Can Fuzzy Logic Make Technical Analysis 20/20?

Xu-Shen Zhou and Ming Dong

One of the most challenging areas in technical analysis is the automatic detection of technical patterns that would be similarly detected by the eyes of experts. In this study, cognitive uncertainty was incorporated in technical analysis by using a fuzzy logic–based approach. The results show that the algorithm can detect subtle differences in a clearly defined pattern. Significant postpattern abnormal returns were found that varied directly with the fuzziness of a pattern. This approach can be valuable for investors as a way to incorporate human cognition into historical trading statistics so as to form future winning strategies.

Technical analysis of securities, which is based on prices and volume rather than underlying company fundamentals, has been a practice among practitioners and academic researchers for many decades. Recent applications of artificial intelligence (AI) technologies and the positive results of statistical tests of effectiveness in technical analysis have generated greater interest in the approach. AI technologies, such as genetic algorithms, fuzzy logic, pattern recognition, and machine learning, have contributed computerized assistance to make the process of knowledge discovery more efficient and closer to human cognitive abilities (in this field, "knowledge discovery" usually refers to finding nontrivial and useful patterns in the data, such as those presented by stock charts).

Leigh, Purvis, and Ragusa (2002) introduced a decision support system that would incorporate pattern recognizers, neural networks, and genetic algorithms. In forecasting the NYSE Composite Index through technical analysis, the system achieved high-quality results. Wong, Wang, Goh, and Quek (1992) developed a fuzzy neural system for stock selection. The system was intended to resemble the experts' knowledge. On the one hand, using a genetic algorithm, Allen and Karjalainen (1999) found technical trading rules for the S&P 500 Index. They then applied these rules to out-of-sample daily prices of the S&P 500. After transaction costs, the rules did not earn excess returns over a simple buy-and-hold strategy. On the other hand, also using a genetic algorithm for finding optimal

parameters of trading rules, Fernández-Rodríguez, González-Martel, and Sosvilla-Rivero (2001) applied the trading rules to the General Index of the Madrid Stock Market and found that the rules were always better than a risk-adjusted buy-and-hold strategy (for reasonable trading costs). Neely, Weller, and Dittmar (1997) also found economically significant out-of-sample excess returns in the foreign exchanges by using the trading rules generated by a genetic algorithm.

Most technical analysis research focuses on general trading rules, such as the rules based on moving averages;[1] only a few studies have examined visual technical patterns, such as head-and-shoulders shapes and double tops. Levy (1971) tested the predictive power of 32 "five-point chart patterns" and found no predictive power in the chart patterns for U.S. stock markets. The tests did not include volume, however, and the chart patterns did not follow the rules practitioners say they use. Neftci (1991) found that even well-defined trading rules are useless in prediction unless the process under consideration is nonlinear. Brock, Lakonishok, and LeBaron (1992) examined the trading range breakout (resistance and support levels) in the Dow Jones Index from 1897 to 1986, and they developed a trading strategy based on buy and sell signals. A buy signal was generated when the price rose above the resistant level, which was defined as the local maximum. A sell signal was generated when the price dropped below the support level, which was the local minimum. The result shows that such buy and sell signals are informative. Chang and Osler (1999) studied the profitability and efficiency of the head-and-shoulders pattern in foreign exchange markets. They found that the technical pattern is profitable but not efficient because simpler trading rules dominated the trading strategy based

Xu-Shen Zhou is assistant professor of finance at Bloomsburg University, Pennsylvania. Ming Dong is assistant professor of computer science at Wayne State University, Detroit.

on the head-and-shoulders pattern. Lo, Mamaysky, and Wang (2000) proposed using pattern recognition and statistical inference methods in technical analysis for visual technical patterns. Their method allowed computer programs to automatically detect these patterns. They used the conditional (conditioned on the technical patterns) and unconditional distributions of returns to test the informativeness of technical analysis and found evidence that technical patterns are informative.

Despite these advances in technical analysis, challenges remain in two key areas. The first is the area of automatic detection of technical patterns that would be similarly detected by expert investors. Such a detection process would closely resemble or capture human cognitive abilities—even intuition. This challenge has produced fewer academic studies than studies of patterns in other technical trading rules and produced inconclusive results. Regarding expert traders, Lo and Repin (2001) noted:

> The most successful traders seem to trade based on their intuition about price swings and market dynamics, often without the ability (or the need) to articulate a precise quantitative algorithm for making these complex decisions (Schwager 1989, 1992; and Niederhofer 1997). Their intuitive trading rules are based on the associations and relations between various information tokens that are formed on a subconscious level. (p. 13)

Because of the way the successful traders make decisions, a subtle difference in technical patterns may be apparent to experienced traders but not to average traders. Computer pattern-recognition programs should be designed to capture such slight differences and extract the useful information from the noise.

The second challenge is to statistically test the effectiveness of technical analysis. Controversy and confusion exist regarding how useful and informative technical analysis is. Different test methods, because of their conflicting results, have only added to the controversy.

The study we report here contributes to the research on technical analysis by making improvements in these two challenging areas. As Zadeh (1978) pointed out, human cognitive uncertainty can be introduced into the automatic detection and analysis process. Human cognitive uncertainty is the uncertainty that deals with the phenomena arising from human thinking, reasoning, cognition, and perception. This reformulation of technical indicators takes machines a step closer to thinking and reasoning like human experts in the stock markets.

Our approach to technical analysis is based on fuzzy logic, which is one of the best tools to model cognitive uncertainty. Fuzzy logic has been used in finance in business decision making (Hutchinson 1998) and in the analysis of financial variables (Dolan 1994), financial markets (Chorafas 1994), mechanical artificial trading (Ruggiero 1994), and commercial software for analyzing candlestick patterns in the futures markets (Ruggiero 1995). The use of fuzzy logic in this article to analyze the effectiveness of major visual technical patterns, however, has not been attempted in previous studies.

Fuzzy Logic and Smoothing

We used fuzzy logic to introduce human cognitive uncertainty into automatic technical pattern detection and analysis. To capture price information accurately and reduce noise, we first smoothed the stock prices by using the Gaussian kernel method as used by Lo, Mamaysky, and Wang.[2] Then, we identified the extrema—that is, the local stationary maximum and minimum values for the price. In this section, we provide a brief review of fuzzy logic and the Gaussian kernel–based smoothing method.

Fuzzy Logic. Fuzzy logic refers to a logical system that generalizes classical two-value logic for reasoning under uncertainty. Various classes of uncertainties can be classified into two broad categories—statistical and cognitive. *Cognitive uncertainty* arises from human thinking, reasoning, and cognition (Gupta 1991). It can be further classified into *vagueness* and *ambiguity*. Vagueness is associated with the difficulty of making sharp or precise distinctions in the world, whereas ambiguity is associated with the situation of two or more alternatives such that the choice between them is left unspecified (Klir 1987).

Set and *element* are two basic notions of set theory. In classical set theory, an element either belongs to a certain set or it does not. In the real world, however, such certainty is often unrealistic because of imprecise measurements, noise, vagueness, subjectivity, and so on. For example, the concept of "tall" is inherently fuzzy. Any set of tall people would be subjective. Moreover, some people might be obviously tall, whereas others are only relatively tall. Fuzzy set theory deals with such a situation.

A fuzzy set directly addresses such situations by allowing membership in a set to be a matter of degree. The degree of membership is expressed by a number between 0 and 1, where 0 means entirely not in the set, 1 means completely in the set, and a number in between means partially in the set. Usually, the membership function of fuzzy set A is denoted μ_A and the membership value of x in A is

denoted as $\mu_A(x)$. Fuzzy sets usually overlap (to reflect "fuzziness" of the concepts) and, for completeness, should cover the whole universe under consideration.

Figure 1 provides an example of the concept of "income" in fuzzy sets. Income u can belong to three fuzzy subsets—Low, Medium, and High—with different membership values. For example, when $u = 20,000$, its membership for fuzzy subset Low is μ_{Low} and its membership for fuzzy subset Medium is μ_{Medium}. The solid line in Figure 1 shows the trapezoid membership functions for the three fuzzy subsets.

The most commonly used membership functions are the triangular membership function and the trapezoid membership function. As shown in **Figure 2**, the trapezoid membership can be fully characterized by four parameters—l, lp, r, and rp.

Gaussian Kernel–Based Smoothing. Any study of technical analysis starts from the recognition that the stock market is a nonlinear dynamic system and that nonlinearity contains certain regularities or patterns. In general, the stock price at time t, P_t, can be described by the following equation:

$$P_t = H(X_t) + e_t, \text{ with } t = 1, 2, \ldots, T, \qquad (1)$$

where

H = a dynamic system
X_t = a state vector at time t
e_t = noise

**Figure 1. "Income" Example of Fuzzy Sets**
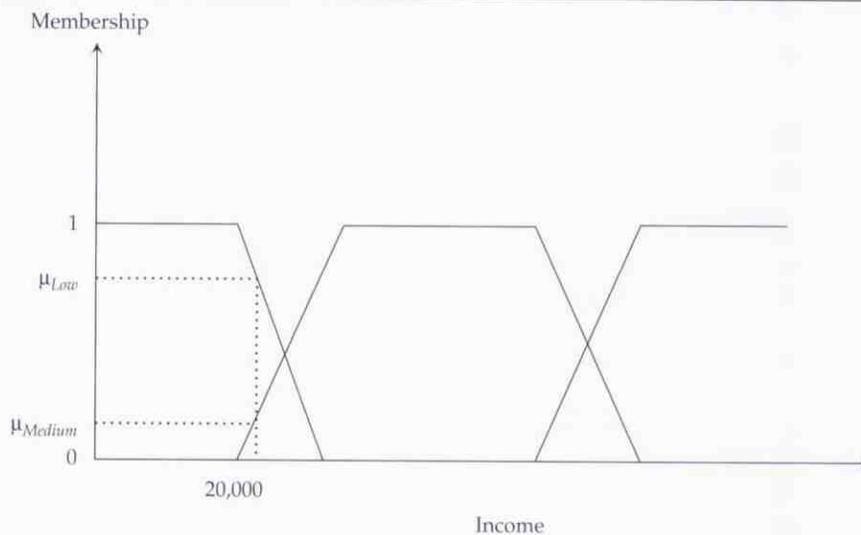
Figure 2. Trapezoid Membership Function
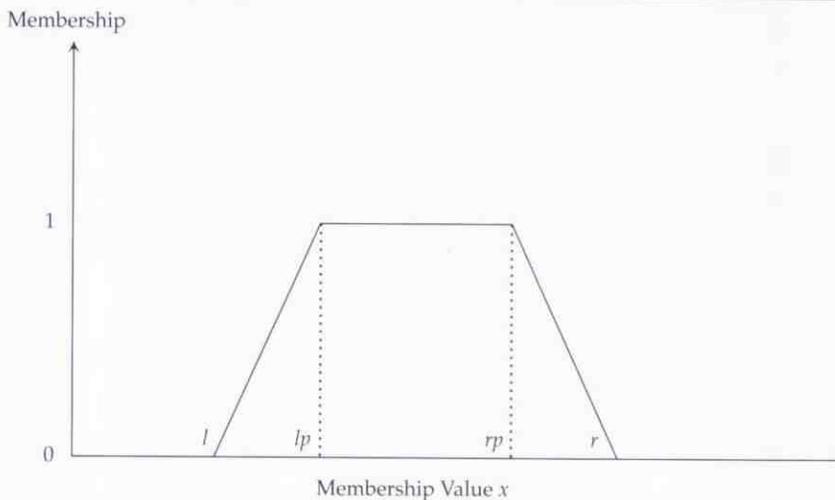
One of the most common methods for eliminating noise is smoothing, in which the noise is greatly reduced by averaging the data. Assume we have n observations of P_t^i, with $i = 1, 2, \ldots, n$; then, it can be easily shown that $\hat{H}(X_t) = \bar{P}_t \to H(X_t)$ when $n \to \infty$. Of course, P_t is a time series and we cannot get n observations of $P(t)$. If we assume H is sufficiently smooth, however, we can use the average over a predefined neighborhood instead of over n observations. In this case, $\bar{P}_t$ can be calculated by the weighted sum as follows:

$$\bar{P}_t = \sum_S w_i P_i, \, i \in S, \tag{2}$$

where S is the predefined neighborhood and w_i is the corresponding weight for data point P_i.

One popular approach to choosing the weights is to use Gaussian kernel regression. If there are n data points in the neighborhood of point t, we can generate n Gaussian distributions, with each distribution centered at one of the data points. Then, we have

$$\bar{P}_t = \sum_{i=1}^n P_i \frac{1}{(\sigma^2 2\pi)^{1/2}} e^{-(P_i - P_t)^2 / 2\sigma^2}, \tag{3}$$

with $i = 1, 2, \ldots, n$,

where σ^2, the variance of the Gaussian distribution, acts as a smoothing parameter. If σ^2 is too large, the data are oversmoothed. Conversely, if σ^2 is too small, the data will be undersmoothed.

We collected the data of the NASDAQ Index from 22 October 2001 through 21 February 2002 and smoothed it using the Gaussian kernel approach with standard deviations of $\sigma = 1$ and $\sigma = 3$. **Figure 3** shows the two smoothing effects, with Panel A for $\sigma = 1$ and Panel B for $\sigma = 3$.

Fuzzy Logic–Based Automating Technical Analysis

The first step in automating technical analysis is the detection of technical patterns. The detection must be able to match the judgment of a professional technical analyst. Following Lo et al., we used a sequence of five consecutive local extrema, $E_1, \ldots, E_5$, to describe a pattern template. In general, any pattern template with five such extrema can be described by the tree shown in **Figure 4**. We can control the shape of the pattern template by defining the three-layer comparisons and three weights, w_1, w_2, w_3, in the tree. By studying each pattern on the node of the tree, we can analyze all the technical pattern templates.

In this study, we first focused on the eight pattern templates proposed by Lo et al. They are head-and-shoulders (HS), inverse head-and-shoulders (IHS), broadening tops (BTOP), broadening bottoms (BBOT), triangle tops (TTOP), triangle bottoms (TBOT), rectangle tops (RTOP), and rectangle bottoms (RBOT). For convenience in the discussion that follows, we duplicate here the definitions of HS and RTOP in Lo et al.:

- *A head-and-shoulders pattern* (HS) is characterized by a sequence of five consecutive local extrema, $E_1, \ldots, E_5$, such that

  E_1 is a maximum,

  $E_3 > E_1$ and $E_3 > E_5$,

  E_1 and E_5 are within 1.5 percent of their average, and E_2 and E_4 are within 1.5 percent of their average.

- *A rectangle tops pattern* (RTOP) is characterized by a sequence of five consecutive local extrema, $E_1, \ldots, E_5$, such that

  E_1 is a maximum,

  Tops are within 0.75 percent of their average,

  Bottoms are within 0.75 percent of their average,

  Lowest top > highest bottom.

From these definitions, if E_1 is a maximum, Node 5 in Figure 4 contains an HS pattern and any node on the bottom (Nodes 8 to 15) contains RTOP. Furthermore, according to the definitions, Node 9 contains BTOP and Node 14 contains TTOP. Therefore, if E_1 is a maximum, RTOP and HS overlap on Nodes 10 and 11 (they are the leaves of Node 5), RTOP and BTOP overlap on Node 9, and RTOP and TTOP overlap on Node 14. Similarly, if E_1 is a minimum, Nodes 8 through 15 contain RBOT, Node 6 contains IHS, Node 9 contains TBOT, and Node 14 contains BBOT. Thus, RBOT and IHS overlap on Nodes 12 and 13, RBOT and TBOT overlap on Node 9, and RBOT and BBOT overlap on Node 14.

Although these definitions are straightforward, their crisp (as opposed to fuzzy) nature suffers from inadequate handling of the uncertainty of human perception and reasoning. Consequently, they cannot truly reflect the judgments of a professional technical analyst. Introducing fuzzy logic into the definition of technical patterns provides a better way to match the opinion of professional technical analysts.

For this purpose, we first identified a visual technical pattern based on the preceding definitions. We then calculated the membership value of the pattern using membership functions. Different membership functions can be applied to different conditions of the pattern template. For illustration, consider the following example of a U.S. stock.

Figure 3. Smoothing Effect of Gaussian Kernel on NASDAQ Data, 22 October 2001 through 21 February 2002

