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Chasing trends: recursive moving average trading rules and internet stocks

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Abstract

The recent rise and fall of Internet stock prices has led to popular impressions of a speculative bubble in the Internet sector. We investigate whether investors could have exploited the momentum in Internet stocks using simple moving average (MA) trading rules. We simulate real time technical trading using a recursive trading strategy applied to over 800 moving average rules. Statistical inference takes into account conditional heteroscedasticity and joint dependencies. No evidence of significant trading profits is found. Most Internet stocks behave as random walks; this, combined with high volatility, may be the reason for the dismal performance of the moving average rules.

JEL classification: G14
Keywords: Internet stocks; Moving average rules; Recursive strategy; Bootstrap

1. Introduction

Technical analysis is a common tool for predicting asset prices over short horizons. In a survey of London foreign exchange dealers, Taylor and Allen (1992) find that over 90% of respondents use some form of technical analysis to predict returns: moving average (MA) rules are the most popular.

Finance researchers are generally skeptical about the usefulness of technical analysis. In his classic book, *A Random Walk down Wall Street*, Malkiel (1996) dismisses technical analysis as being every bit as scientific as astrology (p. 144). He argues that even a random

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walk can generate "cycles" in stock prices but because these cycles are stochastic, stock prices remain unpredictable.

In recent years, however, researchers have begun to pay more serious attention to technical analysis. This is partly due to an influential paper by Brock et al. (1992) who show that even simple trading rules can generate profits that are both economically and statistically significant. They find that trading rules based on moving averages and trading range breaks significantly outperform a cash benhmark when applied to a century of daily data on the Dow Jones Industrial Average (DJIA) index. Moreover, the profits generated by these simple trading rules cannot be explained by random walk or low-order autoregressive moving average models with time-varying volatilities, suggesting that the profits are neither due to chance nor a compensation for risk. As the DJIA comprises large-capitalization stocks, their results also indicate that weak-form inefficiency may be pervasive in the stock market.

Ready (1997) examines three of the most profitable MA rules reported by Brock et al. and two genetic algorithm trading rules studied by Allen and Karjalainen (1999). His aim was to determine whether these trading rules are able to consistently outperform a buy-and-hold strategy. His data consist of daily returns on the S&P 500 index for non-overlapping 5-year sub-periods between 1970 and 1995. Ready finds that apart from the earliest sub-period (1970–1974), the trading rules generally underperformed the buy-and-hold strategy. Furthermore, adjusting for price slippage due to non-synchronous trading eliminates excess returns in every sub-period.[1] Ready concludes that the MA and genetic algorithm rules were profitable only in the 1960s.

The instability of technical trading rules has been confirmed by a number of other studies. LeBaron (1999) finds that when 10 more years (1988–1999) were added to the original Brock et al. (1992) sample, what was once the consistently best performing trading rule (the 150-day MA rule) failed badly in the most recent decade.

In a similar vein, Sullivan et al. (1999) test whether the best trading rule selected at the end of 1986 for the DJIA continued to perform well over the next 10 years. The y find that the best trading rule to emerge in 1986 from a universe of nearly 8000 technical trading rules is the 5-day MA. In the next decade, however, this rule underperformed the cash benchmark, indicating that the best historical trading rule fails the profitability test in more recent times.

The instability of trading rules is not specific to the U.S. market. Using U.K. data, Mills (1997) finds that MA trading rules outperformed a buy-and-hold strategy only up to 1974 but failed to do so in the following 20 years.

Summarizing the evidence, Jegadeesh (2000) concludes that technical analysis is a method built on weak foundations and that there is no plausible explanation why technical patterns in asset prices should be expected to repeat themselves.

Most studies of technical analysis in stock markets focus on indices such as the DJIA or the S&P 500. In this paper, we use an alternative dataset to explore the usefulness of technical trading rules. Our sample consists of 30 leading Internet stocks that are components of the Amex Inter@active Internet Index, also known as the @NET Index. This is an interesting sample because Internet stocks are a new phenomenon and thus provide researchers with data that are relatively free of data snooping biases. Moreover,

[1] To adjust for "price slippage", Ready (1997) computes returns by assuming trade takes place 1 day after a signal is observed.

the apparent strong momentum in Internet stock prices raises the interesting question of whether investors could have exploited the supposed "inefficiency" via technical analysis. This momentum is clearly seen in Fig. 1a. which plots the @NET index for the period September 25, 1998–January 25, 2002 (the sample period for this study). For comparison, we also plot the S&P 500 index as the overall stock market proxy. Both indices are normalized at 100 as of September 25, 1998.

The spectacular rise of Internet stock prices is clearly evident. From September 25, 1998 to its peak on March 9, 2000, the @NET Index surged by 422%, outperforming the broader market by a whopping 391%. Following the burst of the Internet stock "bubble", the @NET Index lost 79% of its value from March 10, 2000 to the end of the sample period, or a compound average decline of 0.33% a day. In contrast, the S&P registered a loss of just over 30% over the same period.

It is this spectacular rise and fall in Internet stock prices that has led to popular impressions of a speculative bubble in this sector. While it is difficult to mount decisive tests for speculative bubbles (see, e.g., Ofek and Richardson, 2001), the strong momentum

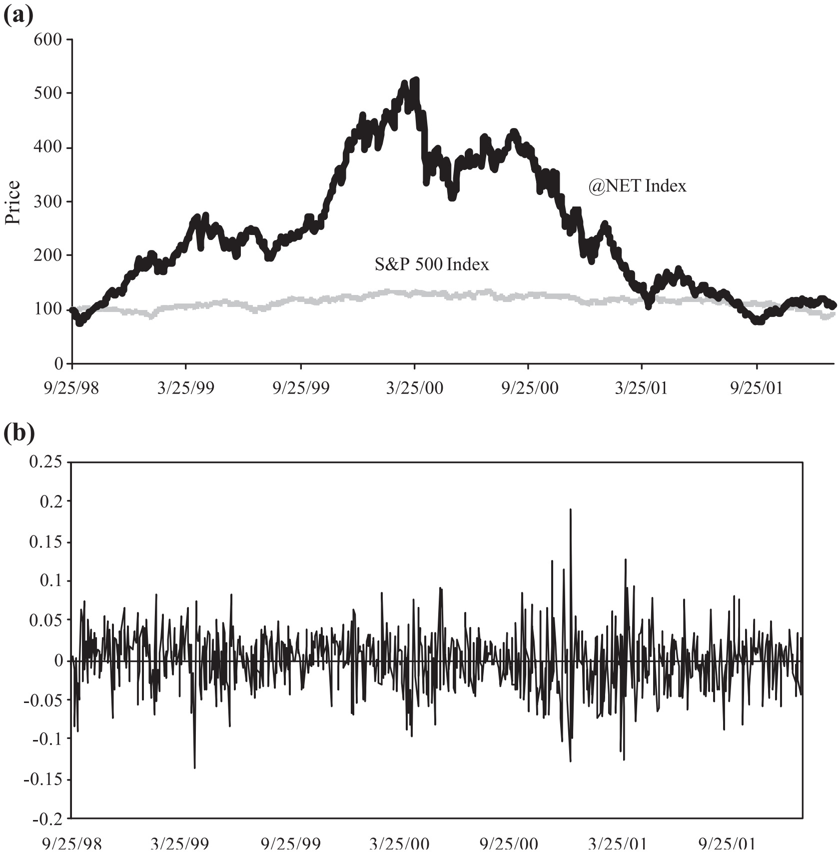


Fig. 1. (a) Normalized S&P 500 and @Net Index (9/25/98–1/25/02). (b) Daily returns of @NET index (9/25/1998–1/25/2002).

in Internet stocks suggests that technical trading rules might be highly profitable for such firms. We test whether this is the case. We focus on rules based on moving averages since surveys of professional traders show that MA rules are very widely used. Moreover, since MA rules have been extensively studied, our study adds directly to this literature.

Our study differs from previous studies of MA rules in several ways. First, while previous studies focus on a small set of MA rules, we draw from a large universe of over 800 MA rules. Sampling from a large universe of rules is important because technical trading rules are basically ad hoc. Second, we do not search for the best ex-post MA rule as do most previous studies since this may lead to data snooping biases.[2] Instead, we implement a simple recursive trading strategy to simulate real-time speculation. Specifically, the investor is assumed to trade each day using the MA rule that is considered "best" using data up to the previous day. Following Sullivan et al. (1999), we define the best MA rule as the rule that has the highest cumulative returns to date. Unlike the standard approach used in the literature, our approach is ex-ante as it allows investors to update their priors about the best trading rule as the information set expands. Our approach also incorporates model uncertainty into the investor's choice of specific trading rules.

This paper is organized as follows. Section 2 discusses the recursive trading methodology, the universe of MA rules considered in this study and transaction cost issues. Section 3 describes the data and presents preliminary descriptive statistics of the data. As a prelude to technical analysis, we test whether Internet stock prices violate the random walk property in having positively autocorrelated returns. Two tests of the random walk are reported in Section 4: the variance ratio of Lo and MacKinlay (1988) and the spectral shape test of Durlauf (1991). Section 5 reports the results of the recursive trading strategy applied to individual stocks in the @Net Index as well as an equal-weighted and value-weighted portfolio of these stocks. The results show that the recursive strategy outperforms a buy-and-buy strategy for some stocks and for the two portfolios before risk-adjustments. Section 6 shows graphically how "optimal" MA rules chosen by the recursive strategy evolve over time. To evaluate the statistical significance of recursive trading profits on a risk-adjusted basis, we report the results of a bootstrap test under the null hypothesis that Internet stock prices follow a random walk with asymmetric time-varying volatility. The bootstrap results (Section 7) show that profits from the recursive strategy can be largely explained by time-varying risk. Section 8 concludes the paper with a summary of the main results.

2. Methodology

2.1. Recursive trading strategy

There are probably an unlimited number of technical trading rules for predicting stock prices and it is tempting to experiment with many of them in search of profitability. This search can lead to data-snooping biases or the uncovering of spurious patterns in asset

[2] When large numbers of trading rules are tested on a given sample, some rules will appear to work by chance even though ex-ante, investors cannot exploit this information.

prices. Sullivan et al. (1999) and Hansen (2001) propose a method to adjust for data-snooping biases in statistical tests involving technical trading rules. These tests are computationally very demanding, however, so data-snooping biases can be corrected for only a finite set of trading rules. Also, by construction, these tests can correct only in-sample data-snooping biases and do not apply to out-of-sample forecasts such as those that we consider.

