P_t))\}\,,$$

where EMA^{n_i} is as defined in equation (4.2) for $i = 1, 2, 3$ and one should note that EMA^{n_3} is applied to the process $\text{EMA}^{n_1}(P_t) - \text{EMA}^{n_2}(P_t)$. Analogously, the time S_1 of the first sell signal is given by

$$S_1 = \min\{t \geq B_1 : \text{EMA}^{n_1}(P_t) - \text{EMA}^{n_2}(P_t) \leq \text{EMA}^{n_3}(\text{EMA}^{n_1}(P_t) - \text{EMA}^{n_2}(P_t))\}\,.$$

Subsequent buy and sell signals are then generated by the natural recursions. To be explicit we have

$$B_v = \min\{t \geq S_{v-1} : \text{EMA}^{n_1}(P_t) - \text{EMA}^{n_2}(P_t) > \text{EMA}^{n_3}(\text{EMA}^{n_1}(P_t) - \text{EMA}^{n_2}(P_t))\}\,,$$

and we have

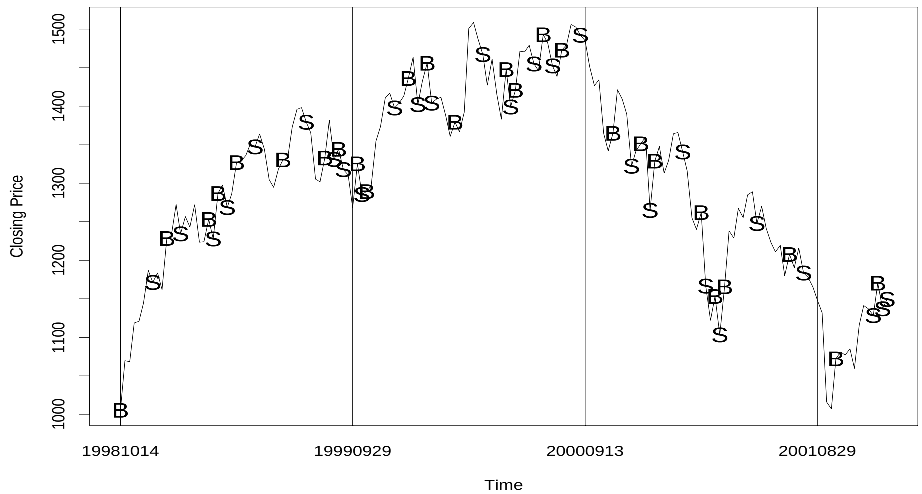
$$S_v = \min\{t \geq B_v : \text{EMA}^{n_1}(P_t) - \text{EMA}^{n_2}(P_t) \leq \text{EMA}^{n_3}(\text{EMA}^{n_1}(P_t) - \text{EMA}^{n_2}(P_t))\}$$

for the time B_v of the v^{th} buy signal and the time S_v of the v^{th} sell signal.

Even though the formula for the MACD strategy looks complicated, it just uses a linear combination of past prices to determine the buy and sell signals. Figure 4.2 illustrates the signals generated by the MACD(12, 26, 9) strategy when it is applied to the weekly closing prices of the S&P 500 index from 1998 to 2001.

[1]The difference of a pair of moving averages produces what is generally referred to as an oscillator. An oscillator is so named because the resulting curve swings back and forth across the zero line.

Figure 4.2: Plot of MACD$(12, 26, 9)$ strategy applied to Closing Prices of S&P 500 Index



4.2 Relevant Literature

Apparently the MACD strategy has not been addressed by any academic study, but the simpler MA strategy has been examined in several scholarly investigations. In particular, the MA strategy has been considered by Brock, Lakonishok, LeBaron (1992) and in a section of Siegel (2002, pp. 283–297).

Brock, Lakonishok, and LeBaron

Brock, Lakonishok, LeBaron (1992) tested the moving average strategy on daily return data on the Dow Jones Industrial Average from 1897-1986. However, this moving average strategy is more general than what we defined earlier as it is based on the difference between two moving averages (in our definition the second average is a one period average). Another contrast from our approach is the use of a band around the difference between the short and long moving averages to eliminate "whiplash" signals. This use of the band modifies the strategy, which now generates buy and sell signals only when the difference between the long and short averages fall outside the bands. The authors apart from looking at a variety of periods for the short and long averages also use a variety of band sizes including bands of size zero. Three key points emerge from the results.

1. The average daily return (averaged over all periods considered for the MA strategy) following buy signals is 0.42% which is much higher than -0.25%, the average daily return following sell signals.

2. The standard deviation of returns following buy signals is less than the standard deviation of returns following sell signals.

3. The use of bands around the moving averages appears to increase the difference between returns following buy signals and returns following sell signals for both the MA strategies.

Siegel

In *Stocks for the Long Run* Siegel notes that one of the most popular methods for market timing uses the relationship between a moving average of the price process and the current price. In his analysis, Siegel applies the MA^{200} strategy on daily data from the Dow Jones Industrial Average for 1886-2001, and the NASDAQ Composite Index from 1972-2001. Similar to the approach taken by Brock, Lakonishok, and LeBaron (1992), the MA^{200} strategy is modified to generate signals when the current price falls outside a 1% band. Six interesting findings emerge from the analysis.

1. For data on the Dow Jones Industrial Average, the annualized returns for the MA^{200} strategy are higher than the annualized returns from a buy-and-hold strategy before accounting for transaction costs.

2. However, after accounting for one-way transaction costs of 1/2%, the annualized returns from a buy-and-hold strategy are higher than the annualized returns from the MA^{200} strategy.

3. On the other hand, the risk associated with the MA^{200} strategy (as measured by the standard deviation of returns) is lower than the risk associated with the buy-and-hold strategy.

4. In the sub-period 1990-2001, the buy-and-hold strategy yields higher annualized returns and lower risk than the MA^{200} strategy both before and after accounting for one-way transaction costs. Note that this result coincides with our observation in Chapter 2 of the poor performance of the filter rule in this sub-period.

5. For data on the NASDAQ Composite Index, the annualized returns for the MA^{200} strategy are higher than the annualized returns from a buy-and-hold strategy even after accounting for transaction costs. Also, the risk associated with the MA^{200} strategy (again captured by the standard deviation in returns) is always lower than the risk associated with the buy-and-hold strategy. This again coincides with our general observations on the CRSP NASDAQ Value-weighted index for the filter rule.