A. σ = 1

NASDAQ Index

Days

B. σ = 3

NASDAQ Index

Days

.... NASDAQ Index   ———— Index after Smoothing
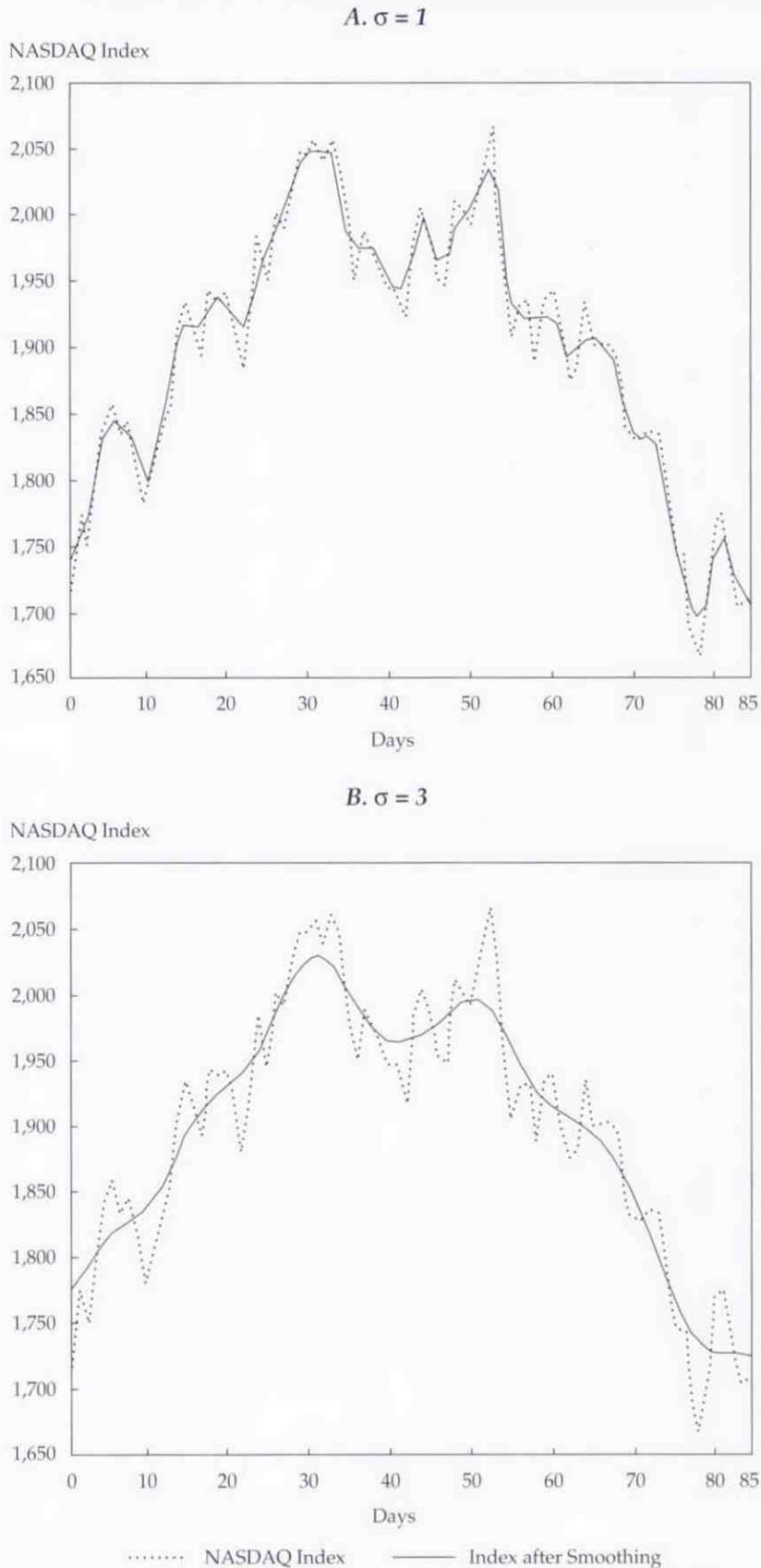
Figure 4.   Pattern Template with Five Extrema, Three-Layer Comparisons, and Three Weights
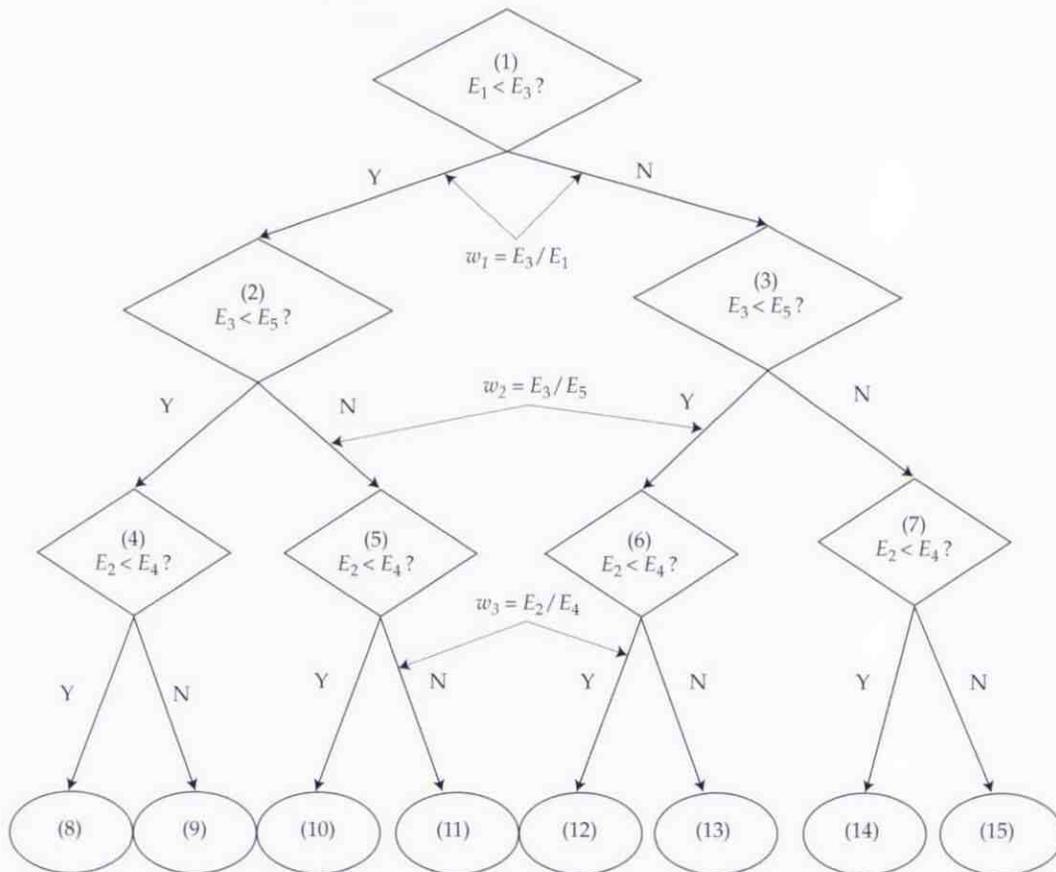
Figure 5 shows the smoothed stock prices after Gaussian kernel–based smoothing and detection of the corresponding extrema. The data used for Panel A are the daily prices of Printrak International from 27 December 1999 through 12 January 2000; the data used for Panel B are Printrak data from 22 December 1998 through 8 January 1999. We first examined the two patterns and found that both satisfied the four conditions of the HS template. We then calculated the membership values for the patterns. Visually, they are obviously different. For example, the price difference between the two local minimums of the pattern in Panel A is much less than the difference in the pattern in Panel B. Fuzzification allows us to model those subtle differences with ease. In fact, according to our fuzzification process, the membership of the pattern in Panel A is 1.0 whereas the membership of the pattern in Panel B is only 0.67.

Fuzzification Process. We followed a consistent method of fuzzification for all eight pattern templates. To model the subtle differences of patterns within the same pattern template, we fuzzified the crisp conditions of each pattern template by using the trapezoid membership function

shown in Figure 2. The parameters of trapezoid membership functions for each condition of each pattern template are shown in **Table 1**. For example, the second row of Table 1 shows the parameters for fuzzification of the first condition of the HS pattern template. Here, the fuzzification is based on the variable x that is defined as

$$x = \frac{E_3 - Ave_1}{Ave_1 - Ave_2}, \tag{4}$$

where $Ave_1 = (E_1 + E_5)/2$ and is the average value of the first and last maximums and $Ave_2 = (E_2 + E_4)/2$ and is the average value of the first and second minimums. Under such definitions, variable x indicates how high "the head" is above "the shoulders" relative to the distance between "the shoulders" and "the body" (the two minimums). According to visual observation, when x is less than 0.1, the head is so close to the shoulders that the entire pattern looks nearly flat. Therefore, we set the membership value in that case to zero. When x is above 40, the head is very high and looks like a spike in price instead of the normal HS pattern. So, again, we set the membership value to zero. When x is in the (1, 5) range, the head, the

Figure 5.   Fuzzification Effect: Printrak International

A. 27 December 1999 through 12 January 2000

Price ($)

Days

B. 22 December 1998 through 8 January 1999

Price ($)

Days

——— Smoothed Price   ● Maximums   ■ Minimums
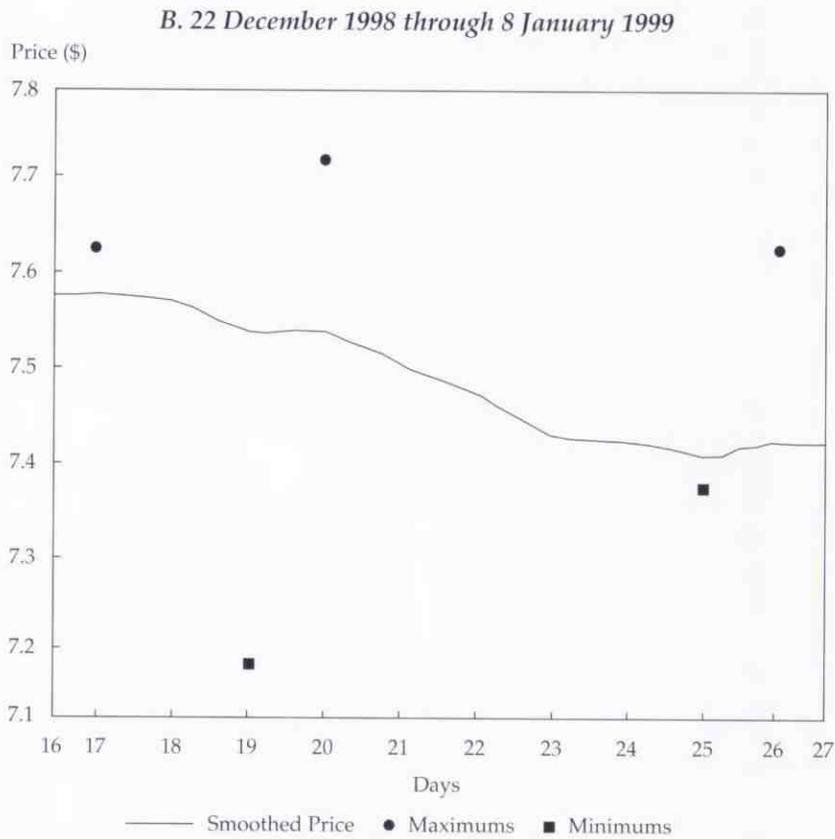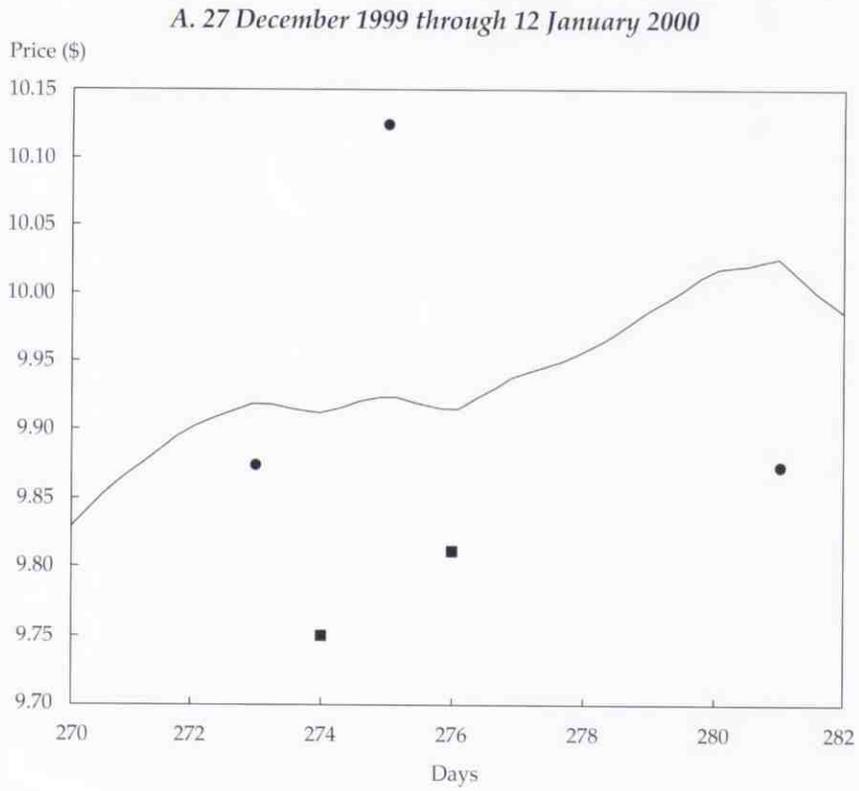
Table 1. Trapezoid Membership Function Parameters