To mitigate data-snooping biases, we do not search for ex-post successful trading rules. Rather, we assume agents trade recursively using rules that are considered "best performing" based on information up to the previous day. Our methodology departs from the usual one adopted in the literature, which is to apply the same trading rule over a specified sample period. This ex-post approach implicitly gives investors the benefit of hindsight and as demonstrated by Sullivan et al. (1999), results using ex-ante trading strategies may be very different. In contrast, our methodology simulates the experience of technical trading in "real time" and is consistent with the suggestion made by Pesaran and Timmerman (1995) that "as far as possible, rules for predicting stock returns *should* be formulated and estimated without the benefit of hindsight" (p. 102, italics added). Although there are many ways to define an optimal trading rule, the approach we use is based on Sullivan et al. (1999) and is quite simple and intuitive. Specifically, we define the best rule for a particular day as the rule with the highest cumulative return up to the previous day.

The cumulative return criterion is a natural rule-selection criterion for risk-neutral investors. Consider a technical trader whose wealth at time t is W_t. His objective is to maximize expected utility of wealth at the end of the next period by allocating a percentage of wealth, q_t, to a risky asset and the balance in a risk-free asset, which for simplicity, pays zero interest. Let $k \in K$ be a particular trading rule in the class of trading rules, K where k: $\mathbf{P}_t \rightarrow \{-s, 0, l\}$, $\mathbf{P}_t = \{P_t, P_{t-1}, P_{t-2} \ldots P_{t-N+1}\}$ is the price history of the risky asset up to t, t, l $(-s)$ denotes a long (short) position in the risky asset, and 0 denotes a risk-free cash position. As Skouras (2000) shows, a risk-neutral technical trader who solves the recursive problem, $\underset{k \in K}{\operatorname{argmax}} \sum_{t=N}^{t-1} k(\boldsymbol{P_i} k) R_{i+1}$ is using a consistent rule that maximizes his expected utility $E_t\, U(W(1+qR_{t+1}))$ because any predictor with the same sign as the conditional mean is best under risk neutrality. Moreover, under some assumptions on market efficiency bounds with respect to trading rules, the expected profit maximizing rule is also variance minimizing (see Skouras, 2001).

2.2. Moving average rules

We apply our recursive strategy to "crossover" rules based on moving averages of the stock price. Although it is difficult to make a strong case for any particular trading rule, MA rules are very widely used by practitioners and as shown by Neftci (1991), they are one of the few technical trading rules that are statistically well defined in the sense of being Markov-time (i.e., the signals generated are based on only information available to date).[3] Moreover, Brock et al. (1992) and Sullivan et al. (1999) show that historically, MA

[3] Conversely, any trading rule that is not Markov-time would be anticipating the future. As Neftci (1991) shows, many commonly used technical trading rules such as those based on "head-and-shoulder" patterns and trend lines are not Markov-time.

rules have been profitable even for large firms for which market efficiency is generally presumed to hold.[4]

In the simplest form, a MA crossover rule operates on the assumption that buy signals are generated when the current stock price crosses its moving average from below while sell signals are generated when the stock price crosses its moving average from above. The rationale for this interpretation is that a trend is said to have emerged when the stock price penetrates the moving average. Specifically, an upward (bullish) trend emerges when the price rises above its moving average, while a downward (bearish) trend emerges when the price falls below its moving average.

There are numerous variations of this basic crossover rule. For example, buy and sell signals can be detected by the crossover of a long moving average by a short moving average. Another variation is to impose some form of filter to weed out false signals, i.e., signals that would result in losses. A common filter is a fixed percentage band filter to buy only when the buy signal exceeds the moving average by a fixed percentage, say 1%, and sell only when the sell signal falls below the moving average by a specified percentage. Such filters are meant to confirm that a trend is indeed in place before one initiates a trade, thus minimizing the effects of whipsaw price movements.

The ability of a moving average to reveal an underlying price trend depends on the "window" length used in computing the moving average. The longer the window period, the smoother the result ing price trend. A long MA, however, does not respond as quickly to new trend reversals as a short MA. Since the choice of the moving average window is arbitrary, we examine a wide range of window periods.

The MA rules used in this study are expressed as MA (S, L, b, d), where S and L are short and long moving averages, respectively, b is the band filter (equal to 0 or 0.01), and $d=1$ if we trade on the day following the emission of a signal and $d=0$ if we trade on the same day as the signal. We allow for a 1-day lag between a signal and trade as a simple way to control for non-synchronous trading.

There are two aspects of the non-synchronous trading problem. First, if some stocks last trade before the market closes, then as shown by Scholes and Williams (1977), this will impart positive autocorrelation to the returns of a portfolio that includes these stocks with no associated trading opportunity. Second, if orders are positively correlated, as they are likely to be when there is momentum, buy (sell) interest at the close will be followed by more of the same at the next day's opening. Following Ready (1997), we adjust for this potential "price slippage" by using the next day's closing price as a proxy for the first real trading opportunity following the previous day's close.

Most studies of technical analysis examine only a small selection of trading rules on the implicit assumption that the selection is locally representative. However, focusing on a few arbitrarily chosen rules makes results drawn from these studies subject to standard data-mining criticisms. To mitigate this problem, we sample from a much larger universe of trading rules among MA rules. While this still falls short of the full universe of trading

[4] Using data for the Dow Jones index for 1897–1996, Sullivan et al. (1999) report that the best performing trading rule in terms of cumulative return from the Brock et al. universe is the 50-day MA rule. Sampling from a larger universe of 7846 trading rules over the same period, and adjusting for data-snooping, they find that the best performing rule is a 5-day MA.

rules (including rules that have yet to be used), our choice of MA rules is certainly more robust than the ad hoc selection in previous studies.

We define our universe of MA rules by setting $S=1, 5,\ldots,95$ and $L=5, 10,\ldots,100$ in increments of 5 days. For example, when $S=1$, and $L=5$, signals for day t are generated by crossovers of that day's closing price with its 5-day MA. When $S=5$, and $L=50$, the crossover is that of a 5-day MA with the 50-day MA and so on. This defines 210 MA combinations for a given b and d for an overall total of 840 MA rules.

2.3. "Double-or-out" strategy

Following Bessembinder and Chan (1995), we implement a "double-or-out" investment strategy as follows. On a buy signal, the investor borrows at a risk-free interest rate to hold a double long position in the stock. This position is held until a sell signal emerges, upon which one long position is sold and the proceeds are invested in the risk-free security. On days classified as neutral, the investor is assumed to hold one long position in the stock. By construction, the double-or-out strategy does not require the investor to go short on sell signals. This is important since it is both risky and difficult to short sell Internet stocks.[5]

2.4. Transaction costs

Since technical trading may generate very high turnover, it is important to factor in transaction costs. The level of transaction costs incurred depends partly on size of trade (e.g., retail vs. institutional trades). To check the sensitivity of our results to transaction costs, we compute returns using two sets of transaction costs. For retail investors, we assume a single-trip transaction cost of 3%, representing brokerage commissions and bid-ask spreads. This estimate is based on Odean's (1998) study of the average transaction cost incurred by individual investors who trade with a large discount brokerage firm Institutions can trade at much lower cost by paying lower brokerage rates and by trading within quoted spreads. For institutional investors, we assume a single trip cost of 0.5%, which is close to that estimated by Elkins/McSherry (1997), a firm that provides trade execution services for large pension funds, investment banks and brokers. See also Ito (1999).

To evaluate the performance of the recursive strategy, we compare the cumulative returns of the strategy with that of a buy-and-hold investment. The cumulative buy return for each stock is calculated as follows:

$$\mathrm{CBR} = 2\left[\sum_{i=1}^{B} \ln P_{1,i}(1-c/2) - \ln P_{0,i}(1+c/2)\right] - R_f \tag{1}$$

where B is the total number of buy holding periods, $P_{0,i}$ is the price at which the stock is bought at the beginning of the period, $P_{1,i}$ is the price at which the stock is sold at the

[5] The volatility of Internet stocks makes short selling a highly risky strategy. Also, short selling may be difficult given the limited number of shares available for trading in Internet stocks. See Ofek and Richardson (2001, p. 34).

end of the buy period, c is the transaction cost expressed as a percentage of price and R_f is total interest cost over buy periods. The interest rate used is the yield on 3-month Treasury bill.

In sell periods, the investor holds only cash, i.e., Treasury bills. Thus, the cumulative sell return is simply the sum of the daily interest earned:

$$\mathrm{CSR} = \sum_{j=1}^{S} R_{f,j} \tag{2}$$

where S is the total number of sell periods and $R_{f,j}$, is the total interest earned for sell period j.

Finally, on neutral days when no signal is emitted, the investor simply holds a long equity position and the cumulative neutral return is

$$\mathrm{CNR} = \left[\sum_{k=1}^{N} \ln P_{1,k}(1-c/2) - \ln P_{0,k}(1+c/2)\right] \tag{3}$$

where N is the total number of neutral periods, $P_{0,k}$, is the price at which the stock is bought at the beginning of the neutral period, and $P_{1,k}$ and is the price at which the stock is sold at the end of the period. The overall cumulative return of the recursive strategy is simply the sum of the cumulative buy, sell and neutral returns.

3. Data and preliminary analysis

3.1. Data

The data for this study consist of daily prices of the 30 Internet stocks that are components of the Amex Inter@active Week Internet Index, also known as the @Net Index. The @Net Index is value-weighted and is a benchmark measure of the performance of Internet-related firms (Cooper et al., 2001). Index firms include Internet infrastructure and service providers and firms that market Internet content, software and e-commerce. Prominent companies in the index include Cisco Systems, America Online, Yahoo!, Amazon.com and eBay.

The sample period is from September 25, 1998 through January 25, 2002 and comprises 838 daily closing prices of all firms with a continuous listing record. This sample period includes both bull and bear markets. The bull market period runs from the start of the sample to March 9, 2000, when the @NET Index rose by 422%. The bear market period, which is the remainder of the sample, saw the @NET Index decline by 79%. All prices for this study come from Bloomberg and are adjusted for dividends, new issues and stock splits. The names of the 30 stocks and some summary statistics are given in Table 1.