6. Based on his analysis of the MA strategy, Siegel gives a cautious approval to the use of the MA strategy as a speculative tool, although he notes that it is important that transaction costs are kept to a minimum.

4.3 Choice of parameters for MACD and MA strategies

The analysis of the MACD and MA strategies depends on the specific decisions for their implementation, and here we follow the same methodology used in the analysis for the filter rule. The next task on hand is to decide on the particular choice of parameters for the two strategies. This process as we noted in the analysis of filter rules in Chapter 2 presents a potential data-snooping problem.

First, for the MA strategy, Siegel observed that the MA^{200} strategy works well on daily data and since we work with weekly and monthly data, we use a 40-period (200-day / 5 trading days in a week) moving average for weekly data, the MA^{40} strategy, and for monthly data we use the MA^{10} strategy, assuming that there are roughly 20 trading days in a month.

For the MACD strategy we make a rather unintuitive choice, we use the MACD(12,26,9) strategy on both weekly and monthly data. To clarify as to why this is unintuitive, practitioners in Wall Street typically use a MACD(12,26,9) strategy on daily data and rather than converting the parameters to weekly or monthly scale we directly borrow the daily parameter values and proceed to implement them.

The choice of parameters for the MA strategy does present a potential data-snooping problem since we adapt the MA^{200} strategy which appears to work well on daily data. On the other hand, we use the MACD(12,26,9) strategy for weekly and monthly data knowing fully well that the parameters could have been optimized (loosely speaking) by the practitioners for daily data.

4.4 Results for Market Indexes

Tables 4.1 and 4.2 display the results of applying the MACD strategy, the MA strategy, and the buy-and-hold strategy to the CRSP NYSE-AMEX value-weighted index, the CRSP NYSE-AMEX equal-weighted index, the S&P 500 index, the CRSP NASDAQ value-weighted index, and the CRSP NASDAQ equal-weighted index. The tables here are organized in the same manner as in Chapter 2 and 3.

MACD strategy

We begin with a few basic observations, followed by a more detailed look at the results.

- For both weekly and monthly data, the MACD(12,26,9) strategy outperforms the buy-and-hold strategy before adjusting the risk for the CRSP NASDAQ indexes.
- For weekly data from the CRSP NYSE-AMEX equal-weighted index, the MACD strategy outperforms the buy-and-hold strategy before adjusting for risk.
- For monthly data from the S&P 500 index, the MACD strategy outperforms the buy-and-hold strategy before adjusting for risk.

- On a risk adjusted basis, the MACD strategy outperforms the buy-and-hold strategy for all indexes except the S&P 500 index. Furthermore, the market timing tests indicate the presence of timing ability in the MACD strategy for the CRSP NYSE-AMEX equal-weighted index and the CRSP NASDAQ indexes.

Performance before adjusting for risk

As we just noted, the MACD strategy yields higher annualized returns than the buy-and-hold strategy for the CRSP NYSE-AMEX equal-weighted index and the CRSP NASDAQ indexes. The best performance of the MACD strategy occurs for the CRSP NASDAQ value-weighted index where the one-way break even transaction cost is 0.72%. However, we note that in comparison the filter rule netted a one-way break even transaction cost of 1.7%.

Performance after adjusting for risk

Similar to what we observed for the filter rule the risk measures do result in lower values for the MACD strategy when compared to the buy-and-hold strategy for all the market indexes. For example, the annualized standard deviation and the maximum drawdown for the CRSP NYSE-AMEX value-weighted index under the MACD strategy are 8.98% and 15.48%, while the corresponding values under the buy-and-hold strategy are 14.38% and 45.71% respectively.

On a risk adjusted basis the performance of the MACD strategy is superior to the buy-and-hold strategy for all market indexes except the S&P 500 index. The highest value for the annualized differential RAP measure is 12.67% which occurs for the CRSP NASDAQ equal-weighted index. The annualized differential RAP measure is -0.92% for the S&P 500 index indicating the poor performance of the MACD strategy even after matching the risk to the buy-and-hold strategy.

Market Timing Tests

Table 4.1: MACD Rule Versus Buy-and-Hold Strategy for Market Index Data from 1962-2001

	Annualized return (%) Buy-and-Hold	Annualized return (%) MACD Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) MACD Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) MACD Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) MACD Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
CRSP NYSE-AMEX											
Value-Weighted	11.47	10.39	14.38	8.98	73.43	50.02	45.71	15.48	83	1047	-0.22
Equal-Weighted	18.77	19.47	15.11	9.67	904.43	1140.52	49.69	24.50	68	1088	0.17
NYSE-AMEX-NASDAQ											
S&P500	7.90	7.12	14.78	9.20	20.24	15.19	46.99	25.29	91	1020	-0.15
CRSP NASDAQ											
Value-Weighted	11.51	14.73	20.45	13.02	23.63	54.04	70.40	54.13	57	794	0.72
Equal-Weighted	27.18	27.93	15.77	9.83	1075.97	1276.67	55.13	29.54	47	808	0.18
Monthly Data											
CRSP NYSE-AMEX											
Value-Weighted	11.47	10.91	14.81	10.67	72.32	59.23	44.82	23.43	16	293	-0.62
Equal-Weighted	13.51	10.85	19.04	13.23	147.55	57.92	59.50	27.81	20	306	-2.36
NYSE-AMEX-NASDAQ											
S&P500	7.86	8.28	14.86	10.59	19.72	22.97	46.18	23.65	19	281	0.40
CRSP NASDAQ											
Value-Weighted	11.57	12.03	22.79	16.51	23.71	26.73	68.11	30.60	11	221	0.54
Equal-Weighted	14.33	15.14	21.89	15.27	48.09	58.92	52.09	29.91	11	206	0.92