Pattern/Condition	l	lp	rp	r
HS/IHS				
Condition 1	0.1	1.0	5.0	40
Condition 2	$-\infty$	$-\infty$	$0.005[(E_1 + E_5)/2]$	$0.04[(E_1 + E_5)/2]$
Condition 3	$-\infty$	$-\infty$	$0.005[(E_1 + E_4)/2]$	$0.005[(E_1 + E_4)/2]$
BTOP/BBOT				
Condition 1	0.1	0.8	1.2	10
Condition 2	1.2	2.0	4.0	15
TTOP/TBOT				
Condition 1	0.1	0.8	1.2	10
Condition 2	1.2	2.0	4.0	15
RTOP/RBOT				
Condition 1	$-\infty$	$-\infty$	$0.005[(E_1 + E_3 + E_5)/3]$	$0.04[(E_1 + E_3 + E_5)/3]$
Condition 2	$-\infty$	$-\infty$	$0.005[(E_2 + E_4)/2]$	$0.04[(E_2 + E_4)/2]$
Condition 3	1.0	5.0	∞	∞

Note: See Figure 2 for the meaning of parameters l, lp, r, and rp.

shoulders, and the body are well placed to provide a perfect visualization of the HS pattern. In these situations, we set the membership value to 1.

Based on this procedure, we can get those parameters for fuzzification of the first condition of the HS pattern template. Although the choices of variable and parameters are *ad hoc*, adjustments are made so the patterns with more symmetrical visual shapes are assigned higher membership values (for example, the more symmetrical the two shoulders look, the higher the membership value for the HS pattern is). In the future, we can redefine the variable x in Equation 4 or adjust the parameters to achieve the best out-of-sample prediction results in experiments.

Similarly, we could define the variables for all the fuzzification processes (each condition and each pattern template) that are listed in **Table 2**. We fuzzified each variable by using the corresponding membership function defined in Table 1. We then obtained the pattern fuzzification membership value by averaging over all memberships within the pattern template. For example, if the membership values of three conditions for the HS pattern template were 0.8, 0.6, and 1.0, the membership value of that pattern for the HS pattern template was $(0.8 + 0.6 + 1.0)/3 = 0.8$.

Data and Sample Selection

To test our approach, we selected data from the Center for Research in Security Prices daily database for 2000. We first listed all of the companies each year from 1962 to 2000 and selected companies that were assigned CRSP size deciles from 1 to 10

Table 2. Variables for All Fuzzification Processes
(each condition and each pattern template)

Pattern/Condition	Variable
HS/IHS	
Condition 1	$(2E_3 - E_1 - E_5)/(E_1 + E_5 - E_2 - E_4)$
Condition 2	$0.5\lvert E_5 - E_1 \rvert$
Condition 3	$0.5\lvert E_4 - E_2 \rvert$
BTOP/BBOT	
Condition 1	$(E_5 - E_3)/(E_3 - E_1)$
Condition 2	$(E_5 - E_4)/(E_1 - E_2)$
TTOP/TBOT	
Condition 1	$(E_5 - E_3)/(E_3 - E_1)$
Condition 2	$(E_1 - E_2)/(E_5 - E_4)$
RTOP	
Condition 1	$0.5[\max(E_1, E_2, E_5) - \min(E_1, E_3, E_5)]$
Condition 2	$0.5\lvert E_2 - E_4 \rvert$
Condition 3	$100[\min(E_1, E_3, E_5)/\max(E_2, E_4) - 1]$
RBOT	
Condition 1	$0.5[\max(E_1, E_3, E_5) - \min(E_1, E_3, E_5)]$
Condition 2	$0.5\lvert E_2 - E_4 \rvert$
Condition 3	$100[\min(E_2, E_4)/\max(E_1, E_3, E_5) - 1]$

(a certain number of companies each year are not assigned to any decile). Decile 1 contains the smallest companies and Decile 10 contains the largest. CRSP size deciles are assigned at the end of each year on the basis of the entire universe of CRSP-listed NYSE, Amex, and NASDAQ companies. From each decile, we randomly selected 200 companies with replacement (so, some companies were

selected more than once). Because the number of companies in the CRSP universe changed dramatically between the 1960s and the 1990s, our sampling method ensured that our sample would contain the number of companies each year within the size deciles proportional to the total number of companies in that year.

We then applied our algorithm to each stock in the sample for a sample period. Each stock's sample period started 12 months after the stock was included in the CRSP database. A year was chosen because we needed to match the sample company with a control company based on the past year's stock performance. Because we also needed to measure the stock's performance up to six months after the occurrence of a technical pattern, our sample period ended six months before the last day that a stock's data were available in CRSP. To be included in our sample, the company also had to meet the following criteria:

1. It had to be listed on the NYSE, Amex, or NASDAQ and had to be an ordinary common stock of a U.S.-based corporation (CRSP share codes 10 and 11). We selected stocks based on this criterion to be consistent with the selection criteria imposed by event-study researchers, such as Michaely, Thaler, and Womack (1995) and Boehme and Sorescu (2002). After this screening, the sample contained 1,699 stocks.

2. The company had to have been in the CRSP database for 24 consecutive months. Based on this criterion, each sample stock would have at least six months of data available for our pattern detection.

3. At least 80 percent of the price observations for the company in the sample period had to be available. Following Lo et al., we also omitted missing price observations when we applied our algorithm to the data.

Our final sample consisted of 1,451 stocks, for which we detected a total of 44,150 occurrences of technical patterns.

Statistical Tests

The debate surrounding trading profitability based on technical patterns and major corporate events is inconclusive, in part because different research methods have been used. The variability in methods, in turn, stems from the fact that we do not have a well-specified dynamic general equilibrium asset-pricing model. The "bad model" problem can be alleviated, however, in the examination of short-term postevent performance (Fama 1998).

Following Boehme and Sorescu's method of matching sample with control companies, we com-

puted short-term abnormal returns of sample companies relative to a group of control companies matched one to one on the basis of size and one-year price momentum.[3] Although we did not control for book-to-market ratio, our control company–matching method allowed measurement of the effectiveness of technical analysis to be comparable to the measurement of the effectiveness of corporate event studies.

We applied our algorithm to adjusted stock prices (adjusted for all corporate events, including stock splits and dividends). We chose this approach because investors look at the adjusted stock price chart every time an event such as a stock split occurs. For any trading day, we used adjusted stock prices m days before and r days after the trading day in the Gaussian kernel–smoothing method (in this study, m was 10 days and r was 3 days). We let $t = 0$ be the day when the pattern had been completed for r days. We calculated postpattern returns starting from $t = 1$, so the return on $t = 1$ did not contain information that was used in detecting technical patterns.

To find a size- and momentum-matched control company, we first chose all companies in CRSP with a market value of equity between 70 percent and 130 percent of the market value of equity of the sample company at $t = 0$ (i.e., r days after the completion of a pattern). From this set of companies, we selected the company with the one-year total return closest to that of the sample company that had six more months of daily return data in CRSP. Having six months of daily returns allowed us to measure abnormal returns for up to 120 trading days.

We computed the abnormal returns for company i on day t, AR_{it}, as

$$AR_{it} = R_{it} - R_{ct}, \text{ with } t = 1, \ldots, 120, \tag{5}$$

where R_{it} is the return for company i for day t and R_{ct} is the return for the corresponding control company for that day.

We put all companies that completed a certain pattern in a portfolio. For each day t, we computed a mean abnormal return, MAR_t, across all the companies in the portfolio:

$$MAR_t = \sum_{i=1}^{N_t} \frac{AR_{it}}{N_t}, \tag{6}$$

where N_t is the total number of companies in the portfolio.

We then calculated the cumulative abnormal return, CAR_t, from day 1 to day t:

$$CAR_t = \sum_{i=1}^{t} MAR_t. \tag{7}$$

Results

Applied to a random sample of 1,451 stocks from 1962 through 2000, our algorithm detected 44,150 patterns (3,562 of them belonging to more than one pattern template) based on the definitions presented in Lo et al. The percentage of the total patterns detected by type is as follows: HS, 17.12 percent; IHS, 15.88 percent; RTOP, 22.16 percent; RBOT, 22.98 percent; BTOP, 6.05 percent; BBOT, 5.40 percent; TTOP, 4.82 percent; and TBOT, 5.59 percent.

Table 3 presents the number of patterns detected, by decile, for each pattern for stocks with trading prices of at least $2.00. For these stocks as a group on the day the last extremum occurred, RTOP and RBOT patterns occurred most frequently. HS and IHS were the second most frequently occurring patterns. For the stocks with a price of $2.00 or more, for all the pattern templates, the number of patterns detected generally increased with the size of the companies. **Table 4** provides the number of patterns detected for stocks with trading prices below $2.00. The number of patterns decreased with increasing size deciles. This result is not surprising because the larger companies have fewer stocks with lower prices ($2.00).