As Table 1 shows, the @Net Index comprises relatively large firms. The median market capitalization is \$1567 million. Only four firms have market values of less than \$500 million. They are: Broadcom, DoubleClick, Internet Security Systems and tellant. Most

Table 1
List of internet stocks

Name of firm	Ticker symbol	Market cap (US$ millions)	Average daily volume	Buy-and-hold return (%)
Amazon.com	AMZN	5448	9,083,202	– 17.58
America Online	AOL	25,213	18,139,685	96.08
BEA Systems	BEAS	1684	7,000,152	224.16
Broadcom	BRCM	392	6,654,573	116.80
Check Point Software Technologies	CHKP	786	4,334,411	827.29
CIENA	CIEN	1467	11,427,933	93.44
CheckFree	CKFR	554	968,556	60.44
CNET Networks	CNET	667	1,801,714	– 22.95
3Com	COMS	11,496	7,476,930	79.93
Cisco Systems	CSCO	103,299	46,002,285	17.84
DoubleClick	DCLK	375	3,142,176	119.29
eBay	EBAY	1783	4,702,609	668.13
EarthLink Network	ELNK	1064	1,691,107	– 62.45
E*TRADE Group	ET	1015	4,936,656	132.77
Intuit	INTU	2666	2,699,729	178.54
Internet Security Systems	ISSX	460	1,005,106	148.34
i2 Technologies	ITWO	1100	6,113,671	86.40
Level 3 Communications	LVLT	10,459	3,737,596	– 87.36
Network Associates	NETA	5104	3,710,077	– 29.51
Novell	NOVL	4335	4,901,627	– 58.01
Qwest Communications International	Q	3554	6,837,262	456.93
QUALCOMM	QCOM	3554	11,870,671	75.27
RealNetworks	RNWK	982	2,169,204	704.00
RSA Security	RSAS	501	1,012,317	454.97
Siebel Systems	SEBL	2221	7,836,073	45.22
Stellant	STEL	30	337,726	– 12.09
Sun Microsystems	SUNW	19,982	25,918,112	664.52
Symantec	SYMC	775	1,436,902	– 36.05
VeriSign	VRSN	625	4,791,899	– 35.17
Yahoo!	YHOO	12,992	10,201,900	413.63

All stocks are listed on Nasdaq (ticker symbols are in the second column). The third column shows each firm's market capitalization as of the start of the sample period (September 25, 1998). Average daily trading volume and buy-and-hold returns are computed over the entire sample period (September 25, 1998–January 25, 2002).

firms trade actively. The median trading volume is 4.8 million shares a day, which is about half the average number of shares traded daily for Yahoo!, one of the most popular Internet stock. A total of 23 firms have higher average daily trading volume than the median firm. As expected, the smaller firms tend to have lower trading volume. Overall, this is a sample of large and liquid Internet firms. The high volume indicates that the quoted Internet prices are real, that is, investors could easily trade large number of shares at these prices.[6]

[6] It is not clear whether the high volume is due to a few investors trading among themselves or a large number of investors. There is, however, some evidence to suggest that the Internet sector attracts more retail than institutional interests. See Ofek and Richardson (2001).

3.2. Descriptive statistics

Table 2 presents summary statistics for the stocks in our sample. Note that the summary statistics are cross-sectional averages of the 30 Internet stocks. Panel A reports statistics for the full sample period. Statistics for the bull and bear subperiods are shown in Panels B and C, respectively.

Over the full sample period, the average daily continuously compounded return of the typical Internet stock was 0.06% (15.1% annualized). An investor who purchased and held an equal-weighted portfolio of the 30 stocks from the beginning through the end of the sample period would have seen his wealth increased by 171.4%. To put this into perspective, old economy stocks as represented by the S&P 500 index actually fell by 7.8% during the sample period. Of the 30 Internet stocks, 20 outperformed the S&P 500,

Table 2
Descriptive statistics

1	2 Mean daily return	3 Standard deviation of daily return	4 Buy-hold return		5 Variance ratio at lags 2	4	8	12	6 No. of stocks rejecting RW null
Panel A. Full sample (9/12/98–1/25/02)									
Average	0.0006	0.0607	1.714	Average	1.003	0.965	0.939	0.919	5
					(0.467)	(0.498)	(0.478)	(0.596)	
Min	−0.0025	0.0407	−0.874	EW	1.121*	1.107	1.104	1.091	
					(0.008)	(0.214)	(0.436)	(0.589)	
Max	0.0027	0.0799	8.273	VW	1.050	1.045	1.055	1.030	
					(0.253)	(0.582)	(0.658)	(0.849)	
Panel B. Bull market (9/25/98–3/9/00)									
Average	0.0057	0.0560	8.971	Average	1.014	0.996	0.942	0.891	1
					(0.488)	(0.569)	(0.516)	(0.493)	
Min	−0.0007	0.0286	−0.246	EW	1.321*	1.464*	1.426*	1.319	
					(0.000)	(0.000)	(0.022)	(0.161)	
Max	0.0097	0.0762	34.67	VW	1.198*	1.319*	1.292	1.132	
					(0.000)	(0.004)	(0.098)	(0.546)	
Panel C. Bear market (3/10/00–1/25/02)									
Average	−0.0032	0.0675	−0.687	Average	0.991	0.926	0.898	0.873	3
					(0.512)	(0.471)	(0.528)	(0.548)	
Min	−0.0072	0.0367	−0.966	EW	1.042	0.950	0.916	0.883	
					(0.456)	(0.638)	(0.616)	(0.581)	
Max	−0.0001	0.0887	−0.052	VW	0.982	0.906	0.886	0.846	
					(0.752)	(0.370)	(0.476)	(0.442)	

The sample period is from September 25, 1998 through January 25, 2002 (838 observations). Daily returns are continuously compounded and are reported as decimals. "Average" refers to cross-sectional mean of the 30 @NET Index component stocks. Column 5 presents variance ratio statistics for selected lags (p-values in parentheses). EW and VW denote equally weighted (value-weighted) portfolio of the 30 stocks. The last column shows the number of stocks that reject the random walk null according to the variance ratio test.

* Statistic is significant at 5%.

and 13 firms registered cumulative returns of more than 100%. The best performing stock was Check Point Software, whose stock price rose by 827%.

While the full-sample returns of the Internet stocks are impressive, their performance in the bull market period is even more breathtaking. The average daily return of the 30 stocks during this period was 9.5 times higher than the average return over the entire sample period. An equal-weighted portfolio of the 30 stocks held over this period produced a cumulative return of 897%, compared to only 30.5% for the S&P 500. The best-performing stock during the bull market period was VeriSign, an Internet infrastructure firm whose stock price soared by 3467%.

Panel C summarizes performance statistics for the bear market period (March 10, 2000 to January 25, 2002). Every one of the 30 Internet stocks experienced a decline in stock price, with cumulative losses ranging from 5.2% to 96.6%. Reflecting the severity of the correction, 25 stocks lost more than half of their values after the peak of the market. By the end of the sample period, stock prices of 10 firms were below where they started.

Table 2 also shows that the returns of Internet stocks were extremely volatile. For the full sample period, the average standard deviation of the 30 stocks was 6.07%. This translates into an annual standard deviation of 96.36%, making the typical Internet stock almost five times as volatile as the S&P 500 portfolio.[7] As noted by Schwert (2001), this high volatility is not specific to the Internet sector but is true of technology firms in general. Consistent with previous studies, e.g., Pagan and Sossounov (2000), stock volatility is higher during the bear market period than in the bull market period.

4. Random walk tests

4.1. Variance ratio test

Technical trading rules are designed to exploit momentum in stock prices. For trading trading rules to be effective, stock prices should diverge from a random walk in that their returns should exhibit significant positive autocorrelations. As a prelude to technical analysis, it is therefore interesting to ask whether Internet stock prices do violate weak-form efficiency.

A simple and intuitive test for the random walk property is the variance ratio test of Lo and MacKinlay (1988). If stock prices follow random walks, the variance of kth-period

[7] The high volatility of Internet stocks may be due to several factors: (a) high rate of information arrival, reflecting rapid changes in technology and tastes, (b) heterogeneous opinions about the value of Internet firms as in Varian (1987) and Kandel and Pearson (1995), (c) a high degree of estimation risks as in Lewellen and Shaken (2000), (d) heterogeneity in private information as in Grundy and Kim (2002) and (e) noise trading as in De Long et al. (1990) and Frey and Stremme (1993). LeBaron (1992) finds that daily and weekly autocorrelations stock returns are inversely related to volatility. Thus, stocks are less predictable when volatility is high. This is consistent with the idea that high volatility reflects significant disagreements among investors over the interpretation of public information. See also Dacorogna et al. (2001) and Antweiler and Frank (2002).

returns should be k times the variance of single period returns; that is, the following variance ratio statistic should equal one:

$$\mathrm{VR}(k) = \left(\frac{1}{k}\right)\left(\frac{var(r_t^k)}{var(r_t)}\right) \tag{4}$$

where r_t^k is k-period return on day t and r_t is the return on day t. Lo and MacKinlay (1988) show that VR(k) can be written as a weighted average of the first $k-1$ autocorrelation coefficient estimators, where the weights are linearly declining. Specifically,

$$\mathrm{VR}(k) = 1 + \frac{2(k-1)}{k}\widehat{\rho}_1 + \frac{2(k-2)}{k}\widehat{\rho}_2 + \ldots + \frac{2}{k}\widehat{\rho}_{k-1} \tag{5}$$

where ρ_j is the jth-order autocorrelation coefficient of the daily returns. Roll (1984) shows that a bid-ask bounce effect can cause the first-order autocorrelation in returns to be negative, assuming bid-ask errors are identically and independently distributed. This implies that even if stock prices follow random walks, the variance ratio at lag one will be less than one. Using a direct measure of bid-ask errors, Kaul and Nimalendran (1990) find that bid-ask errors are negatively autocorrelated for only the first lag but are serially uncorrelated for higher lags, which is consistent with Roll's conjecture that the bid-ask effect is independently distributed over time. For our sample, the bid-ask bias does not appear to be a major problem as only two stocks show significant first order autocorrelations (of which one is actually positive).[8]

Column 5 of Table 2 reports variance ratio statistics for lags of 2 to 12 days. The variance ratios are heteroscedastic-consistent (see Theorem 2.3 in Lo and MacKinlay, 1988) and are adjusted for small-sample bias according to the adjustment factor proposed by Kaul and Nimalendran (1990).[9] The first row in column 5 reports the average of variance ratio statistics across the 30 stocks.

Because returns of individual firms may have a high idiosyncratic noise component, we also compute variance ratios for two portfolios. The first portfolio is a value-weighted (VW) portfolio constructed using the market value of the 30 firms at the start of the sample period (September 25, 1998). The second portfolio is an equal-weighted (EW) portfolio that applies a weight of 1/30 to each stock with daily rebalancing to maintain equal weights.[10]

[8] The two stocks are Network Associates: $\rho_1 = 0.093$ (p-value: 0.047) and Novell: $\rho_1 = -0.091$ (0.025). The average first order autocorrelation for the 30 stocks is 0.00039 (0.449). All p-values are adjusted for ARCH effects. See Diebold (1988).

[9] The small sample bias causes variance ratios to be downward biased. Moreover, the bias increases when the measurement interval, k, increases with the sample size.