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio MACD Rule	Annualized RAP (%) MACD Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio MACD Rule	Cumby-Modest Regressions α	β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
CRSP NYSE-AMEX											
Value-Weighted	0.28	0.34	12.21	0.74	0.40	0.49	0.00	0.00	0.51	0.00	0.06
Equal-Weighted	0.75	1.25	26.27	7.50	1.10	2.08	0.00	0.00	3.43*	0.10	4.58*
NYSE-AMEX-NASDAQ											
S&P500	0.04	-0.02	6.96	-0.92	0.05	-0.03	0.00	0.00	-0.47	0.00	-0.54
CRSP NASDAQ											
Value-Weighted	0.16	0.50	18.44	6.94	0.22	0.73	0.00	0.00	1.75	0.06	2.35*
Equal-Weighted	1.20	2.01	39.85	12.67	1.72	3.42	0.00	0.01	4.61*	0.15	5.40*
Monthly Data											
CRSP NYSE-AMEX											
Value-Weighted	0.32	0.39	12.52	1.05	0.47	0.56	0.00	0.00	0.56	0.07	1.49
Equal-Weighted	0.35	0.31	12.64	-0.86	0.54	0.45	0.01	0.00	-0.37	0.04	0.81
NYSE-AMEX-NASDAQ											
S&P500	0.07	0.14	8.89	1.03	0.10	0.20	0.00	0.00	0.71	0.05	1.06
CRSP NASDAQ											
Value-Weighted	0.18	0.28	13.79	2.22	0.26	0.40	0.00	0.00	0.32	0.12	2.34*
Equal-Weighted	0.32	0.51	18.49	4.16	0.47	0.77	0.00	0.01	0.81	0.15	2.78*

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

From the market timing test results we see that the MACD strategy shows significant market timing for both the CRSP NASDAQ indexes and the CRSP NYSE-AMEX equal-weighted index. For example, for the CRSP NYSE-AMEX equal-weighted index, the t-ratio associated with the slope of the Cumby-Modest regressions is 3.53, while the Kuipers score is 0.10 and the value of the Pesaran-Timmermann z-test is 4.58.

Monthly Data

Looking at the results for monthly data, we see that MACD strategy continues to yield higher annualized returns than the buy-and-hold strategy for all the two CRSP NASDAQ indexes, but surprisingly also for the S&P 500 index. The one-way break even transaction cost for the S&P 500 index is 0.40%, while the highest value of the transaction cost occurs for the CRSP NASDAQ equal-weighted index, a value of 0.92%.

On a risk adjusted basis, except the CRSP NYSE-AMEX equal-weighted index, the MACD strategy outperforms the buy-and-hold strategy. Furthermore, the market timing tests indicate the presence of timing ability for the two NASDAQ indexes.

MA strategy

Overall, the results of application of the MA strategy to the market indexes follows the same pattern as the results of the application of the MACD strategy. However, there are some interesting differences and insights to drawn, and we list five of them below.

1. For weekly data from the S&P 500 index the MA^{40} strategy outperforms the buy-and-hold strategy with a one-way break even transaction cost of 0.48%. This result is very different from that of the MACD strategy and the filter rule.

2. For the other indexes, the MA strategy does better (as measured by one-way break even transaction costs) than the MACD strategy but not better than the filter rule.

3. On a risk adjusted basis, the MA strategy outperforms the buy-and-hold strategy for all the indexes. Furthermore, the MA strategy has the ability to time the market as evidenced by significant values for the market timing tests for all the indexes.

Table 4.2: MA Rule Versus Buy-and-Hold Strategy for Market Index Data from 1962-2001

	Annualized return (%) Buy-and-Hold	Annualized return (%) MA Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) MA Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) MA Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) MA Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
CRSP NYSE-AMEX											
Value-Weighted	11.47	11.04	14.38	10.81	73.43	63.18	45.71	23.67	63	1535	-0.11
Equal-Weighted	18.77	19.16	15.11	11.32	904.43	1030.41	49.69	21.34	49	1594	0.13
NYSE-AMEX-NASDAQ											
S&P500	7.90	9.48	14.78	10.73	20.24	36.06	46.99	22.77	60	1412	0.48
CRSP NASDAQ											
Value-Weighted	11.51	15.00	20.45	14.14	23.63	57.95	70.40	35.72	39	1049	1.14
Equal-Weighted	27.18	30.09	15.77	11.89	1075.97	2075.56	55.13	28.23	25	1145	1.31
Monthly Data											
CRSP NYSE-AMEX											
Value-Weighted	11.47	10.63	14.81	11.77	72.32	53.55	44.82	23.43	29	353	-0.51
Equal-Weighted	13.51	13.20	19.04	14.17	147.55	132.45	59.50	27.81	30	339	-0.17
NYSE-AMEX-NASDAQ											
S&P500	7.86	8.52	14.86	10.99	19.72	25.07	46.18	23.95	30	324	0.40
CRSP NASDAQ											
Value-Weighted	11.57	12.67	22.79	17.30	23.71	31.52	68.11	39.59	24	244	0.59
Equal-Weighted	14.33	16.26	21.89	15.92	48.09	77.98	52.09	37.64	21	235	1.14

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio MA Rule	Annualized RAP (%) MA Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio MA Rule	Cumby-Modest Regressions α	β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
CRSP NYSE-AMEX											
Value-Weighted	0.28	0.34	12.26	0.79	0.40	0.47	0.00	0.00	0.13	0.04	2.01*
Equal-Weighted	0.75	1.04	23.12	4.35	1.10	1.52	0.00	0.00	1.37	0.09	4.75*
NYSE-AMEX-NASDAQ											
S&P500	0.04	0.20	10.28	2.39	0.05	0.27	0.00	0.00	0.55	0.05	2.23*
CRSP NASDAQ											
Value-Weighted	0.16	0.48	18.03	6.53	0.22	0.67	0.00	0.00	1.55	0.06	2.58*
Equal-Weighted	1.20	1.84	37.21	10.04	1.72	2.78	0.00	0.01	3.98*	0.14	5.98*
Monthly Data											
CRSP NYSE-AMEX											
Value-Weighted	0.32	0.33	11.63	0.15	0.47	0.47	0.00	0.00	0.07	0.06	1.40
Equal-Weighted	0.35	0.45	15.41	1.90	0.54	0.68	0.01	0.00	0.39	0.05	1.28
NYSE-AMEX-NASDAQ											
S&P500	0.07	0.16	9.14	1.28	0.10	0.22	0.00	0.00	0.61	0.06	1.48
CRSP NASDAQ											
Value-Weighted	0.18	0.30	14.34	2.77	0.26	0.43	0.01	0.00	-0.14	0.10	2.05*
Equal-Weighted	0.32	0.56	19.58	5.24	0.47	0.85	0.00	0.01	1.45	0.14	2.64*

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

4.5 Results for Deciles

Tables 4.3 and 4.4 display the results of applying the MACD strategy, the MA strategy, and the buy-and-hold strategy to the 10 size-sorted portfolios. The results are essentially similar to what we observed for the filter rule, and so we just point out five interesting observations that emerge from weekly data.