We also report, in **Table 5**, the number of patterns detected within various ranges of membership values within the pattern. Because the frequency counts are different from pattern template to pattern template and were affected by our fuzzification procedures for each pattern template, Table 5 shows lower frequencies for the HS and IHS patterns below a 0.7 membership value than for RTOP and RBOT patterns in the same range.

Out of 41,727 patterns detected, we found (not tabulated) 879 overlapping HS-RTOP and 808 overlapping IHS-RBOT patterns, accounting for 8.74–11.92 percent of the total number of HS, IHS, RTOP, and RBOT patterns. The number of other overlapping patterns ranged from 71 to 100, which accounted for 2.71–4.87 percent of the total number of those single patterns. Because our statistical tests on postpattern abnormal returns were based on stand-alone patterns, caution should be exercised in interpreting the results when there are potential overlapping patterns. When overlapping patterns give the same bullish or bearish signals, the postpattern performance may be slightly overestimated. When overlapping patterns give conflicting buy and sell signals, the results may be slightly underestimated.

Although formal treatments of overlapping patterns are not found in previous literature, our fuzzy logic approach can be a useful tool in dealing with the patterns, especially with contradictory buy and sell signals.[4] If two patterns, A and B, overlap, one can treat the overlapping pattern as if it were the one with the larger membership value and assign a new membership value to it. If the bullish or bearish signal of one pattern—say, Pattern A—is not clear, one simply ignores that pattern and treats the overlapping pattern as Pattern B. For example, let $m1$ and $m2$ be the membership value of the two patterns that overlap. Assume that $m1 > m2$ and $\gamma \subset (0,1)$. We can assign a new membership value, M, to the pattern. If the two overlapping patterns are both bullish or both bearish, $M = m1 + (\gamma)(m2)$. If one bullish and one bearish pattern are detected, $M = m1 - (\gamma)(m2)$. Of course, M could be any function of $m1$ and $m2$, not necessarily a linear one, but using the linear function is straightforward (γ needs to be determined empirically). We discuss the bullish and bearish signals of overlapping patterns later in the article and leave the estimation of γ to future work.

Table 3. Number of Patterns Detected for Stocks with Trading Prices of at Least $2.00, 1962–2000

	HS	IHS	RTOP	RBOT	BTOP	BBOT	TTOP	TBOT
All stocks	7,376	6,865	8,853	9,242	2,620	2,323	2,053	2,395
NASDAQ	2,664	2,335	3,983	4,128	723	650	639	709
Decile 1	172	178	286	320	56	84	57	56
Decile 2	407	333	588	629	116	119	117	122
Decile 3	511	479	763	817	139	131	119	130
Decile 4	543	527	866	902	165	135	173	185
Decile 5	677	587	941	1,008	173	165	179	191
Decile 6	679	569	826	859	191	189	192	230
Decile 7	777	731	1,028	1,048	286	220	232	258
Decile 8	967	900	1,179	1,202	379	318	271	346
Decile 9	1,065	1,005	1,104	1,155	414	370	296	338
Decile 10	1,578	1,556	1,272	1,302	701	592	417	539

Table 4. Number of Patterns Detected for Stocks with Trading Prices Less Than $2.00, 1962–2000

	HS	IHS	RTOP	RBOT	BTOP	BBOT	TTOP	TBOT
All stocks	184	144	931	903	52	62	75	72
NASDAQ	130	97	423	410	36	51	60	60
Decile 1	52	40	207	198	18	15	27	26
Decile 2	54	46	195	193	14	21	21	22
Decile 3	33	17	147	138	9	8	14	14
Decile 4	25	15	120	141	6	8	6	5
Decile 5	9	16	136	127	2	6	4	3
Decile 6	6	3	49	37	2	1	0	1
Decile 7	4	4	37	44	0	1	1	0
Decile 8	1	1	24	13	1	2	1	1
Decile 9	0	2	16	12	0	0	1	0
Decile 10	0	0	0	0	0	0	0	0

Table 5. Number of Patterns for Stocks of at Least $2.00 by Membership Range, 1962–2000

Membership	HS	IHS	RTOP	RBOT	BTOP	BBOT	TTOP	TBOT
$n \leq 0.7$	251	272	5,027	5,042	1,699	1,380	1,395	1,651
$0.7 < n \leq 0.8$	867	840	1,604	1,744	298	279	186	222
$0.8 < n \leq 0.9$	2,025	1,883	867	889	288	272	152	192
$0.9 < n < 1$	2,694	2,448	527	604	239	275	213	223
$n = 1$	1,539	1,422	828	963	96	117	107	107
Total	7,376	6,865	8,853	9,242	2,620	2,323	2,053	2,395

As noted previously, RTOP can overlap with HS, BTOP, and TTOP. Although the study by Lo et al. and this study contain positive postpattern returns, RTOP is considered to be a bearish signal (Edwards and Magee 1997). Patterns of HS and BTOP are also bearish patterns (Edwards and Magee). Therefore, if both RTOP and HS or both RTOP and BTOP are detected in a pattern, one can treat the pattern as if it were the one with the larger membership value. TTOP and TBOT are symmetrical triangle patterns that do not give clear signals (Edwards and Magee; Bulkowski 2002); thus, an RTOP and TTOP overlapping pattern can be treated as an RTOP pattern. Similarly, an RBOT and TBOT overlapping pattern can be treated as an RBOT pattern. RBOT is a bullish pattern (Edwards and Magee), and it can also overlap with two other bullish patterns, IHS and BBOT (Stevens 2002). Therefore, the overlapping patterns can be treated as either RBOT, IHS, or BBOT, depending on their membership values.

Cumulative Abnormal Returns. In this section, we divide the results on CARs into three parts: The first part presents the results for the effects of small trading prices and the exchange where the stock is traded; the second part deals with the effects of different membership values within a technical pattern; and the last part provides the results for different subperiods.

**Effects of Small Price and Exchange.** CARs for up to 120 days after the completion of eight patterns are shown in **Figure 6**. The total number of patterns detected is 44,150. Of the eight patterns examined, Figure 6 shows CARs of head-and-shoulders, rectangle tops, and rectangle bottoms to be statistically significant for most of the days after the completion of the patterns. CARs of the inverse head-and-shoulders pattern are significant for only a few days five months after the pattern was detected. The magnitude of CARs is moderate. The highest CAR for 120 days is 3.65 percent (the CAR of RBOT). This percentage is equal to 0.0304 percent daily abnormal returns, on average.

Based on the definitions of patterns discussed previously, automatic pattern detection can be greatly affected by the prices of the stocks. For example, a bid-and-ask spread of 1/16 amounts to 3.125 percent at a $2.00 price. Thus, the stocks trading at prices below $2.00 can easily meet the criterion of rectangle tops and rectangle bottoms, which require that tops and bottoms be within 0.75 percent of their average and the lowest top be higher than the highest bottom. Because the patterns detected by our algorithm may not be seen as patterns by investors, we removed the patterns when stocks were trading at prices below $2.00 on the day that the last extremum occurred. The resulting CARs are shown in **Figure 7**. With those stocks removed, the

Figure 6. CARs after Completion of Eight Patterns, 1962–2000
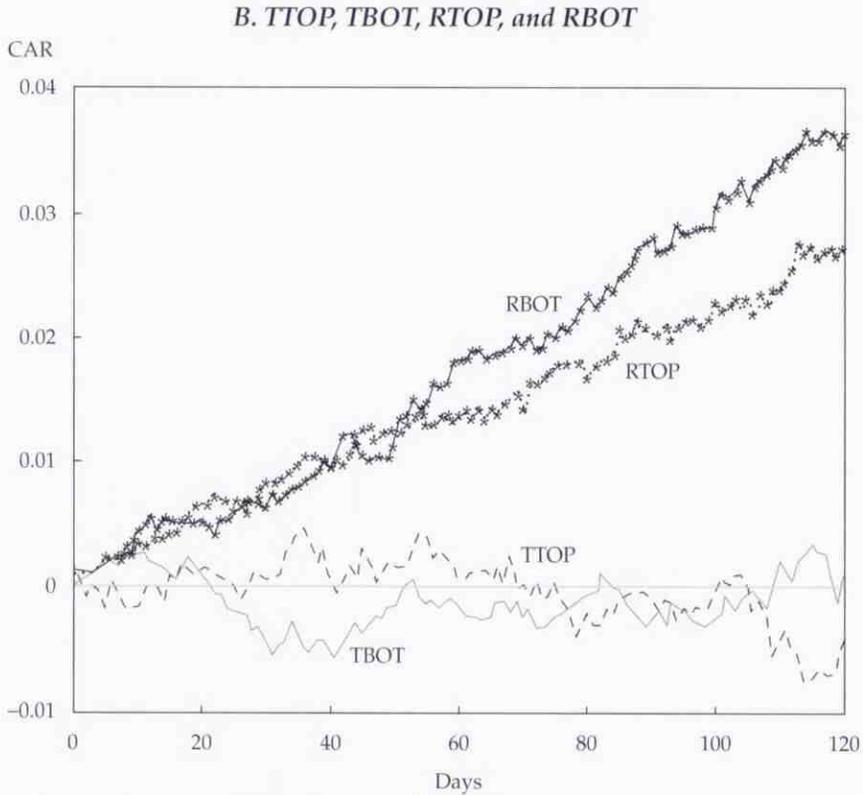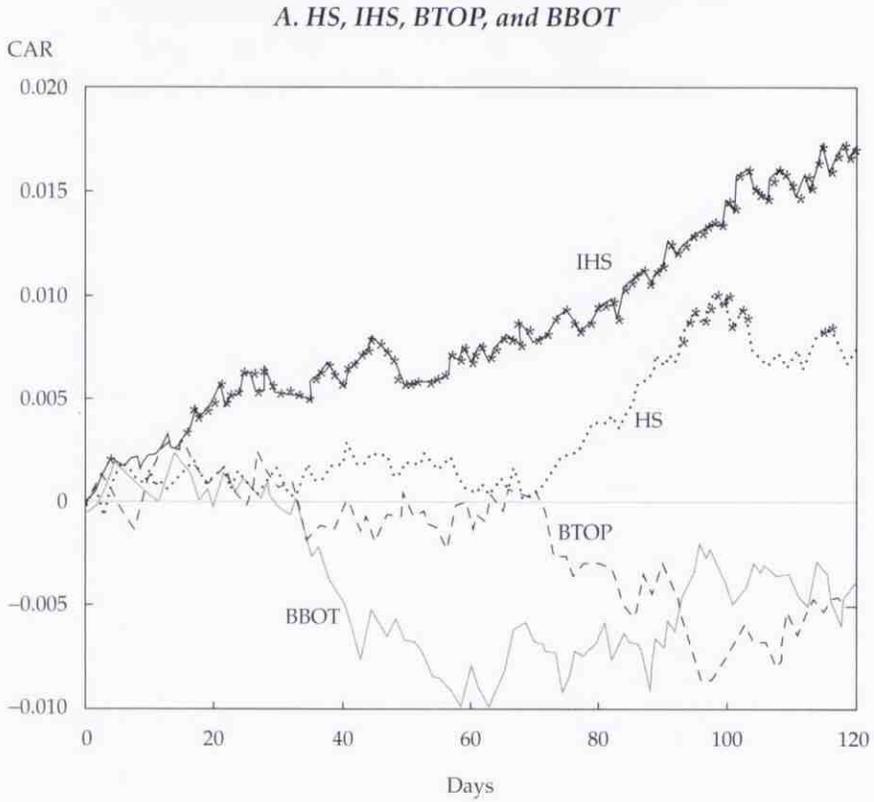
A. HS, IHS, BTOP, and BBOT