[10] The first-order autocorrelation for the EW and VW portfolios are 0.12 (p-value 0.01) and 0.046 (0.29), respectively. Positive autocorrelations do not necessarily imply that index returns are tradeable (the market inefficiency interpretation) since nonsynchronous trading of component stocks may explain between anywhere between 36% and 85% of the serial correlation as shown by Kadlec and Patterson (1999). Also, Ahn et al. (2002) show that stale price quotes provide a more convincingly explanation of positive portfolio autocorrelations at the daily interval than explanations based on irrational pricing.

Three aspects of the variance ratio test results are worth noting. First, for the entire sample period, the average VR(2) statistic is 1.003, implying that the returns for a typical Internet stock display weak positive first-order autocorrelation. Interestingly, the sign of the autocorrelation is the opposite of what one would expect if returns are affected by the bid-ask bounce effect.

Second, there is little evidence against the random walk model for individual stocks. On average (i.e., across the 30 stocks), variance ratios for all lags are not statistically different from one, even at 10%. Furthermore, beyond lag two, variance ratios decline monotonically below 1.0, indicating that violations of the random walk property (if any), are due to negative rather than positive autocorrelations. Finally, the last column of Table 2 indicates that only five stocks deviate from the random walk for the entire sample period and no more than three stocks for the two subperiods.[11]

Third, as expected, the two portfolios show more evidence of deviations from the random walk. Closer inspection of Table 2, however, reveals that departures from the random walk occur mainly in the bull market period, where both portfolios show significant positive autocorrelations.

In summary, the variance ratio test results indicate that trend chasing strategies are unlikely to be effective for individual stocks, but might be profitable for portfolios in the bull period.

4.2. Spectral shape tests

It is well known that the variance ratio test has low asymptotic power against a variety of mean-reverting alternatives (Lo and MacKinlay, 1989; Deo and Richardson, 2001). An alternative test that may be more powerful against such alternatives is the spectral shape test proposed by Durlauf (1991).

Spectral shape tests take advantage of the fact that under the random walk null hypothesis, the spectral distribution function of returns is linear. Thus, deviations of the sample spectral distribution from a straight line may be used to test for the presence of serial correlation.

Durlauf (1991) introduces four spectral shape test statistics to test the random walk null, all of which are functionals of the normalized difference between the sample and theoretical spectral distribution functions. We apply one of these statistics, namely the Anderson–Darling (AD) statistic. The AD statistic can be expressed as:

$$\mathrm{AD} = \int_0^1 \frac{U_n^2(t)}{t(1-t)}\,\mathrm{d}t \qquad t\epsilon(0,1) \tag{6}$$

where

$$U_n(t) = \sqrt{2n}\int_0^{\pi t}\left[\frac{I_k(\lambda)}{\hat{\sigma}^2} - \frac{1}{2\pi}\right]\mathrm{d}\lambda \tag{7}$$

[11] Of the five stocks that reject the random walk null, two are due to positive autocorrelations at VR(2) and three are due to negative autocorrelations at VR(4).

Table 3
Results of spectral shape test

Period	AD statistic	No. of stocks rejecting RW null
Full sample (9/25/98–1/25/02)		6
Average	1.22 (0.383)	
EW	4.31 (0.005)*	
VW	0.953 (0.32)	
Bull market (9/25/98–3/9/00)		1
Average	0.80 (0.525)	
EW	12.40 (0.00)*	
VW	5.89 (0.001)*	
Bear market (3/10/00–1/25/02)		1
Average	1.04 (0.426)	
EW	1.13 (0.247)	
VW	0.521 (0.615)	

This table reports results of the Anderson–Darling (AD) test of the martingale hypothesis for 30 @NET Index component stocks. The sample period is from September 25, 1998 to January 25, 2002 (838 observations). The AD statistic is $\int_0^1 \frac{U_n^2(t)}{t(1-t)}\mathrm{d}t$ where $U_n(t)$ is the cumulative deviation of the standardized periodogram from $1/2p$ (the value under the null) and is computed using a quadratic kernel with bandwidth vn. The p-values (in parentheses) are based on the finite sample distribution of the AD statistic reported in Appendix A. "Average" refers to the cross-sectional mean and EW and VW denotes equally weighted (value-weighted) portfolio of the 30 stocks.

* Denotes statistical significance at 1%.

n is the sample size and

$$\frac{I_k(\lambda)}{\hat{\sigma}^2} = \frac{1}{2\pi}\sum_{j=-(k-1)}^{k-1} w_k(j)\rho_j\cos\lambda j \tag{8}$$

is the standardized periodogram at Fourier frequency λ, $w_k(j)$ is a sequence of declining weights, symmetric about zero and $w_k(0)=w_{k\rightarrow\infty}(j)=1$ for all j.

The intuition behind the AD statistic is as follows. If stock returns are a martingale difference series, the normalized spectral density function of returns, $f(\lambda) = \frac{1}{2\pi}\sum_{j=-\infty}^{\infty}\rho_j\cos(\lambda j)$ is a constant equal to $1/2\pi$. The AD statistic is simply the cumulative deviations of the standardized periodogram from its value under the null, where the standardized periodogram is a consistent estimator of $f(\lambda)$.[12]

Under standard regularity conditions, Durlauf (1991) shows that $U_n(t)$ converges to a Brownian bridge under the null. Conversely, $U_n(t)$ and by extension, the AD statistic are consistent against any stationary alternative to the random walk.[13] We apply a hetero-scedastic-robust version of the AD statistic due to Deo (2000). Details of this statistic are given in Appendix A where we also report the results of a simulation study showing that

[12] Note that the AD statistic uses the *cumulative* periodogram deviations rather than simply the periodogram deviations because it is well known that the periodogram is an inconsistent estimate of the spectral density function (see Priestley, 1981). Thus, periodogram deviations will not converge to a rectangle. The cumulative deviations, however, will converge under the null due to the averaging of individual frequency estimates.

[13] Unlike the variance ratio test in which the asymptotic sampling theory requires the autocorrelation lags (q) to increase with n but at a much slower rate, the limiting distribution for the spectral shape statistics is invariant to the choice of the lag weight sequence since it washes out asymptotically.

the AD test has good size under the random walk null and is generally more powerful against popular mean-reverting alternatives as compared to the variance ratio test.[14]

Table 3 reports the AD test statistic along with finite sample *p*-values obtained by simulations.

Results of the AD test are consistent with the variance ratio test results. Specifically, the random walk null hypothesis is not rejected for most stocks. As before, the portfolios show more evidence against the random walk, with the EW portfolio displaying more predictability than the VW portfolio (especially in the bull market period). In the bear market period, however, both portfolios follow random walks.

5. Performance of the recursive trading strategy

5.1. Full sample results

Table 4 presents the cumulative returns of the recursive strategy for the full sample period. Cumulative returns are in decimals and are net of transaction cost of 0.5% single trip. Panel A presents the results for all 30 stocks, grouped according to firm size (the average of each firm's market capitalization at the beginning and end of the sample period). Group 1 consists of the smallest firms while Group 3, the largest. The last three rows in Panel A summarize the profitability of the recursive strategy across all stocks.

As shown in the third-to-last row of Panel A, the average cumulative return across all 30 stocks is negative. The average cumulative return for same day trade and no band filter is − 30.2%. There appears to be no systematic effects of applying the 1-day trade delay or the band filter on profitability.

It is interesting to note that larger firms (Group 3) performed better than smaller firms, contradicting the notion that the market for small firms is less efficient than for large firms. The average cumulative return of Group 3 stocks is 63.2% with no trade delay. It ranges from 47.7% to 85.9% for other trade configurations. In contrast, stocks in Groups 1 and 2 incurred cumulative losses of between − 44.6% and − 109.3%, respectively.

A natural benchmark for evaluating the performance of the recursive trading rule is the return obtained from a buy-and-hold strategy. We therefore compute excess returns by subtracting each stock's buy-and-hold return from the cumulative return of the recursive strategy. Note that this way of evaluating the performance of technical trading rules uses each stock as its own risk control and addresses the fact that all asset pricing models are incomplete.

The second-to-last row of Panel A shows that no more than 10 stocks outperformed the buy-and-hold strategy. We use a two-tailed Wilcoxon test to assess whether there is a

[14] For the size experiment, the null model is the random walk with EGARCH(1,1) errors to capture volatility asymmetry, an important feature of stock returns (see Pagan and Schwert, 1990; Bekaert and Wu, 2000). The simulation results show that the AD statistic has good size properties under this null when the sample is reasonably large, e.g., 800, roughly the same as the entire sample period of this study. For power, we simulate two interesting alternatives to the random walk: a "short memory" AR(1) model in returns and a "long memory" fractionally integrated model. The results show that the AD test compares favorably with the variance ratio test for both of these alternatives.

Table 4
Cumulative returns of recursive strategy (full sample period)

Panel A	Stocks			
	Lag = 0		Lag = 1	
Filter	0%	1%	0%	1%
Group 1				
STEL	– 0.288	– 1.882	– 0.320	– 2.681
DCLK	– 1.449	– 1.518	– 1.001	0.123
RSAS	– 0.389	– 1.618	0.074	– 2.796
CNET	– 0.999	– 3.111	1.178	– 1.359
ELNK	– 0.685	– 1.616	0.486	– 1.880
CKFR	– 2.272	– 0.464	– 1.083	0.303
CIEN	3.544	1.272	3.116	– 0.078
ET	– 2.201	– 1.404	– 1.496	– 1.147
ITWO	0.295	2.296	0.704	2.177
SYMC	– 0.017	0.138	0.452	– 0.182
	– 0.446	**– 0.791**	**0.211**	**– 0.752**
Group 2				
ISSX	– 1.499	– 0.112	– 2.876	0.400
NOVL	– 2.120	– 1.541	– 2.876	– 1.188
AMZN	– 1.858	– 2.766	– 0.933	– 2.777
RNWK	– 0.278	0.771	– 0.305	0.930
VRSN	– 0.862	0.729	– 1.004	– 1.345
LVLT	– 3.284	– 1.264	– 3.219	– 1.288
BRCM	– 0.480	– 1.768	– 1.627	– 1.773
INTU	0.052	– 1.604	– 2.500	
SEBL	1.714	2.140	1.436	0.294
COMS	– 2.313	– 2.094	– 2.033	– 2.053
	– 1.093	**– 0.75**	**– 1.336**	**– 1.130**
Group 3				
CHKP	2.714	2.046	3.115	3.157
BEAS	3.205	5.172	2.961	4.947
YHOO	0.082	– 1.793	– 0.326	– 2.972
NETA	– 1.195	0.784	– 1.288	0.615
Q	0.106	– 2.120	0.319	– 2.466
EBAY	– 3.117	– 0.526	– 2.991	– 0.328
QCOM	3.728	2.657	3.917	2.178
SUNW	0.430	1.275	0.801	0.962
AOL	0.244	1.428	0.070	– 0.776
CSCO	0.125	– 0.329	– 0.163	– 0.542
	0.632	**0.859**	**0.642**	**0.477**
Average (all stocks)	**– 0.302**	**– 0.227**	**– 0.161**	**– 0.468**
No.>BH	7	10	9	7
Wilcoxon test	– 2.50	– 1.94	– 1.92	– 2.60
	(0.016)	(0.052)	(0.055)	(0.01)