- Similar to the filter rule, the MACD strategy outperforms the buy-and-hold strategy for all decile portfolios except Decile 10, but the MA strategy performs at least as well as the buy-and-hold strategy for all decile portfolios.

- The one-way break even transaction costs monotonically reduce as we move from Decile 1 to Decile 10, and are similar for the MA strategy and the MACD strategy. However, the performance of the filter rule is superior to both these strategies except for Decile 10.

- For all decile portfolios except Decile 10, on a risk adjusted basis, the MACD strategy outperforms the MA strategy, and both these active strategies outperform the buy-and-hold strategy. However, the filter rule is still the best performing strategy among the three strategies after accounting for risk, for all size-sorted portfolios except Decile 10.

- For Decile 10, the MA strategy is the only strategy that outperforms the buy-and-hold strategy after adjusting for risk.

- The evidence on the ability of the MACD and MA strategy to time the market (based on the significance of the Kuipers score) is similar to the evidence that we observed for the filter rule, namely that there is evidence of timing behavior for all decile portfolios except Decile 9 and Decile 10.

Table 4.3: MACD Rule Versus Buy-and-Hold Strategy for Decile Data from 1962-2001

	Annualized return (%) Buy-and-Hold	Annualized return (%) MACD Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) MACD Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) MACD Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) MACD Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
Decile 1	14.28	20.38	16.11	10.12	196.60	1541.06	62.75	29.34	64	1047	1.60
Decile 2	12.37	16.91	16.16	10.08	101.20	483.91	65.49	29.36	68	1070	1.14
Decile 3	13.20	17.35	16.60	10.30	135.19	563.11	63.09	30.18	65	1078	1.09
Decile 4	13.53	15.53	16.38	10.09	151.54	302.57	59.27	27.12	74	1073	0.47
Decile 5	13.70	16.19	16.35	9.71	160.99	379.39	53.97	26.22	70	1051	0.61
Decile 6	13.14	15.58	16.23	9.94	132.53	308.19	53.60	25.55	72	1066	0.58
Decile 7	12.37	13.58	16.02	9.84	101.19	154.45	51.96	26.64	73	1072	0.29
Decile 8	13.04	13.49	15.74	9.79	127.95	149.46	44.38	20.57	77	1055	0.10
Decile 9	11.89	11.85	15.52	9.47	85.24	84.21	47.87	17.32	77	1049	0.00
Decile 10	10.90	8.15	14.57	9.07	59.96	22.25	44.14	25.32	95	1035	-0.51
Monthly Data											
Decile 1	13.80	13.51	22.32	15.40	163.43	147.82	67.54	34.14	15	290	-0.33
Decile 2	14.08	12.72	20.85	14.61	180.09	112.01	63.96	31.13	19	301	-1.25
Decile 3	14.79	11.63	20.62	14.18	230.06	76.32	60.60	29.57	19	311	-2.94
Decile 4	15.24	12.17	19.98	14.13	267.78	92.46	55.42	30.07	17	308	-3.17
Decile 5	15.93	12.67	19.26	13.42	338.71	110.30	50.05	29.42	16	307	-3.56
Decile 6	14.26	12.75	18.67	12.87	191.25	113.28	50.49	27.66	17	310	-1.54
Decile 7	16.06	13.44	19.20	14.36	354.76	143.91	48.49	26.66	18	308	-2.53
Decile 8	15.05	12.96	17.58	12.46	251.37	121.98	45.90	25.97	17	310	-2.14
Decile 9	13.34	10.94	16.53	12.08	139.00	59.96	46.26	24.58	18	297	-2.35
Decile 10	13.94	12.31	17.81	14.56	171.39	97.07	44.96	21.58	17	276	-1.68

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio MACD Rule	Annualized RAP (%) MACD Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio MACD Rule	Cumby-Modest Regressions α	β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
Decile 1	0.43	1.28	28.06	13.79	0.61	2.18	0.00	0.01	5.17*	0.14	6.24*
Decile 2	0.31	0.94	22.64	10.26	0.42	1.46	0.00	0.00	3.41*	0.11	4.93*
Decile 3	0.35	0.97	23.45	10.25	0.48	1.51	0.00	0.00	3.67*	0.09	4.08*
Decile 4	0.37	0.81	20.61	7.08	0.52	1.22	0.00	0.00	2.52*	0.07	3.23*
Decile 5	0.39	0.91	22.20	8.50	0.53	1.39	0.00	0.00	2.97*	0.08	3.42*
Decile 6	0.35	0.82	20.76	7.61	0.49	1.26	0.00	0.00	2.56*	0.10	4.41*
Decile 7	0.31	0.63	17.47	5.09	0.43	0.93	0.00	0.00	1.83	0.05	2.19*
Decile 8	0.36	0.62	17.20	4.15	0.50	0.93	0.00	0.00	1.80	0.07	3.14*
Decile 9	0.29	0.47	14.70	2.82	0.41	0.70	0.00	0.00	1.15	0.04	1.67
Decile 10	0.24	0.08	8.62	-2.27	0.34	0.12	0.00	0.00	-1.24	-0.01	-0.72
Monthly Data											
Decile 1	0.32	0.44	16.55	2.75	0.50	0.69	0.01	0.00	0.46	0.09	1.94
Decile 2	0.35	0.41	15.26	1.18	0.53	0.61	0.01	0.00	0.00	0.06	1.25
Decile 3	0.39	0.34	13.84	-0.94	0.59	0.49	0.01	0.00	-0.58	0.07	1.52
Decile 4	0.42	0.38	14.41	-0.81	0.63	0.55	0.01	0.00	-0.35	0.05	1.11
Decile 5	0.48	0.44	15.25	-0.67	0.71	0.63	0.01	0.00	-0.43	0.09	1.90
Decile 6	0.40	0.47	15.45	1.19	0.60	0.69	0.01	0.00	-0.03	0.09	2.11*
Decile 7	0.48	0.47	15.69	-0.36	0.77	0.77	0.01	0.00	0.14	0.04	0.94
Decile 8	0.47	0.50	15.51	0.46	0.72	0.77	0.01	0.00	0.17	0.05	1.14
Decile 9	0.40	0.35	12.48	-0.84	0.60	0.50	0.01	0.00	-0.37	0.07	1.47
Decile 10	0.40	0.38	13.55	-0.38	0.73	0.79	0.01	0.00	-0.41	0.06	1.29