CAR

Days

B. TTOP, TBOT, RTOP, and RBOT

CAR

Days

Note: Asterisks indicate CARs that are statistically significantly different from 0 at the 5 percent level.

Figure 7.   CARs after Completion of Eight Patterns for Stocks with Trading Prices of at Least $2.00, 1962–2000
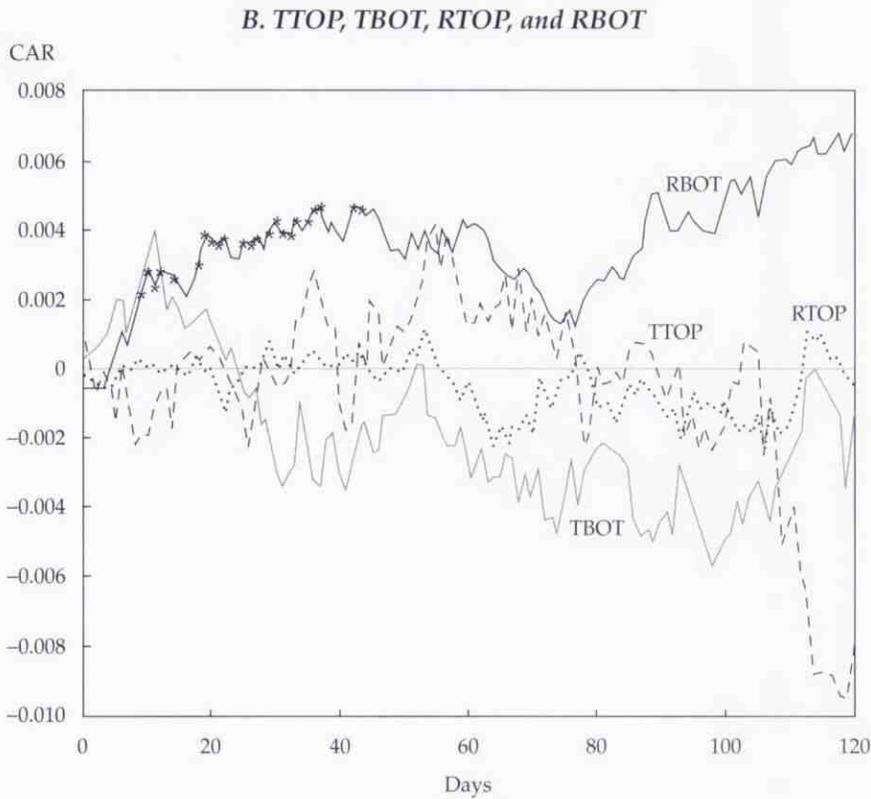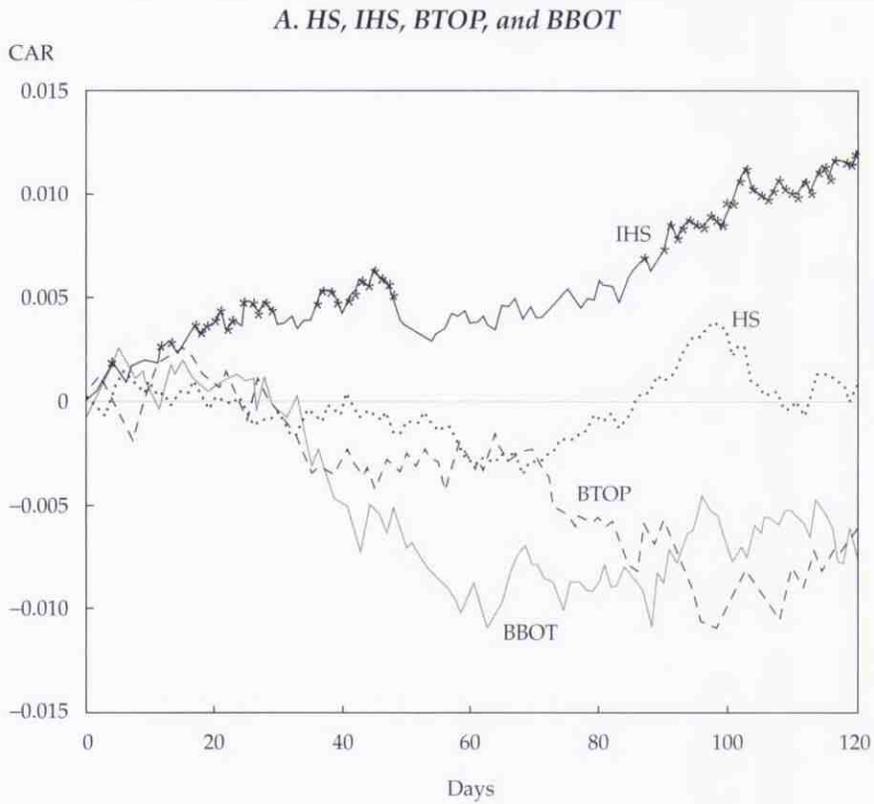
A. HS, IHS, BTOP, and BBOT

B. TTOP, TBOT, RTOP, and RBOT

Note: Asterisks indicate CARs that are statistically significantly different from 0 at the 5 percent level.

significance of CARs for the HS and RTOP patterns disappears. The number of days of significant CARs for the patterns of IHS and RBOT decreases dramatically. The magnitude of CARs also diminishes. The highest CAR, only 1.18 percent for 120 days, is less than one-third of the CAR when the stocks below $2.00 were included. These results suggest that one needs to be cautious when using computer algorithms to detect technical patterns and interpreting the inferences of statistical tests.

To check the robustness of the impact of low trading prices on the abnormal returns, we computed CARs for stocks in the CRSP size deciles above 5. We wanted to know whether the impact of low price was caused by the small-size effect. The results shown in **Figure 8** are similar to those in Figure 6. Hence, Figure 8 suggests that it is primarily low trading prices (the effects of bid–ask spread), rather than market capitalization, that affect the statistical inferences of abnormal returns.

We also compared CARs for stocks listed on the NYSE and Amex versus those listed on NASDAQ. Within that division, we also computed CARs separately for all stocks and for stocks with trading prices of at least $2.00. (Results not graphed here.) Overall, the patterns in NASDAQ stocks generated more significant CAR results than those in NYSE/Amex stocks, especially when we included the stocks with all prices. For instance, IHS in NASDAQ stocks generated overwhelming significance for most days, and the magnitude of the CARs (above 3 percent for 120 days) was much larger than that of IHS in the NYSE/Amex group. CARs for RTOP and RBOT were significant for both NYSE/Amex and NASDAQ stocks, but the CARs for NASDAQ stocks were about twice as high as those for NYSE/ Amex stocks. For stocks trading above $2.00, the significance of CARs for RTOP and RBOT totally disappeared for NASDAQ stocks and the number of days of significance was drastically reduced for RTOP and RBOT in NYSE/Amex stocks. The number of days of significance for CARs for stocks on NASDAQ for IHS also fell drastically, but significant days increased for BBOT.

These results on the impact of where the stock is listed are consistent with those in the Lo et al. study. In their results, the technical indicators for NASDAQ stocks exhibited much greater significance in the statistical tests than did those for NYSE/Amex stocks.

Our results suggest further that the effect of small trading prices on CARs mainly pertains to the RTOP and RBOT patterns and is more severe for NASDAQ stocks. Because of the trading price effect, the remainder of the results we present will be for stocks with trading prices of $2.00 or above on the day the last extremum occurred.