Table 4 (*continued*)

Panel B	Portfolios			
	Lag = 0		Lag = 1	
Filter	0%	1%	0%	1%
VW portfolio	− 0.615	0.196	− 0.608	0.244
EW portfolio	− 1.321	0.020	− 1.636	0.158

The sample period is 25/09/98–25/01/02 (838 observations). Panel A reports cumulative returns of 30 Internet stocks (all returns are in decimal form). Cumulative returns are net of transaction cost of 0.5% single-trip, with and without 1-day lag after a trading signal is observed and with and without a 1% band filter. Stocks are sorted into three groups of 10 stocks each based on their average market capitalization at the start and end of period. Group 1 (Group 3) stocks are the smallest (largest) in terms of market capitalization. Figures in bold denote group averages. "No.>BH" is the number of firms with cumulative returns exceeding a buy-and-hold strategy. The Wilcoxon test statistic is a two-tailed test of difference in median cumulative returns between the recursive strategy and the buy-and-hold strategy. Panel B reports excess cumulative returns (over a buy-and-hold investment) of an equal-weighted (EW) and value-weighted (VW) portfolio. Portfolio returns are net of transaction cost of 0.25% single trip.

significant difference in median cumulative return between the recursive and buy-and-hold strategy. The results, shown in the last row of Panel A, indicate that the median cumulative return is significantly *lower* under the recursive strategy than under the buy-and-hold strategy.

It is also interesting to evaluate the performance of the recursive strategy against a fixed MA strategy that applies the same MA rule over the entire sample (i.e., the usual way in which technical trade rules are tested in the literature). Given the high volatility of Internet stocks, we focus on two fixed MA rules that use only 1 to 2 weeks of data to define the price trend. The two fixed MA rules are: MA(1,5) and MA(1,10) where the long moving average is 5 and 10 market days, respectively. Results show that these rules produced marginally positive cumulative returns and thus outperform the recursive strategy. Their performance, however, still trails far behind that of the buy-and-hold strategy.[15]

Idiosyncratic noise in individual stock returns makes it difficult to detect the presence of predictable components in stock returns. To investigate whether idiosyncratic risks stand in the way of technical trading profits, we also apply the recursive strategy to the two portfolios. Panel B reports the portfolio results in the form of excess cumulative returns over a buy-and-hold strategy. The portfolio returns are computed net of transaction cost of 0.25% single trip to simulate the cost of trading an equity index fund.[16]

As expected, the portfolio results are more positive than those for individual stocks. With the 1% band filter, both portfolios outperformed their respective buy-and-hold benchmarks for all periods. With same-day execution, the excess cumulative return is

[15] Specifically, the average (across 30 stocks) cumulative returns from implementing these two fixed MA rules with a 1% band filter are 0.1% and 22.8%, respectively, while the average buy-and-hold return for the 30 stocks is 171%. Of the 30 stocks, only 10 outperformed the buy-and-hold strategy under the MA(1,5) rule while 12 outperformed the buy-and-hold strategy under the MA(1,10) rule. All returns are computed net of transaction cost of 0.5% per one-way trip.

[16] The 0.25% single trip transaction cost is approximately equal to the sum of online commissions and bid-ask spread for buying and selling a $10,000 investment in an actively traded stock index fund. See Dellva (2001).

Table 5
Cumulative returns of recursive strategy (bull market)

Panel A	Stocks			
	Lag = 0		Lag = 1	
Filter	0%	1%	0%	1%
Group 1				
STEL	2.341	1.365	1.973	1.570
NOVL	− 0.108	− 0.136	− 0.428	0.184
RSAS	1.348	1.529	1.344	1.117
SYMC	0.536	0.671	0.864	0.565
ISSX	− 0.804	− 1.092	− 1.400	− 1.494
CKFR	0.229	1.121	0.714	1.973
NETA	− 0.231	0.805	0.114	0.308
SEBL	0.861	0.510	0.968	− 0.014
RNWK	2.083	1.912	2.736	2.286
ITWO	1.959	3.847	1.653	2.493
	0.821	**1.053**	**0.854**	**0.899**
Group 2				
INTU	0.165	0.059	0.226	− 0.096
AMZN	0.160	− 0.542	0.441	− 0.453
ELNK	0.132	− 0.184	0.060	− 1.063
DCLK	1.735	1.472	2.237	2.743
BEAS	2.899	4.066	2.525	3.665
CIEN	3.650	3.242	2.851	1.698
CNET	0.278	1.263	1.894	2.116
LVLT	0.858	1.357	0.871	1.651
EBAY	− 0.692	− 0.584	− 0.791	− 0.056
CHKP	2.180	3.079	2.399	3.542
	1.136	**1.323**	**1.271**	**1.375**
Group 3				
BRCM	0.376	1.592	− 0.065	1.820
VRSN	1.648	5.157	1.455	4.054
ET	− 1.748	− 1.079	− 0.604	− 0.695
QCOM	3.454	4.889	3.786	5.084
COMS	0.412	1.099	0.324	1.133
Q	1.158	− 0.998	1.288	− 1.206
YHOO	0.640	0.254	0.517	− 0.113
SUNW	1.117	2.426	1.614	2.246
AOL	0.208	1.100	0.432	0.885
CSCO	0.204	1.822	− 0.015	1.185
	0.747	**1.626**	**0.873**	**1.439**
Average (all stocks)	**0.902**	**1.334**	**0.999**	**1.238**
No. > BH	6	9	7	8
Wilcoxon test	− 3.75	− 2.21	− 3.73	− 2.70
	(0.00)	(0.00)	(0.00)	(0.01)

Table 5 (*continued*)

Panel B	Portfolios			
	Lag = 0		Lag = 1	
Filter	0%	1%	0%	1%
VW portfolio	− 1.425	0.194	− 1.653	− 0.020
EW portfolio	− 1.011	0.549	− 0.839	0.137

The sample period is 25/09/98–3/9/00 (367 observations). Panel A reports cumulative returns of 30 Internet stocks (all returns are in decimal form). Cumulative returns are net of transaction cost of 0.5% single-trip, with and without 1-day lag after a trading signal is observed and with and without a 1% band filter. Stocks are sorted into three groups of 10 stocks each based on their average market capitalization at the start and end of period. Group 1 (Group 3) stocks are the smallest (largest) in terms of market capitalization. Figures in bold denote group averages. "No.>BH" is the number of firms with cumulative returns exceeding a buy-and-hold strategy. The Wilcoxon test statistic is a two-tailed test of difference in median cumulative returns between the recursive strategy and the buy-and-hold strategy. Panel B reports excess cumulative returns (over a buy-and-hold investment) of an equal-weighted (EW) and value-weighted (VW) portfolio. Portfolio returns are net of transaction cost of 0.25% single trip.

19.6% for the VW portfolio and 2.0% for the EW portfolio. Applying a 1-day trade delay increases the excess profits to 24.4% and 15.8%, respectively.[17]

5.2. Sub-period results

Results for the bull market period from September 1998 through March 2000 are shown in Table 5. Panel A shows that for individual stocks, the recursive strategy is generally profitable over this period. On average, cumulative returns are higher if trades are executed a day after signals are observed. The same effect is achieved by using a 1% band filter, indicating that the filter is able to weed out false signals during this period. With the band filter, Group 3 firms (largest market size) performed best, followed by intermediate-sized firms (Group 2). Similar to the full sample results, returns were lowest for the smallest firms across most trade configurations.

Despite the apparent good performance of the recursive strategy, an investor is generally better off with a buy-and-hold strategy. Table 5 shows that no more than nine firms outperformed the buy-and-hold benchmark. Moreover, the Wilcoxon test indicates that the median firm significantly underperformed this benchmark across all trade configurations. This implies that the distribution of relative cumulative returns is highly left-skewed and that the odds of beating the buy-and-hold strategy were clearly stacked against the investor.

Portfolio results (Panel B) are more encouraging. With same-day execution and the band filter, the excess cumulative returns of the VW (EW) portfolio is 19.4% and 54.9%, respectively. Since the bull market period spans 367 trading days, these results imply an annualized excess return of 12.1% for the VW portfolio and 29.8% for the EW portfolio, respectively. Profitability, however, is sensitive to the filter and timing of trades. Using a 1-day trade delay during this period significantly diminishes excess profits and in fact

[17] We also applied the two fixed MA rules, MA(1,5) and MA(1,10), to the portfolios. The cumulative returns for the EW (VW) portfolios are 75% and 9.74%, respectively, compared to a buy-and-hold return of 72.4% (17.52%) for the EW (VW) portfolios. Returns are calculated net of transaction cost of 0.25% single trip.

Table 6
Cumulative returns of recursive strategy (bear market)

Panel A	Stocks			
	Lag = 0		Lag = 1	
Filter	0%	1%	0%	1%
Group 1				
STEL	2.213	0.110	0.469	0.007
ELNK	− 1.341	0.088	− 1.730	− 0.323
SYMC	0.433	1.724	0.446	1.380
NOVL	− 2.099	− 1.688	− 2.384	− 1.826
CKFR	− 1.311	− 0.305	− 0.708	− 0.180
CNET	− 0.861	− 0.863	− 0.872	− 1.317
LVLT	− 2.169	− 2.667	− 2.113	− 2.987
EBAY	0.746	0.086	0.545	0.460
DCLK	− 2.485	− 2.843	− 2.160	− 2.268
ISSX	− 1.645	− 2.245	− 1.885	− 2.305
	− 0.852	**− 0.860**	**− 1.039**	**− 0.936**
Group 2				
ET	− 0.698	− 0.811	− 1.293	− 0.977
RSAS	− 0.646	0.605	− 0.944	0.686
ITWO	1.739	− 0.020	0.101	0.845
CHKP	− 0.117	0.772	0.563	0.690
BEAS	2.099	1.263	2.756	1.153
COMS	− 0.873	− 0.554	− 0.902	− 0.407
SEBL	0.603	0.260	0.374	0.310
INTU	− 0.935	− 0.456	− 0.387	0.161
RNWK	1.690	− 1.641	0.541	− 2.393
NETA	0.035	1.161	0.329	1.838
	0.290	**0.058**	**0.114**	**0.191**
Group 3				
VRSN	0.419	− 0.527	− 0.704	− 0.578
YHOO	− 0.761	− 0.996	− 0.929	− 1.026
CIEN	0.917	1.144	0.426	1.326
AMZN	− 0.618	− 2.710	− 1.172	− 2.769
Q	0.550	0.182	0.503	0.300
BRCM	− 0.061	1.276	− 0.372	1.283
QCOM	0.505	0.913	0.435	0.443
SUNW	− 0.054	− 0.103	− 0.164	− 0.594
AOL	0.461	− 1.028	0.228	− 2.125
CSCO	0.769	0.529	0.609	0.475
	0.213	**− 0.132**	**− 0.114**	**− 0.326**
Average (all stocks)	**− 0.117**	**− 0.311**	**− 0.346**	**− 0.357**
No.>BH	25	24	24	25
Wilcoxon test	4.62	3.73	4.08	3.51
	(0.00)	(0.00)	(0.00)	(0.00)