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

Table 4.4: MA Rule Versus Buy-and-Hold Strategy for Decile Data from 1962-2001

	Annualized return (%) Buy-and-Hold	Annualized return (%) MA Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) MA Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) MA Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) MA Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
Decile 1	14.28	19.09	16.11	10.62	196.60	1006.88	62.75	22.70	44	1399	1.84
Decile 2	12.37	15.54	16.16	10.67	101.20	304.36	65.49	27.83	59	1436	0.93
Decile 3	13.20	14.87	16.60	11.27	135.19	241.56	63.09	29.50	61	1444	0.47
Decile 4	13.53	15.04	16.38	11.50	151.54	256.21	59.27	23.89	54	1493	0.49
Decile 5	13.70	14.64	16.35	11.48	160.99	222.91	53.97	23.79	53	1503	0.31
Decile 6	13.14	13.57	16.23	11.69	132.53	153.64	53.60	22.33	60	1516	0.12
Decile 7	12.37	13.46	16.02	11.74	101.19	148.18	51.96	29.78	53	1535	0.36
Decile 8	13.04	13.09	15.74	11.49	127.95	130.06	44.38	28.14	64	1504	0.01
Decile 9	11.89	12.04	15.52	11.67	85.24	89.87	47.87	27.19	62	1501	0.04
Decile 10	10.90	10.85	14.57	11.13	59.96	59.04	44.14	21.25	65	1542	0.00
Monthly Data											
Decile 1	13.80	16.02	22.32	15.67	163.43	349.22	67.54	30.40	28	316	1.35
Decile 2	14.08	13.46	20.85	15.47	180.09	145.18	63.96	32.33	35	332	-0.30
Decile 3	14.79	13.76	20.62	15.34	230.06	161.28	60.60	35.71	32	335	-0.55
Decile 4	15.24	13.25	19.98	15.27	267.78	135.00	55.42	35.72	34	349	-1.00
Decile 5	15.93	13.94	19.26	14.82	338.71	171.11	50.05	29.42	33	350	-1.03
Decile 6	14.26	12.50	18.67	14.06	191.25	103.70	50.49	27.66	30	350	-1.02
Decile 7	16.06	14.17	19.20	15.48	354.76	185.32	48.49	26.66	32	361	-1.01
Decile 8	15.05	13.52	17.58	13.59	251.37	148.09	45.90	25.97	30	357	-0.88
Decile 9	13.34	11.15	16.53	13.44	139.00	64.59	46.26	24.58	33	358	-1.16
Decile 10	13.94	14.03	17.81	15.55	171.39	176.90	44.96	21.58	28	361	0.06

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio MA Rule	Annualized RAP (%) MA Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio MA Rule	Cumby-Modest Regressions α	β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
Decile 1	0.43	1.10	25.13	10.85	0.61	1.67	0.00	0.00	3.45*	0.13	6.01*
Decile 2	0.31	0.76	19.74	7.36	0.42	1.10	0.00	0.00	2.53*	0.09	4.44*
Decile 3	0.35	0.66	18.41	5.21	0.48	0.94	0.00	0.00	1.19	0.07	3.63*
Decile 4	0.37	0.67	18.29	4.77	0.52	0.94	0.00	0.00	1.08	0.07	3.56*
Decile 5	0.39	0.63	17.72	4.02	0.53	0.88	0.00	0.00	0.98	0.06	2.82*
Decile 6	0.35	0.53	15.96	2.82	0.49	0.74	0.00	0.00	0.21	0.06	2.97*
Decile 7	0.31	0.52	15.68	3.30	0.43	0.72	0.00	0.00	0.95	0.05	2.45*
Decile 8	0.36	0.50	15.19	2.15	0.50	0.70	0.00	0.00	0.47	0.06	2.82*
Decile 9	0.29	0.40	13.57	1.68	0.41	0.56	0.00	0.00	0.53	0.03	1.64
Decile 10	0.24	0.31	11.93	1.03	0.34	0.44	0.00	0.00	0.56	0.03	1.33
Monthly Data											
Decile 1	0.32	0.59	19.95	6.15	0.50	0.95	0.00	0.01	1.49	0.11	2.53*
Decile 2	0.35	0.43	15.80	1.71	0.53	0.65	0.01	0.00	0.40	0.06	1.39
Decile 3	0.39	0.46	16.18	1.38	0.59	0.67	0.01	0.00	0.23	0.09	2.14*
Decile 4	0.42	0.43	15.26	0.02	0.63	0.61	0.01	0.00	-0.38	0.01	0.34
Decile 5	0.48	0.48	16.08	0.16	0.71	0.70	0.01	0.00	-0.13	0.07	1.73
Decile 6	0.40	0.41	14.38	0.12	0.60	0.59	0.01	0.00	-0.29	0.06	1.39
Decile 7	0.48	0.48	15.95	-0.11	0.77	0.77	0.01	0.00	-0.24	0.06	1.43
Decile 8	0.47	0.50	15.50	0.45	0.72	0.76	0.01	0.00	0.09	0.05	1.31
Decile 9	0.40	0.33	12.17	-1.16	0.60	0.47	0.01	0.00	-0.40	0.02	0.58
Decile 10	0.40	0.47	15.09	1.15	0.73	0.94	0.00	0.01	1.33	0.05	1.32

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

4.6 Results for Sectors

Tables 4.5 and 4.6 report the results of the application of the MACD strategy, MA strategy, and the buy-and-hold strategy on the sector-based portfolios for both weekly and monthly time periods. Here again, the performance of both the MACD and MA strategy are similar to each other and also to the filter rule. We warn the reader that we use the word similar rather loosely, since there are differences in the values of their performance measures but the general pattern of behavior appears to be the same for all the three strategies. We now look at three key points that emerge from the above tables for weekly data.

- Overall, the results to both the MACD and MA strategies for weekly data are similar before adjusting for risk. The subtle differences arise from the fact that the MA strategy fails to beat the buy-and-hold strategy only for the NonDurables sector, while the MACD strategy fails to beat the buy-and-hold for the NonDurables sector, Transportation sector, and the Utilities sector.