Pattern Membership Value Effect. We computed CARs for stocks after the completion of a pattern based on the pattern membership value. We used different membership functions for each pattern template to calculate membership values. We formed two sample portfolios for each pattern, one containing stocks with pattern membership values no larger than 0.7 and the other containing stocks with pattern membership values larger than 0.7. The results for the head-and-shoulders and inverse head-and-shoulders patterns are shown in, respectively, **Figure 9** and **Figure 10**. The corresponding *t*-statistics of tests of CARs that are different from zero for the HS and IHS patterns detected are shown in **Figure 11**.[5]

Keep in mind that technical analysts regard HS as a bearish technical indicator. The results shown in Panel A of Figure 9 indicate that the CARs for the portfolio of stocks with HS membership values of 0.701 to 1 were mostly negative, but Figure 11 indicates that they are not significantly different from zero. The CARs for the portfolio of stocks with HS membership no larger than 0.7, however, were significantly positive every day from the 40th day to the 60th day after the 3rd day of the completion of the HS pattern. Tests of the null hypothesis of equality of the means of the two portfolios (using the *F*-test and the Kruskal–Wallis test, as shown in Panel B of Figure 9) show that for that same period, the CARs of the two portfolios are significantly different.[6]

The results for IHS shown in Figure 10 mirror those for HS except that the CARs for the portfolio of stocks with IHS membership values from 0.701 to 1 were significantly positive, as shown in Figure 11. IHS is a bullish technical indicator, but our results show that the postpattern performance for the portfolio of stocks with IHS membership values no larger than 0.7 was significantly worse than that of the portfolio with control companies on most of the days from the 86th to the 120th day. The *F*-test and Kruskal–Wallis test depicted in Panel B of Figure 10 show that for the same period, the CARs of the two portfolios with different membership values in IHS are significantly different. We obtained similar results for the RBOT pattern.

We did not find significantly different postpattern performances by the portfolios of the other five patterns—BTOP, BBOT, TTOP, TBOT, and RTOP. Nor did we find significant CARs for more than a few postpattern days for the other five patterns, so we do not present the results here.

Based on our fuzzification procedure, a pattern with a membership value below 0.7 meets the classical definition of the pattern but is visually less eye-catching. The results suggest that for HS, IHS, and RBOT patterns, our fuzzy logic–based algorithm can be used to detect subtle differences even

**Figure 8. CARs after Completion of Eight Patterns for Stocks with Size Decile 5 and Above, 1962–2000**
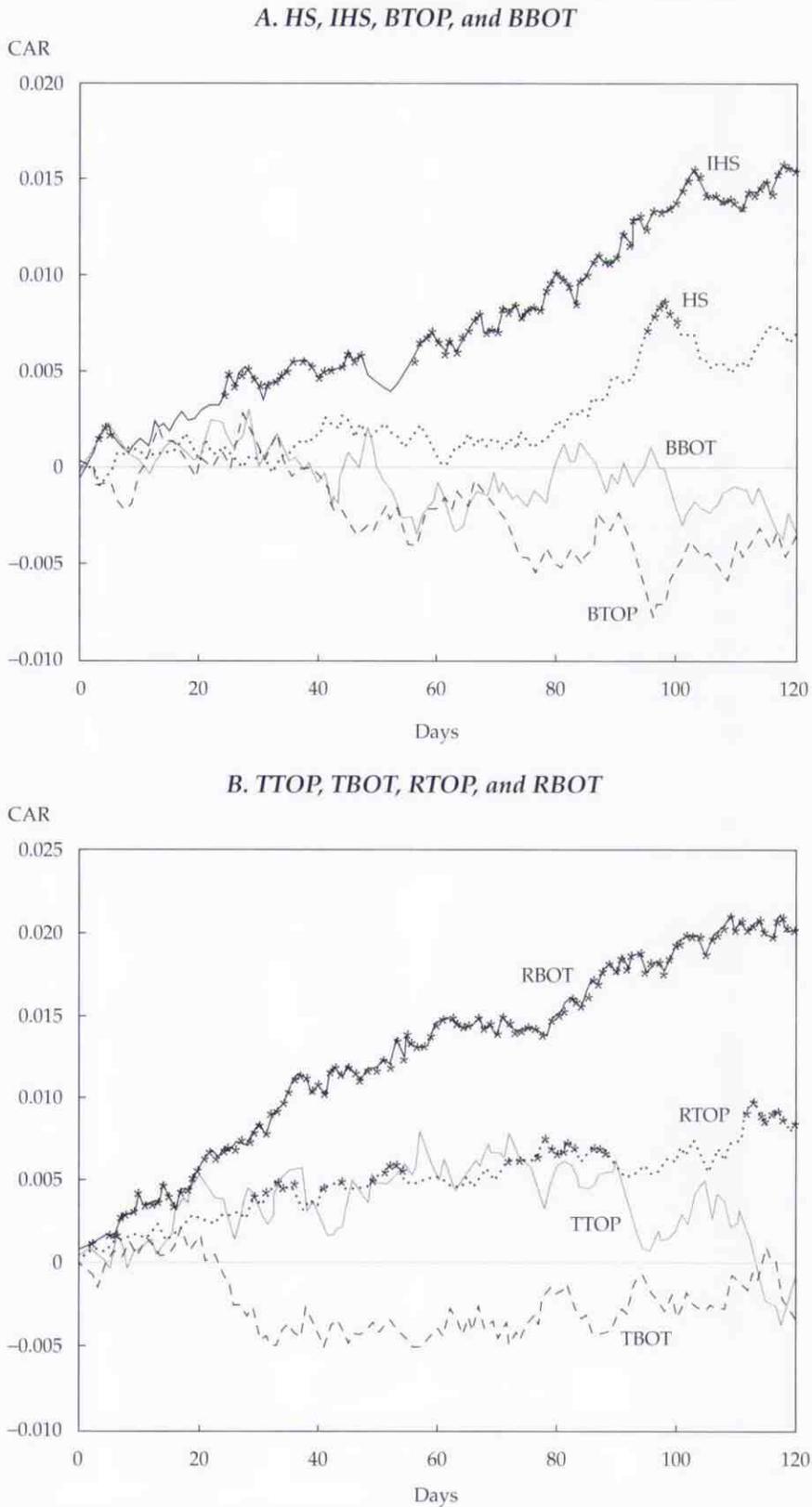
A. HS, IHS, BTOP, and BBOT

B. TTOP, TBOT, RTOP, and RBOT

Note: Asterisks indicate CARs that are statistically significantly different from 0 at the 5 percent level.

**Figure 9.   CARs and Tests of Equality of CAR Means for Portfolios with HS
Pattern Membership, 1962–2000**
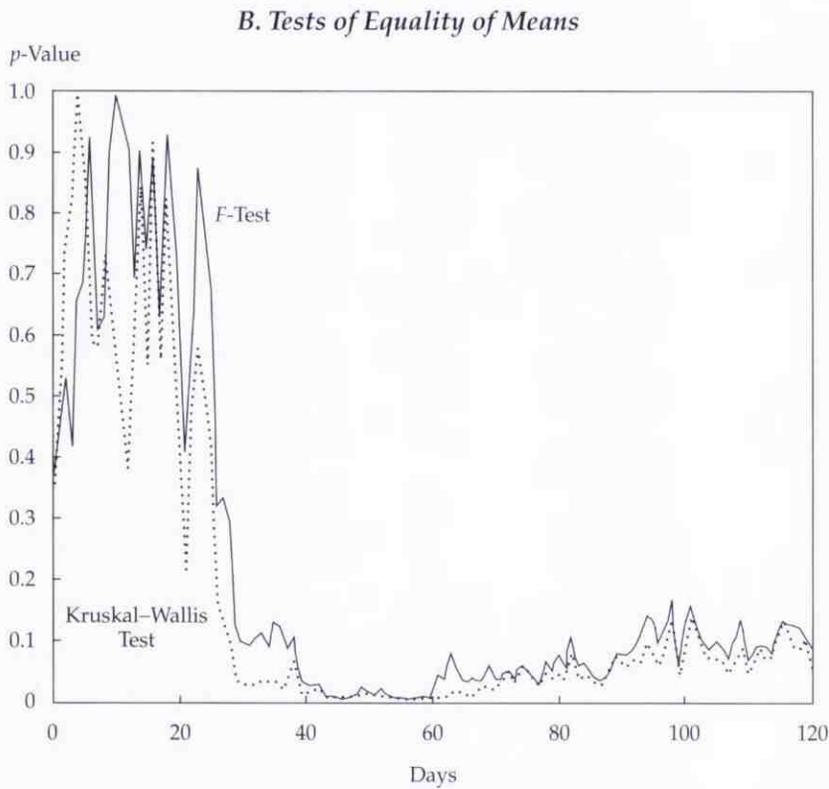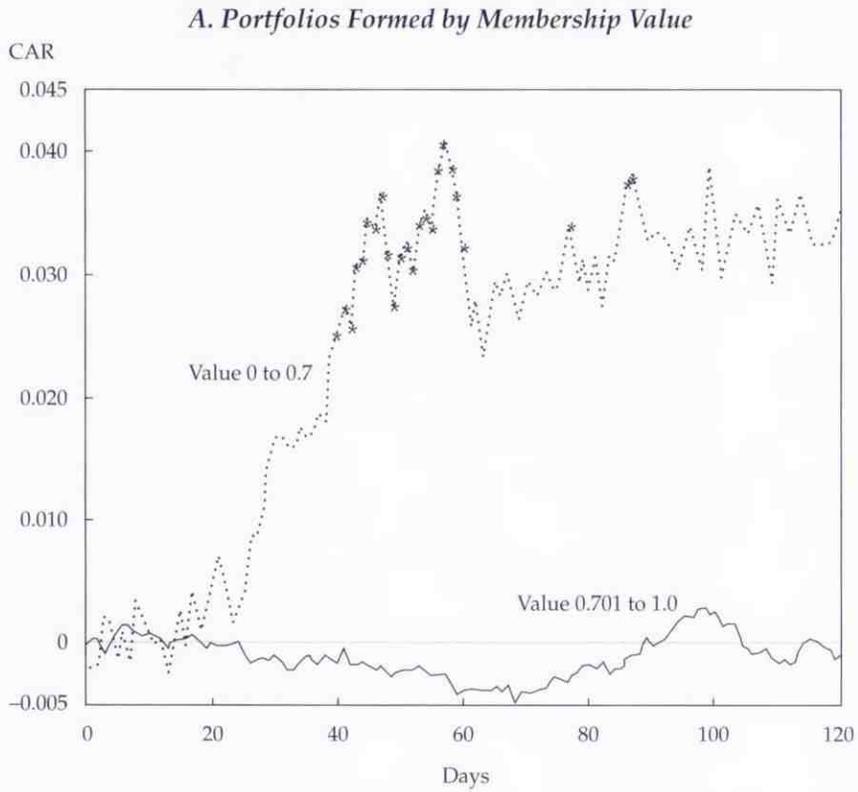
A. Portfolios Formed by Membership Value

B. Tests of Equality of Means

Note: Asterisks indicate CARs that are statistically significantly different from 0 at the 5 percent level.