Table 6 (*continued*)

Panel B	Portfolios			
	Lag = 0		Lag = 1	
Filter	0%	1%	0%	1%
VW portfolio	1.077	1.163	1.000	1.007
EW portfolio	1.105	1.244	1.032	1.172

The sample period is 3/10/00–1/25/02 (471 observations). Panel A reports cumulative returns of 30 Internet stocks (all returns are in decimal form). Cumulative returns are net of transaction cost of 0.5% single-trip, with and without 1-day lag after a trading signal is observed and with and without a 1% band filter. Stocks are sorted into three groups of 10 stocks each based on their average market capitalization at the start and end of period. Group 1 (Group 3) stocks are the smallest (largest) in terms of market capitalization. Figures in bold denote group averages. "No.>BH" is the number of firms with cumulative returns exceeding a buy-and-hold strategy. The Wilcoxon test statistic is a two-tailed test of difference in median cumulative returns between the recursive strategy and the buy-and-hold strategy. Panel B reports excess cumulative returns (over a buy-and-hold investment) of an equally weighted (EW) and value-weighted (VW) portfolio. Portfolio returns are net of transaction cost of 0.25% single trip.

produces a negative excess return of 2% for the VW portfolio. As with individual stocks, investors who traded the portfolios without the filter consistently underperformed the buy-and-hold strategy.

The bull market period is the highlight of this study. It is during this period that Internet stocks showed very strong momentum, reflecting the market's euphoria over new economy firms. Yet, as our results show, investors who relied on moving average rules to beat the market would have been largely disappointed. This is true for individual stocks as well as the portfolios. Although portfolio returns show significant positive autocorrelations over this period, investors had to contend with very volatile returns, with annualized standard deviations of around 42%.

Results for the bear market period from March 2000 through January 2002 are shown in Table 6.

At first glance, Panel A appears to indicate that the recursive strategy performed dismally for individual stocks, as most of the cumulative returns are negative. The bottom of panel A shows that the average cumulative return across the 30 stocks varies between -11.7% and -35.7%, depending on the trade configuration. However, recall that Internet stocks were particularly volatile during this period, thus exposing investors to substantial idiosyncratic risks. Despite this, the recursive rule actually did quite well, with no fewer than 24 firms outperforming the buy-and-hold strategy. This intriguing result can be explained by the "double-or-out" strategy that calls for the investor to exit the stock market and simply hold cash on sell signals. Thus, the investor is shielded from losses due to persistent declines in stock prices, while a buy-and-hold investor would have remained fully invested. Further analysis shows that in the bear market period, the technical trader was out of the market 65% of the time compared to less than half the time during the bull market period. It is this high percentage of days being out of the market and simply earning the risk-free rate that explains the superior performance of the recursive strategy in the bear market period. Consistent with the individual firm results, Panel B shows that the bear market period is the only period when the recursive strategy consistently outperformed the buy-and-hold strategy for both portfolios.

6. Best moving average rules

Our recursive trading strategy samples from over 800 moving average rules daily and is a dynamic strategy that can result in choice of different MA rules over time. Fig. 2 illustrates how the selection of rules evolves over the sample period for the well-known Internet firm, Amazon.com. In Fig. 2a–c, no band filter is used, while Fig. 2d,e assumes a 1% band filter. All plots are based on one-way transaction cost of 0.5%. Short moving averages are represented by the light line and long moving averages by the darker line. The plots show that the recursive strategy seldom picks extreme MA combinations such as those considered by Brock et al. (1992), namely very long moving averages of over 50 days and very short moving averages of between 1 and 5 days. Rather, the best rules that emerge from the recursive strategy tend to fall in between. The exact MA rule chosen appears to be quite sensitive to application of a band filter.

Figs. 3 and 4 graph the best MA rules for the VW and EW portfolios, respectively, without band filter. The best MA rules are different in the two sub-periods. The recursive strategy chooses relatively short MA rules in the bull market period and longer MA rules in the bear market period.

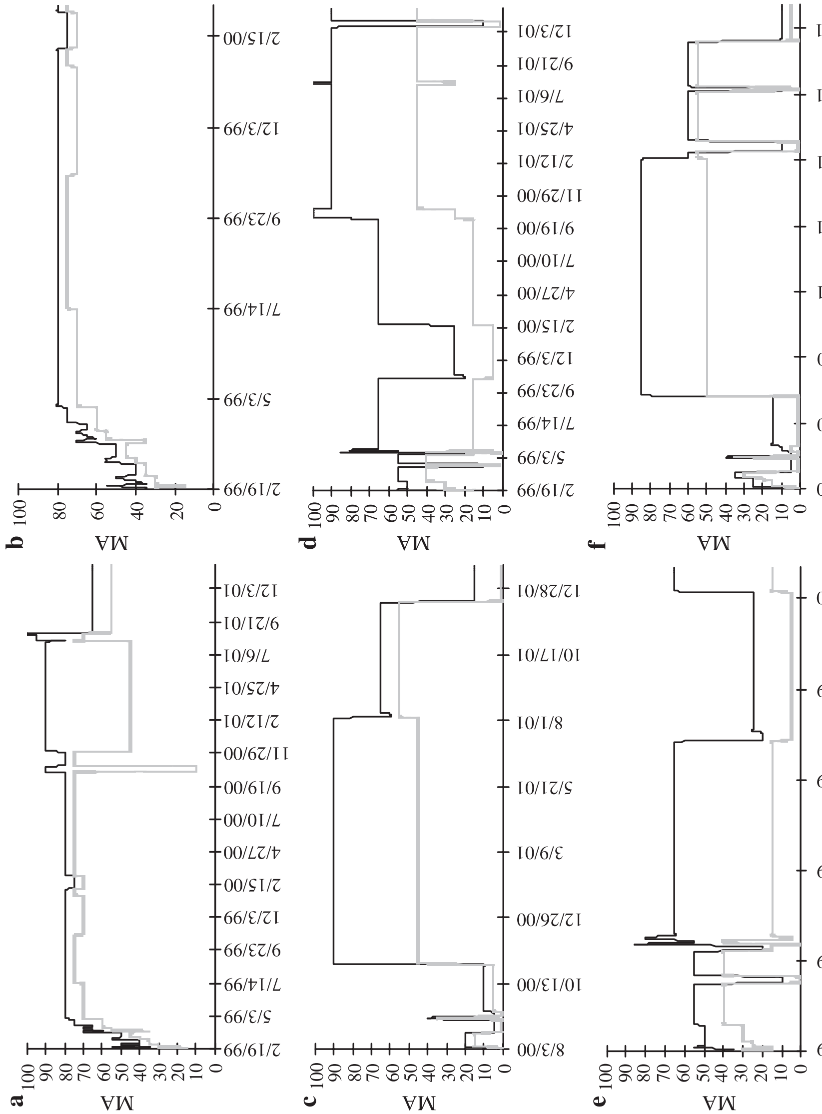
7. Bootstrap tests

We have seen that the recursive strategy outperformed the buy-and-hold benchmark for between 8 and 25 firms during the bull and bear markets, respectively. The recursive rule with a 1% band filter also performed reasonably well against the buy-and-hold strategy for the two portfolios in both sub-periods. We now examine whether these results are statistically significant.

Brock et al. (1992) point out that standard *t*-tests are not appropriate for evaluating the profitability of technical trading rules because such tests cannot account for complex cross dependencies across the different rules. Moreover, *t*-tests assume that the stock return distributions are normally distributed, stationary and time-independent. Cumulative returns deviate from normality not only because single period stock returns exhibit conditional heteroscedasticity but also because of the effects of compounding. Given these complexities, we use a bootstrap method to assess statistical significance.

We apply the bootstrap methodology of Efron (1982) and Freedman and Peters (1984). The essence of this method is to simulate artificial stock prices using estimates of a null model in which stock returns are unpredictable. The null model we use is a geometric random walk model with EGARCH(1,1) errors in returns. This model is simple enough for bootstrap simulations, yet allows for asymmetric, time-varying volatility.

Fig. 2. (a) Best moving average rules for AMZN (full sample period), $c=0.5\%$, no band filter. (b) Best moving average rules for AMZN (bull market period), $c=0.5\%$, no band filter. (c) Best moving average rules for AMZN (bear market period), $c=0.5\%$, no band filter. (d) Best moving average rules for AMZN (full sample period), $c=0.5\%$, band $=1\%$. (e) Best moving average rules for AMZN (bull market period), $c=0.5\%$, band $=1\%$. (f) Best moving average rules for AMZN (bear market period), $c=0.5\%$, band $=1\%$.