- In terms of one-way break even transaction costs, the MA strategy is the best performing strategy for the Basic Industries sector, the Transportation sector, the Finance, Real Estate and Insurance sector, and the Oil and Coal sector, and the Services sector.

- In terms of one-way break even transaction costs, the MACD strategy is the best performing strategy for the Construction sector, Durables sector, and the Trade sector.

- On a risk adjusted basis, the filter rule beats both the MACD and the MA strategy for the Basic Industries sector, NonDurables sector, the Utilities sector, and the Services sector.

4.7 Concluding Remarks

The central aim of this chapter was to examine the risk adjusted returns and the profitability of two momentum based strategies the MACD and MA strategies. We began with the

Table 4.5: MACD Rule Versus Buy-and-Hold Strategy for Sector(value-weighted) Data from 1962-2001

	Annualized return (%) Buy-and-Hold	Annualized return (%) MACD Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) MACD Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) MACD Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) MACD Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
Basic Industries	7.94	12.76	18.64	12.03	20.59	116.07	79.76	48.35	70	1099	1.23
Construction	8.53	12.18	19.45	13.62	25.54	94.60	59.43	26.74	75	1115	0.87
Durables	10.76	12.62	18.45	11.83	57.05	110.52	60.91	37.42	74	1045	0.45
NonDurables	13.17	10.53	14.30	9.41	133.75	52.58	39.93	15.30	81	1050	-0.57
Transportation	10.70	10.54	15.22	9.82	55.94	52.78	55.07	35.28	83	1054	-0.03
Utilities	9.45	9.17	12.11	8.24	35.71	32.21	44.02	14.85	86	1048	-0.05
Trade	12.20	12.77	17.75	11.73	95.03	116.43	58.19	32.89	75	1086	0.14
Fin, RE, Ins	11.38	13.08	15.58	9.79	71.16	129.78	54.36	17.73	76	1076	0.39
Oil and Coal	10.23	12.72	20.00	13.61	47.25	114.31	58.29	28.44	77	1079	0.57
Services	13.03	15.21	22.04	13.63	127.35	271.47	74.61	35.59	83	1102	0.45
Monthly Data											
Basic Industries	7.56	10.75	21.93	15.11	17.67	55.92	80.67	29.69	19	269	2.99
Construction	9.14	7.63	22.29	16.52	31.42	18.17	55.66	32.00	25	248	-1.09
Durables	10.96	9.26	19.21	13.80	60.34	32.77	60.31	36.53	22	299	-1.39
NonDurables	17.88	15.35	25.77	23.89	653.78	278.77	39.10	28.70	15	285	-2.87
Transportation	17.04	14.07	17.06	13.66	494.37	179.23	40.94	18.28	16	291	-3.21
Utilities	10.02	9.74	14.39	10.61	43.17	39.04	42.25	18.50	19	288	-0.26
Trade	12.71	10.29	18.70	13.16	111.82	47.52	57.83	33.22	19	270	-2.27
Fin, RE, Ins	15.24	12.69	16.38	11.52	267.68	110.78	53.38	25.06	17	299	-2.62
Oil and Coal	13.46	13.87	24.97	19.97	144.99	167.34	60.94	32.90	17	303	0.42
Services	15.77	14.02	25.06	18.68	320.74	176.33	74.24	34.55	17	306	-1.77

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio MACD Rule	Annualized RAP (%) MACD Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio MACD Rule	Cumby-Modest Regressions α	Cumby-Modest Regressions β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
Basic Industries	0.03	0.45	15.72	7.78	0.04	0.65	0.00	0.00	2.25*	0.06	2.89*
Construction	0.06	0.35	14.23	5.70	0.08	0.54	0.00	0.00	1.71	0.04	1.59
Durables	0.18	0.44	15.55	4.79	0.26	0.66	0.00	0.00	0.99	0.02	0.79
NonDurables	0.40	0.33	12.16	-1.00	0.57	0.48	0.00	0.00	-0.64	0.01	0.63
Transportation	0.22	0.32	12.27	1.57	0.31	0.48	0.00	0.00	1.06	0.02	0.88
Utilities	0.17	0.22	10.01	0.55	0.25	0.32	0.00	0.00	0.38	0.03	1.48
Trade	0.27	0.46	15.54	3.34	0.39	0.69	0.00	0.00	1.14	0.03	1.54
Fin, RE, Ins	0.26	0.58	16.45	5.07	0.36	0.88	0.00	0.00	1.98*	0.08	3.75*
Oil and Coal	0.14	0.39	15.22	4.99	0.21	0.59	0.00	0.00	2.15*	0.05	2.30*
Services	0.26	0.57	20.04	7.01	0.36	0.87	0.00	0.00	1.33	0.05	2.32*
Monthly Data											
Basic Industries	0.04	0.26	12.55	4.99	0.05	0.40	0.00	0.01	1.68	0.12	2.58*
Construction	0.11	0.05	7.94	-1.19	0.15	0.08	0.00	0.00	-0.07	-0.05	-1.29
Durables	0.22	0.18	10.24	-0.71	0.32	0.25	0.01	0.00	-0.69	0.02	0.41
NonDurables	0.43	0.36	16.03	-1.84	1.18	1.17	0.01	0.00	-0.44	0.10	2.15*
Transportation	0.60	0.54	15.89	-1.14	0.99	0.92	0.01	0.00	0.23	-0.01	-0.36
Utilities	0.23	0.28	10.81	0.79	0.36	0.48	0.00	0.00	0.32	0.03	0.72
Trade	0.32	0.27	11.78	-0.92	0.48	0.39	0.01	0.00	-0.45	0.07	1.55
Fin, RE, Ins	0.52	0.51	15.19	-0.04	0.80	0.78	0.01	0.00	0.11	0.08	1.71
Oil and Coal	0.27	0.36	15.65	2.20	0.46	0.70	0.00	0.01	1.08	0.06	1.44
Services	0.36	0.39	16.50	0.74	0.55	0.61	0.01	0.00	0.15	0.04	0.99

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

Table 4.6: MA Rule Versus Buy-and-Hold Strategy for Sector(value-weighted) Data from 1962-2001

	Annualized return (%) Buy-and-Hold	Annualized return (%) MA Rule	Annualized SD (%) Buy-and-Hold	Annualized SD (%) MA Rule	Terminal value ($) Buy-and-Hold	Terminal value ($) MA Rule	Maximum drawdown (%) Buy-and-Hold	Maximum drawdown (%) MA Rule	Number of Buy signals	Number of periods "In"	One-way break-even cost (%)
Weekly Data											
Basic Industries	7.94	15.19	18.64	12.26	20.59	269.69	79.76	19.00	46	1263	2.76
Construction	8.53	9.13	19.45	14.46	25.54	31.79	59.43	30.50	76	1280	0.14
Durables	10.76	11.43	18.45	13.14	57.05	72.58	60.91	25.70	72	1432	0.17
NonDurables	13.17	11.48	14.30	11.33	133.75	73.67	39.93	27.31	75	1547	-0.39
Transportation	10.70	11.82	15.22	11.19	55.94	83.08	55.07	21.09	70	1439	0.28
Utilities	9.45	10.62	12.11	9.29	35.71	54.31	44.02	19.78	59	1472	0.35
Trade	12.20	12.39	17.75	13.16	95.03	101.84	58.19	36.53	74	1413	0.05
Fin, RE, Ins	11.38	13.32	15.58	11.45	71.16	141.19	54.36	20.39	54	1501	0.63
Oil and Coal	10.23	12.32	20.00	14.20	47.25	99.26	58.29	30.12	64	1384	0.58
Services	13.03	16.36	22.04	15.39	127.35	401.41	74.61	25.51	60	1409	0.95
Monthly Data											
Basic Industries	7.56	11.70	21.93	15.09	17.67	78.24	80.67	35.44	35	290	2.10
Construction	9.14	8.17	22.29	17.05	31.42	22.10	55.66	32.00	45	295	-0.38
Durables	10.96	10.22	19.21	14.55	60.34	46.37	60.31	32.07	33	331	-0.39
NonDurables	17.88	15.83	25.77	24.39	653.78	327.74	39.10	22.72	31	364	-1.11
Transportation	17.04	15.08	17.06	14.58	494.37	254.17	40.94	24.22	31	367	-1.07
Utilities	10.02	9.98	14.39	11.24	43.17	42.57	42.25	18.03	31	342	-0.01
Trade	12.71	11.57	18.70	14.46	111.82	74.76	57.83	34.93	37	329	-0.54
Fin, RE, Ins	15.24	13.99	16.38	13.07	267.68	174.26	53.38	21.35	30	368	-0.71
Oil and Coal	13.46	14.59	24.97	19.97	144.99	214.47	60.94	35.26	31	332	0.63
Services	15.77	16.20	25.06	19.31	320.74	371.87	74.24	33.13	30	332	0.25

	Annualized Sharpe Ratio Buy-and-Hold	Annualized Sharpe Ratio MA Rule	Annualized RAP (%) MA Rule	Annualized RAP (%) Differential	Annualized Sortino Ratio Buy-and-Hold	Annualized Sortino Ratio MA Rule	Cumby-Modest Regressions α	Cumby-Modest Regressions β	t_β	Kuipers Score	PT test of Kuipers Score
Weekly Data											
Basic Industries	0.03	0.64	19.25	11.31	0.04	0.95	0.00	0.01	3.97*	0.11	5.16*
Construction	0.06	0.12	9.73	1.20	0.08	0.17	0.00	0.00	0.24	0.00	-0.07
Durables	0.18	0.31	13.07	2.31	0.26	0.44	0.00	0.00	0.40	0.02	1.00
NonDurables	0.40	0.36	12.55	-0.61	0.57	0.50	0.00	0.00	0.03	0.04	2.07*
Transportation	0.22	0.40	13.41	2.70	0.31	0.58	0.00	0.00	1.95	0.03	1.40
Utilities	0.17	0.35	11.60	2.15	0.25	0.52	0.00	0.00	1.04	0.06	3.16*
Trade	0.27	0.38	14.14	1.94	0.39	0.55	0.00	0.00	0.51	0.03	1.55
Fin, RE, Ins	0.26	0.52	15.47	4.09	0.36	0.75	0.00	0.00	1.51	0.07	3.75*
Oil and Coal	0.14	0.35	14.33	4.10	0.21	0.50	0.00	0.00	1.81	0.08	4.05*
Services	0.26	0.58	20.23	7.20	0.36	0.84	0.00	0.00	1.71	0.09	4.22*
Monthly Data											
Basic Industries	0.04	0.33	13.93	6.38	0.05	0.51	0.00	0.01	1.58	0.13	2.83*
Construction	0.11	0.08	8.60	-0.53	0.15	0.12	0.00	0.00	0.05	0.00	-0.06
Durables	0.22	0.24	11.33	0.37	0.32	0.34	0.01	0.00	0.09	0.02	0.58
NonDurables	0.43	0.37	16.34	-1.52	1.18	1.13	0.01	0.01	0.67	0.07	1.63
Transportation	0.60	0.57	16.50	-0.54	0.99	0.96	0.01	0.00	0.06	0.01	0.28
Utilities	0.23	0.29	10.89	0.87	0.36	0.48	0.00	0.00	0.40	0.07	1.64
Trade	0.32	0.33	12.98	0.27	0.48	0.50	0.01	0.00	0.00	0.06	1.42
Fin, RE, Ins	0.52	0.55	15.82	0.58	0.80	0.83	0.01	0.00	0.00	0.09	2.38*
Oil and Coal	0.27	0.39	16.55	3.09	0.46	0.76	0.00	0.01	0.89	0.08	1.90
Services	0.36	0.49	19.01	3.24	0.55	0.79	0.01	0.00	0.45	0.04	0.92

The annualized return of the risk free asset is 7.11% and the terminal value of a $1 investment from July 1962 to December 2001 is $17.

definition of the two strategies and followed it up with a review of the earlier work on the MA strategy. We then proceeded to state our concerns regarding the choice of the parameters of the two strategies and the implications for data-snooping. Specifically, we realized that the MA strategy presented the strongest case for data-snooping since the parameter was converted from the MA strategy that works well for daily data.

The performance of the MA and MACD strategy for the period 1962-2001, was compared to the performance of the buy-and-hold strategy and the $\lambda = 0.05$-filter rule with the help of weekly and monthly return data obtained from the CRSP NYSE-AMEX equal-weighted index, the CRSP NYSE-AMEX value-weighted index, the S&P 500 index, the CRSP NASDAQ equal-weighted index, the CRSP NASDAQ value-weighted index, the ten size-sorted portfolios and the sector-based portfolios. In short, six noteworthy observations emerged from our results.