a
MA
2/19/99
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b
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2/19/99
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7/14/99
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12/3/99
2/15/00
c
MA
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10/13/00
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3/9/01
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8/1/01
10/17/01
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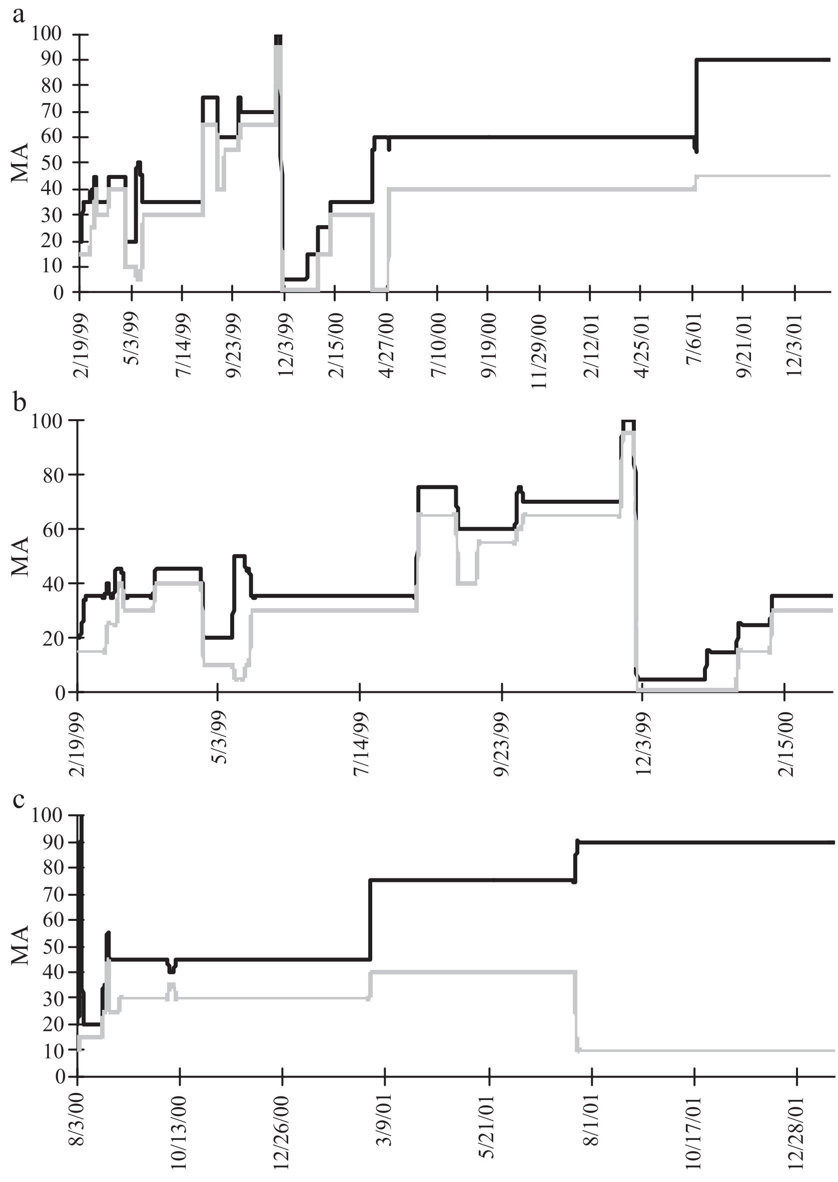

Fig. 3. (a) Best moving average rules for value-weighted portfolio (full sample period). (b) Best moving average rules for value-weighted portfolio (bull market period). (c) Best moving average rules for value-weighted portfolio (bear market period).

The specific null model is as follows:

$$r_t = \mu + \varepsilon_t \quad \varepsilon_t = \sqrt{h_t}\eta_t \tag{9}$$

$$h_t = \exp[\omega + \alpha\,|\,\eta_{t-1}\,| + \beta h_{t-1} + \gamma\eta_{t-1}] \tag{10}$$

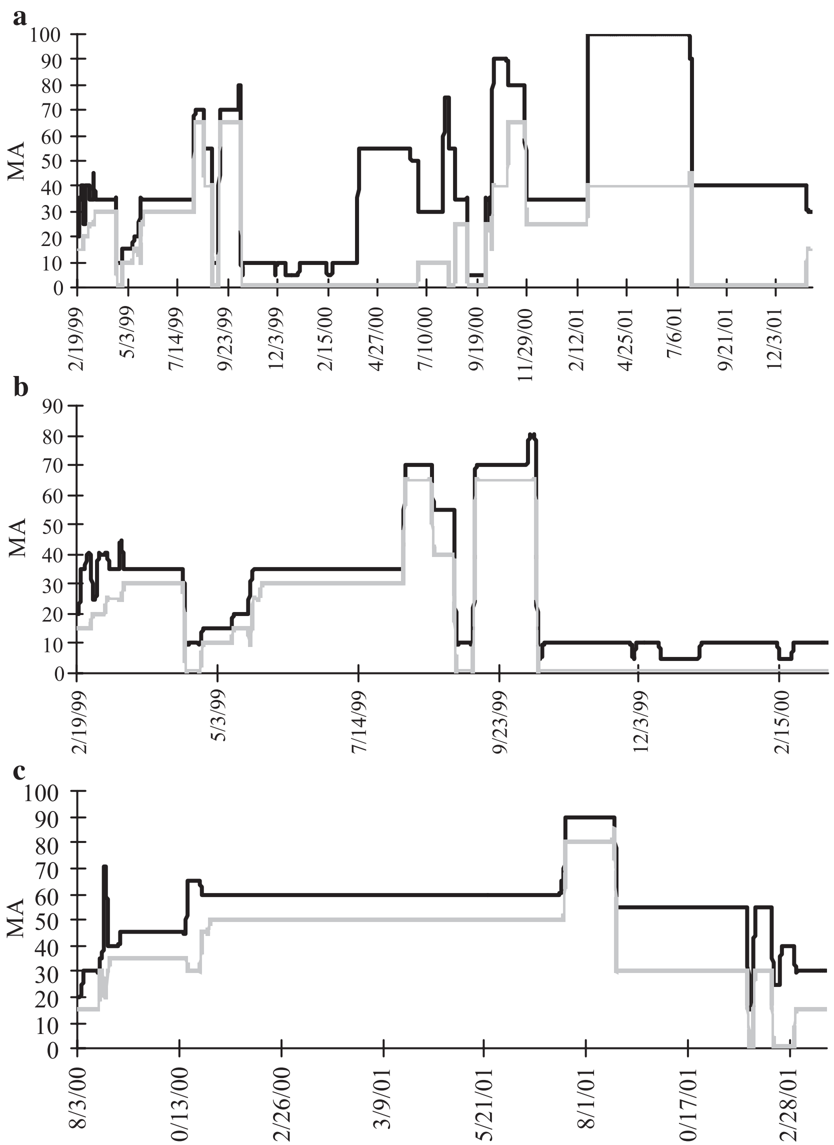

Fig. 4. (a) Best moving average rules for equal-weighted portfolio (full sample period). (b) Best moving average rules for equal-weighted portfolio (bull market period). (c) Best moving average rules for equal-weighted portfolio (bear market period).

where r_t is the continuously compounded daily returns (log of price changes), μ is the drift term, $\eta_t \sim N(0,1)$ and $\{\eta_t\}$ and $\{\varepsilon_t\}$ are mutually independent i.i.d random variables. For $\gamma < 0$, the future conditional variance increases proportionately more with a negative shock than with a positive shock of the same magnitude.

Table 7
Bootstrap results

Bootstrapped p-values					
Bull market (9/25/98–3/9/00)			Bear market (3/10/00–1/25/02)		
Stock	Lag = 0	Lag = 1	Stock	Lag = 0	Lag = 1
Group 1					
STEL	0.735	0.696	STEL	0.426	0.314
DCLK	0.599	0.427	ELNK	0.288	0.450
RSAS	0.483	0.414	SYMC	0.064	0.099
ISSX	0.935	0.999	NOVL	0.705	0.783
CKFR	0.733	0.483	CKFR	0.165	0.157
SYMC	0.462	0.668	CNET	0.502	0.600
VRSN	0.297	0.320	LVLT	0.877	0.862
CNET	0.528	0.296	EBAY	0.179	0.144
ITWO	0.293	0.607	DCLK	0.908	0.952
ELNK	0.511	0.877	ISSX	0.841	0.857
Group 2					
ET	0.923	0.825	ET	0.358	0.444
RNWK	0.388	0.370	RSAS	0.010*	0.013*
BEAS	0.134	0.192	ITWO	0.154	0.143
CHKP	0.587	0.495	CHKP	0.094	0.137
EBAY	0.922	0.777	BEAS	0.083	0.125
CIEN	0.174	0.403	COMS	0.262	0.161
SEBL	0.901	0.998	SEBL	0.220	0.233
INTU	0.803	0.823	INTU	0.702	0.427
COMS	0.256	0.242	RNWK	0.668	0.790
BRCM	0.724	0.576	NETA	0.316	0.056
Group 3					
QCOM	0.140	0.091	VRSN	0.267	0.255
NETA	0.393	0.455	YHOO	0.365	0.403
NOVL	0.737	0.722	CIEN	0.131	0.170
AMZN	0.900	0.842	AMZN	0.816	0.832
LVLT	0.426	0.36	Q	0.009*	0.011*
Q	0.978	0.947	BRCM	0.062	0.057
YHOO	0.883	0.957	QCOM	0.073	0.173
SUNW	0.429	0.500	SUNW	0.333	0.447
AOL	0.468	0.391	AOL	0.906	0.948
CSCO	0.323	0.451	CSCO	0.129	0.096
VW portfolio	0.693	0.677	VW portfolio	0.632	0.638
EW portfolio	0.874	0.758	EW portfolio	0.432	0.504

Bootstrap p-values of the recursive moving average strategy are reported for the null hypothesis that Internet stock prices follow a random walk with EGARCH(1,1) innovations. The number of replications is 500. VW (EW) denotes a value-weighted (equal-weighted) portfolio of 30 Internet stocks that are components of the @Net Index. Bootstrap p-values are fractions of the 500 replications that generate cumulative returns larger than actual stock prices reported in Tables 4–7. Returns are computed based on a 0.25% single trip transaction cost, 1% band filter, with and without a 1-day execution delay. The bull market period is from 9/25/98–3/9/00 and the bear market period is from 3/10/00–1/25/02. Stocks are ranked and separated into three groups of 10 stocks each based on their average market capitalization at the start and end of each period. Group 1 (Group 3) stocks are the smallest (largest) in terms of market capitalization.

* p-value is below 5%.

We estimate this model by maximum likelihood and use the parameter estimates to generate artificial prices under the null. The precise steps for the bootstrap experiment are as follows. First, we compute standardized EGARCH residuals using the parameter estimates. We then randomly resample the standardized residuals with replacement to obtain a series of scrambled standardized residuals. Using the scrambled residuals and parameter estimates, we back out an artificial price series for each stock and aggregate these prices into an equal-weighted and value-weighted portfolio for the portfolio bootstraps. Finally, we apply the recursive strategy to the stock and portfolio artificial prices and compute their respective cumulative returns. We repeat this process 500 times for each stock or portfolio to compute the empirical p-values of the cumulative returns under the null. These p-values are the fraction of the 500 simulations that generate cumulative returns as high as the actual data. If the p-values are greater than 5%, we infer that the trading profits are merely compensation for risk.

Table 7 presents the boostrap p-value results. The simulated p-values are based on 0.5% round trip transaction cost and 1% band filter. We choose these settings because from our previous results, they produced the highest average cumulative returns The bootstrap results show that none of the individual firm p-values is below 5% for the bull market period and only two are below 5% for the bear market period. More surprisingly, p-values for both of two portfolios are also well above 5%. We conclude that profits obtained by the recursive strategy are consistent with a random walk model with asymmetric conditional variance. Our results also support the simulation study by Pagan and Sossounov (2000) who find that even a pure random walk process can provide as good an explanation of actual bull and bear market trends as more complex statistical models.