- For weekly data from the S&P 500 index the MA^{40} strategy outperforms the buy-and-hold strategy with a one-way break even transaction cost of 0.48%. This result is very different from that of the MACD strategy and the filter rule, both of which fail to beat the buy-and-hold strategy.

- For all the other market indexes, the MA strategy does better (as measured by one-way break even transaction costs) than the MACD strategy but not better than the filter rule.

- For all market indexes except the S&P 500 index, on a risk adjusted basis, the MACD strategy performs better than the MA strategy but does not perform better than the filter rule.

- For both the MA and MACD strategies, the one-way break even transaction costs are very similar and monotonically reduce as we move from Decile 1 to Decile 10. However, the performance of the filter rule is superior to both these strategies except for Decile 10.

Table 4.7: Best Performing Strategies for weekly Sector Data from 1962-2001

Sector	One-way break even transaction cost	Annualized differential RAP
Basic Industries	MA^{40}	$\lambda = 0.05$-filter rule
Construction	MACD(12,26,9)	MACD(12,26,9)
Durables	MACD(12,26,9)	MACD(12,26,9)
NonDurables	$\lambda = 0.05$-filter rule	$\lambda = 0.05$-filter rule
Transportation	MA^{40}	MA^{40}
Utilities	$\lambda = 0.05$-filter rule	$\lambda = 0.05$-filter rule
Trade	MACD(12,26,9)	MACD(12,26,9)
Fin, RE, Ins	MA^{40}	MACD(12,26,9)
Oil and Coal	MA^{40}	MACD(12,26,9)
Services	MA^{40}	$\lambda = 0.05$-filter rule

- For all decile portfolios except Decile 10, on a risk adjusted basis, the MACD strategy outperforms the MA strategy, and both these active strategies outperform the buy-and-hold strategy. However, the filter rule is still the best performing strategy among the three strategies after accounting for risk, for all size-sorted portfolios except Decile 10.

- The most interesting observation that emerges here is that for different sectors different strategies seem to be performing better which is unlike our results to the market indexes and decile portfolios where the filter rule seemed to dominate. The following table summarizes the best performing strategies for each of the sectors.

The above results do raise a lot of interesting issues. For example, given that the MA strategy is the only one that is using an optimized value as its parameter, how much of an impact does this fact have on the results? In fact the MA strategy performs better than the other strategies when we use the one-way break even transaction cost as the performance measure and since the transaction costs take into account the number of trades, the importance of choosing appropriate values for the parameter to reduce whipsaws might have a significant impact.

Another interesting feature of the results is the ability of the MA strategy to beat the buy-and-hold strategy and the other two active strategies when applied to weekly data from the S&P 500 index and the CRSP NYSE-AMEX value-weighted index. This superior performance also holds for data from Decile 10 which is a value-weighted index of large firms. However, for the CRSP NASDAQ value-weighted index, the filter rule is still far superior to the MA strategy.

Maybe the most intriguing fact that emerges from the results is the ability of the MACD strategy to beat both the filter rule and the MA strategy after accounting for risk when applied to data on the sector-based portfolios. The MACD strategy outperforms all the other strategies in five out of the ten portfolios, which is surprising given the poor choice we have made for its parameters.

In summary, the results for the MA and MACD strategies coupled with the results to the filter rules do confirm the existence of momentum based strategies that outperform the buy-and-hold strategies for the indexes examined here. Furthermore, we have shown that the outperformance holds even after accounting for transaction costs.

Appendix A

The impact of index weighting schemes on annualized returns

The motivation for this note comes from the following observation[1]: The annualized return of the CRSP NYSE-AMEX equal-weighted index computed based on weekly data is significantly different from the annualized returns to the same index computed on the basis of monthly data. The table below captures the amount of discrepancy and for purposes of reference we also include annualized returns to the CRSP NYSE-AMEX value-weighted index.

Table A.1: Annualized returns for the some common CRSP Indexes

	Exchange	Annualized Returns (in %)	
	Equal-weighted	Weekly Data	Monthly Data
1962–2001	NYSE-AMEX	18.77	13.51
1973–2001	NASDAQ	27.18	14.33
	Value-weighted	Weekly Data	Monthly Data
1962–2001	NYSE-AMEX	11.47	11.47
1973–2001	NASDAQ	11.51	11.57

This fact has been documented in the academic literature by several authors, the most recent of which is Canina, Michaely, Thaler, and Womack (1998). The authors compute

[1]We thank Larry Bernstein, Amber Mountain Capital Management for helpful comments and engaging discussions.

the monthly returns[2] for data from the CRSP equal-weighted index for 1964-1993 in the following two ways.

Before we define the two methods we alert the reader to some notation.

- T denotes the number of time periods in a month.
- N is the total number of assets.
- R_{it} denotes the return to asset i at time t.
- Let w_i denote the weight associated with asset i. For equal-weighted indexes, $w_i \equiv 1$ for all assets and for value-weighted indexes they represent the market size (price * number of shares outstanding).

Method 1: The monthly return for an index computed by compounding the daily returns, denoted R_n^d is given by

$$R_m^d = \prod_{t=1}^{T} \left(1 + \frac{\sum_{i=1}^{N} w_i R_{it}}{\sum_{i=1}^{N} w_i} \right) - 1 \, .$$

Method 2: On the other hand, the monthly returns for an index as calculated by CRSP, R_m^C is defined as

$$R_m^C = \frac{\sum_{i=1}^{N} w_i \left(\prod_{t=1}^{T} \{1 + R_{it}\} - 1 \right)}{\sum_{i=1}^{N} w_i} \, .$$

Based on the above two methods the authors find that the monthly return R_m^d exceeds the monthly return R_m^C by 0.43% on the average (the average difference is computed by averaging over all months from 1964-1993). This works out to 6% on an annual basis, and corresponds to our observations in Table A.1 for the NYSE-AMEX data. However, we note that this discrepancy is worse for the NASDAQ data and is in the order of 13%.

[2]The reader might be a little puzzled by the use of monthly returns when our focus is on annualized returns. We wish to point that once the presence of bias in monthly returns is understood, the argument easily follows for annualized returns.

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