8. Conclusions

Internet stocks have attracted a lot of publicity in recent years as their prices soared and then collapsed in what appears to be a classic speculative bubble. Although the question of whether there was indeed a speculative bubble is difficult to resolve empirically, Internet stocks have clearly experienced very strong price momentum in the recent bull and bear markets. This paper examined whether investors could have exploited this momentum using simple MA-based technical trading rules. Unlike previous studies that focused on the ex-post performance of trading rules, we simulated the experience of technical trading in real time by assuming that investors conditioned their trades only on available information. To do so, we implemented a simple recursive trading strategy in which an investor performed daily trades using signals from the best MA rule to date. We applied this recursive strategy to a sample of 30 Internet stocks, as well as two portfolios consisting of these stocks.

Preliminary analysis of the data showed that the daily autocorrelations of most Internet stocks are small and generally negative. This indicates that investors of Internet stocks have very short holding periods, and/or it pointed towards the presence of active contrarians. For most stocks, the random walk hypothesis cannot be rejected based on either the variance ratio, or spectral shape test.

Consistent with the preliminary findings, the recursive strategy was unable to generate superior returns, relative to a buy-and-hold strategy. The only exception to this was found during the bear market period when investors remained mostly out of the market and simply earned a risk-free interest rate. Results for the value-weighted and equal-weighted portfolios were more encouraging in that the recursive strategy with 1% band filter generated higher returns than the buy-and-hold strategy.

To assess the statistical significance of the trading profits, we used the bootstrap method to generate empirical *p*-values under a random walk null with EGARCH(1,1) errors. The bootstrap results showed that, in contrast to the findings of Brock et al. (1992), our random walk model can explain most of the trading profits. Thus, despite the strong price momentum in Internet stocks, it appears that their daily returns cannot be predicted from the past history of stock prices using moving average rules.

Our study has interesting implications concerning the usefulness of technical analysis. Using simulations, Pagan and Sossounov (2000) showed that stock prices that are modeled as pure random walks can exhibit long swings reminiscent of bull and bear markets. At the daily level, however, stock prices may be quite unpredictable and also highly volatile, as exemplified by Internet stocks. Therefore, generating accurate forecasts from past price histories may be challenging, even for professional traders (see, e.g., Glaser et al., 2003). Nonetheless, some investors will naively extrapolate trends in the belief that the momentum can be exploited. The behavioral finance literature indicates that these "noise traders" possess two key traits. First, they tend to be less informed than other investors. Lacking the information of better-informed investors, they resort to trend chasing, buying when prices have risen and selling when prices have fallen. Our study is a reminder that trend chasing may be futile because technical trading signals are not real information events: the signals are generated simply because a stock price crosses some arbitrary limits. In other words, technical trading signals follow, rather than lead true information events. When stock prices are very volatile, as is the case with Internet stocks, technical trading signals may be useless because the noise-to-signal ratio is too high.

Second, noise traders tend to be overconfident about their forecasting ability (Hirschleifer, 2001). They also tend to underestimate the volatility of stock prices, causing them to see patterns in randomness. Interestingly, Griffin and Tversky (1992) found that it is when predictability is low that people become more overconfident. This suggests that Internet stocks will attract overconfident investors. Although we do not have direct evidence to support this assumption, results from investor profile surveys are consistent with this pattern (see Dhar and Kumar, 2001). These investors will trade actively, but as our study showed, noise trading and transaction costs will significantly reduce their returns. This can happen even if the market for Internet stocks is irrational. As Malkiel (1996) cautioned, an irrational stock market is like a drunken person staggering around on the sidewalk. He is not rational, but neither is he predictable.

Acknowledgements

We would like to thank Blake LeBaron for providing us with helpful comments. As usual, all errors and omissions are ours.

Appendix A

The correlation structure of a stationary time series is determined by its standardized spectral density function. Let $r_t = \mu + \varepsilon_t$ be a time series of returns with unconditional mean μ. Let $f(\lambda)$ denote the standardized spectral density function of return innovations, $\{\varepsilon_t\}$ at frequency λ:

$$f(\lambda) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \rho_j \cos\lambda j$$

where ρ_j is the jth order autocorrelation. Denote the *sample* standardized spectral density function $I_k(\lambda)$:

$$I_k(\lambda) = \frac{1}{2\pi} \sum_{j=-(k-1)}^{k-1} w_k(j) \rho_j \cos\lambda j$$

where $w_k(j)$ is a sequence of declining weights, symmetric about zero and $w_k(0)=(w_{k\to\infty}(j))=1$ for all j. Admissible weight sequences include the Bartlett, Parzen and Quadratic kernels. See Andrews and Mohanan (1992).

To test the null hypothesis that $\{\varepsilon_t\}$ is a martingale-difference series, Durlauf (1991) suggests a class of spectral shape tests. These tests exploit the fact that under the null, the spectral distribution function is linear or equivalently, the spectral density function is a constant ($1/2p$). Thus, given a sample of size n, the martingale null can be tested using the following statistic:

$$U_n(t) = \sqrt{2n} \int_o^{\pi t} \left[\frac{I_k(\lambda)}{\hat{\sigma}^2} - \frac{1}{2\pi} \right] \mathrm{d}\lambda = \frac{\sqrt{2}}{\pi} \sum_{j=1}^{n-1} n^{1/2} \hat{\rho}_j \sqrt{c_{jj}} w_n(j) \frac{\sin j\pi t}{j} \qquad t \epsilon (0,1)$$

where $U_n(t)$is the cumulative deviation of the standardized sample spectral density function from $1/2p$ and c_{jj} is the variance of the sample normalized autocorrelations, $n^{1/2} \hat{\rho}_j$.

A family of spectral shape tests can be constructed based on $U_n(t)$. We consider only one of these: the Anderson–Darling (AD) statistic:

$$\mathrm{AD} = \int_0^1 \frac{U_n^2(t)}{t(1-t)} \mathrm{d}t$$

Under suitable regularity conditions, which include general forms of conditional heteroscedasticity for $\{\varepsilon_t\}$, Deo (2000) shows that $U_n(t)$ converges to the following limiting Gaussian process:

$$U_n(t) = \frac{\sqrt{2}}{\pi} \sum_{j=1}^{n-1} \eta_j \sqrt{c_{jj}} \frac{\sin j\pi t}{j} \qquad t \epsilon (0,1)$$

$$\eta_j \sim \text{i.i.d } N(0,1)$$

He also proves that a consistent estimator of $\sqrt{c_{jj}}$ is:

$$\frac{\hat{\sigma}^2}{\left[(n-j)\sum_{t=1}^{n-j}(r_t-\bar{r})^2(r_{t+j}-\bar{r})^2\right]^{1/2}}$$

Asymptotic critical values of the AD statistic are tabulated by Shorack and Wellner (1987). The 5% asymptotic critical value for this statistic is 2.49.

To study the finite sample properties of the AD statistic, we carry out size and power simulations. For the size simulations, we generated 5000 realizations of a Gaussian random walk process with EGARCH(1,1) innovations for two samples of size 400 and 800 observations which are near the actual sample sizes analyzed in this paper. This null model can be written as:

$$r_t = \mu + \varepsilon_t \quad \varepsilon_t = \sqrt{h_t}\eta_t \quad \eta_t \sim N(0,1)$$

$$h_t = \exp[\omega + \alpha\,|\,\eta_{t-1}\,| + \beta h_{t-1} + \gamma\eta_{t-1}]$$

where $\{\varepsilon_t\}$ and $\{\eta_t\}$ are mutually independent i.i.d. random variables and h_t is the conditional variance of the return innovations. Without loss of generality, we set $\mu=0$. For the EGARCH parameters, $\{\omega, \alpha, \beta, \gamma\}=\{-0.5, 0.2, 0.9, -0.1\}$ corresponding to the average value of these parameter estimates across the 30 stocks.

For the power calculations, two alternative models to the random walk are simulated.

Model 1 (AR1)

$$r_t = \mu + \phi r_{t-1} + \varepsilon_t$$

where $\mu=0$, $\phi=0.1$ and -0.1 and ε_t is an EGARCH(1,1) process with parameter values similar to the size experiment.

Model 2 (Long memory model)

$$(1-L)^d r_t = \varepsilon_t$$

where the differencing parameter $d\in(-0.5,0.5)$ in order for the innovations to be stationary and invertible and ε_t is assumed to follow an EGARCH(1,1) process with similar parameter values as the size experiment. This model is a fractionally integrated process with asymmetric conditional volatility in the return innovations. To back out the returns for this process, we use the recursion:

$$r_t = (1-L)^{-d}\varepsilon_t = \sum_{k=0}^{\infty}(-1)\begin{pmatrix}-d\\k\end{pmatrix}L^k\varepsilon_t$$

where

$$(-1)\begin{pmatrix}-d\\k\end{pmatrix} = \frac{\Gamma(k+d)}{\Gamma(d)\Gamma(1+k)}$$

Table A1
Size (in percent) of the Anderson–Darling spectral test and variance ratio test

Sample size	AD	q	VR(q)
400	4.06	2	4.98
		4	5.30
		8	5.56
		12	5.68
		16	5.58
		20	5.66
800	4.48	2	5.16
		4	5.22
		8	5.46
		12	5.40
		16	5.04
		20	5.14

and the infinite series is truncated at lag 100. We set $d=0.1$ and -0.1. With white noise errors, these parameters imply a theoretical first-order autocorrelation of 0.11 and -0.09, respectively (see Lo, 1991).

Table A2

Sample size	AD		q	VR(q)	
	$\phi=-0.1$	$\phi=0.1$		$\phi=-0.1$	$\phi=0.1$
Power (in percent) of the Anderson–Darling spectral test and variance ratio test under AR1 alternative					
400	38.46	34.16	2	15.86	24.96
			4	15.60	25.44
			8	16.00	24.86
			12	15.72	25.88
			16	16.20	25.34
			20	15.36	25.90
800	66.58	62.46	2	30.38	41.26
			4	29.86	39.26
			8	29.44	40.98
			12	30.66	39.28
			16	29.84	41.26
			20	38.82	38.90
Power (in percent) of the Anderson–Darling spectral test and variance ratio test under long memory alternative					
400	36.40	45.94	2	32.46	56.74
			4	30.66	53.58
			8	32.16	57.36
			12	31.20	53.74
			16	32.12	57.10
			20	29.80	53.90
800	66.38	79.04	2	65.66	81.06
			4	65.38	81.62
			8	65.44	81.26
			12	65.76	81.26
			16	65.60	80.95
			20	65.78	81.70

Table A1 reports the finite sample 5% critical value, and the size and power of the Anderson–Darling test.[18]

Table A2 reports the power of the AD and variance ratio test for the two alternatives.

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[18] In all cases, the bandwidth for computing the statistic is the square root of the sample size so that the number of autocorrelation lags is small relative to the sample size.

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