Figure 10. CARs and Tests of Equality of CAR Means for Portfolios with IHS Pattern Membership, 1962–2000
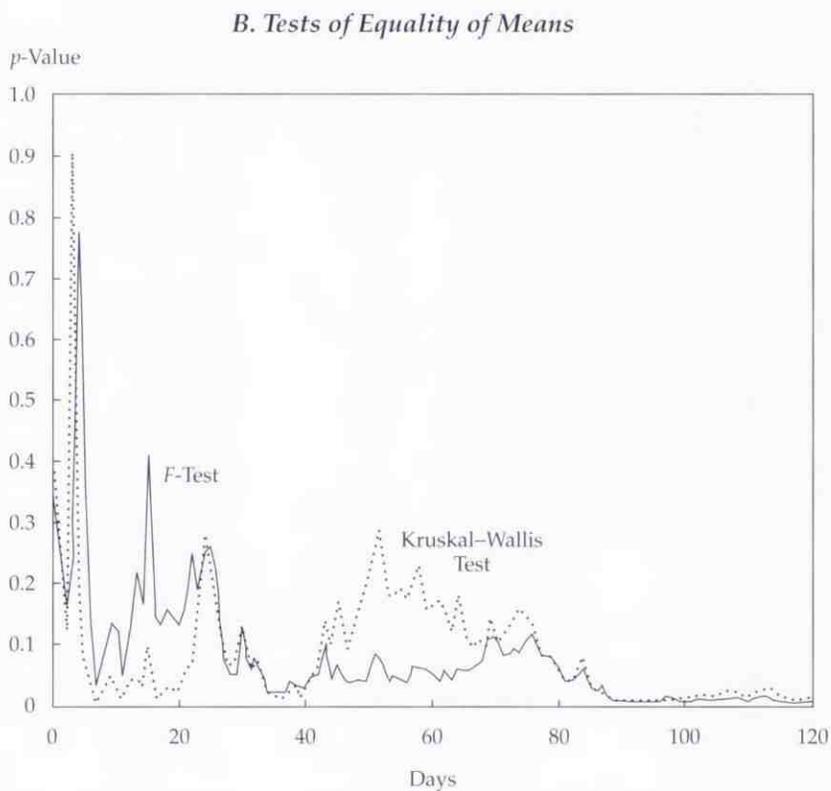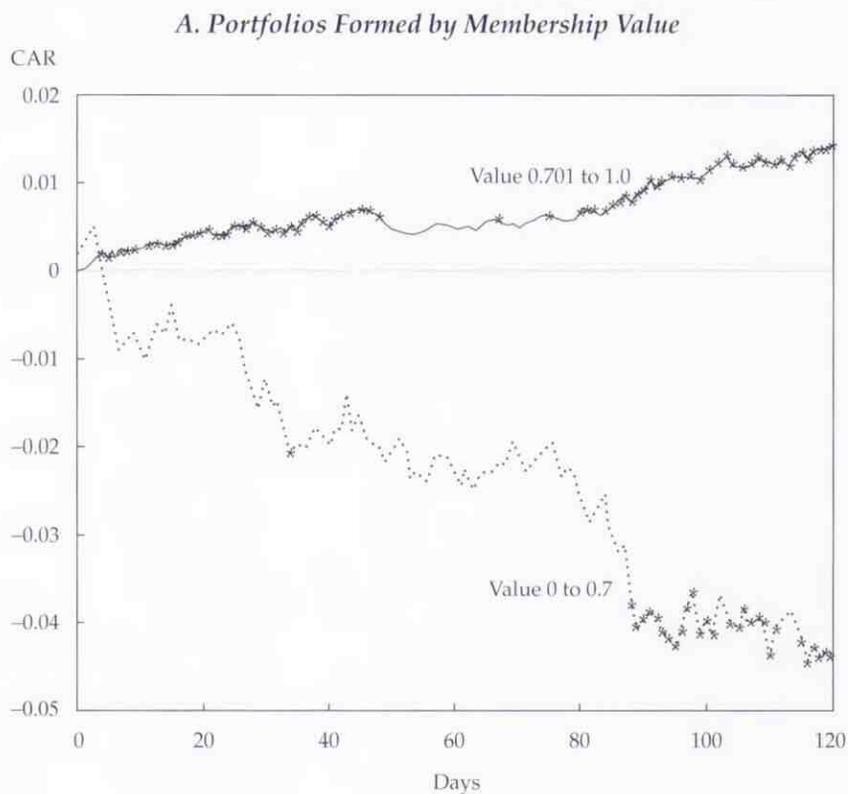
A. Portfolios Formed by Membership Value

B. Tests of Equality of Means

Note: Asterisks indicate CARs that are statistically significantly different from 0 at the 5 percent level.

Figure 11.   Resulting *t*-Statistics of Tests of CARs Different from Zero for Portfolios with HS or IHS Pattern Membership, 1962–2000
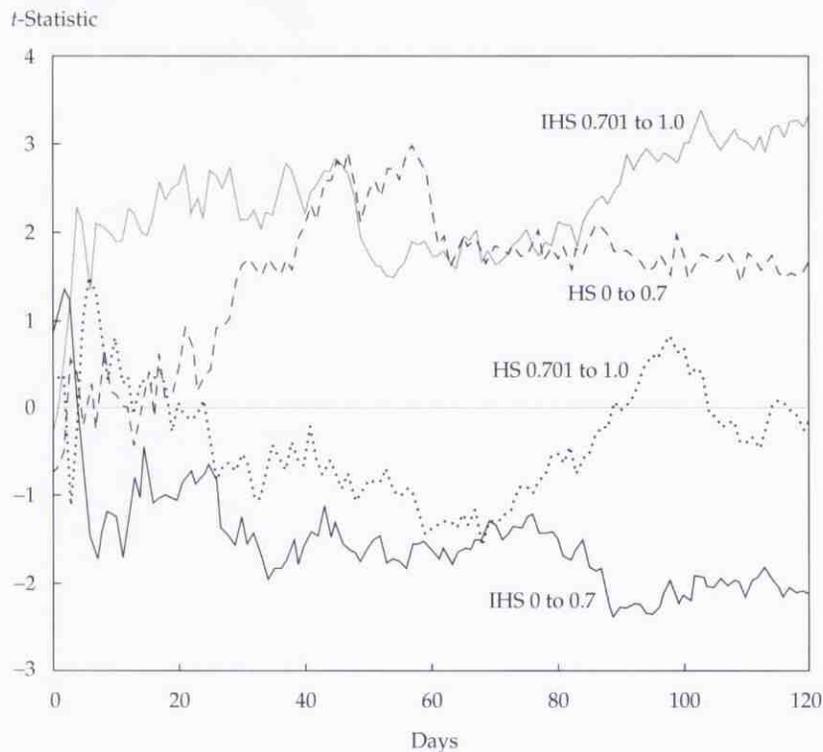
within a single pattern template. These results may explain why so much controversy surrounds technical analysis, in the sense that patterns recognized as the same by most people can still generate entirely different postpattern performances. The results may also explain why an expert technical analyst and an average investor looking at the same stock chart and using the same pattern definition can derive different buy and sell signals. The differences within a pattern detected by the fuzzy logic algorithm may not be apparent to average investors, only to certain experts, so only the experienced technical analysts can avoid using a pattern with a low membership value. Our approach, therefore, can help average investors find visual technical patterns with high membership values and take trading positions largely (or only) in stocks with strong pattern confirmations.

We also formed two different sample portfolios for each pattern, one containing stocks with pattern membership values of 1 and the other containing stocks with pattern membership values other than 1. The results were very similar to those of the two sample portfolios in the previous description. We found significantly different postpattern performances between the portfolios for HS, IHS, and RBOT with the cutoff of 1 but not for BTOP, BBOT, TTOP, TBOT, and RTOP.

All the results from our analysis of membership value suggest that the fuzzification procedures can distinguish the subtle differences within certain patterns but not others. To detect the subtle differences in other patterns, we would need to redefine the fuzzification procedures, choose a different x variable in Equation 4, and adjust the parameters. We leave this issue to future work.

CARs of Subperiods. To check the robustness of the postpattern results, we examined CARs during four subperiods—July 1962 through December 1970, January 1971 through December 1980, January 1981 through December 1990, and January 1991 through December 2000. For example, we formed two portfolios to examine postpattern results for the rectangle top pattern: One had stocks with RTOP membership values of 1, and the other had stocks with membership values of less than 1. The results are shown in **Figure 12**. Results for the first three subperiods (Panels A, B, and C) are similar. For those periods, the postpattern performances of the two portfolios are significantly different. For the 1990s period shown in Panel D, however, the performances of the two portfolios are not significantly different. The cause may be more efficient markets, with increased trading volume and lower trading costs, in the last subperiod.

Figure 12. CARs for RTOP Portfolio with Membership Value of 1 and RTOP Portfolio with Membership Value Less than 1
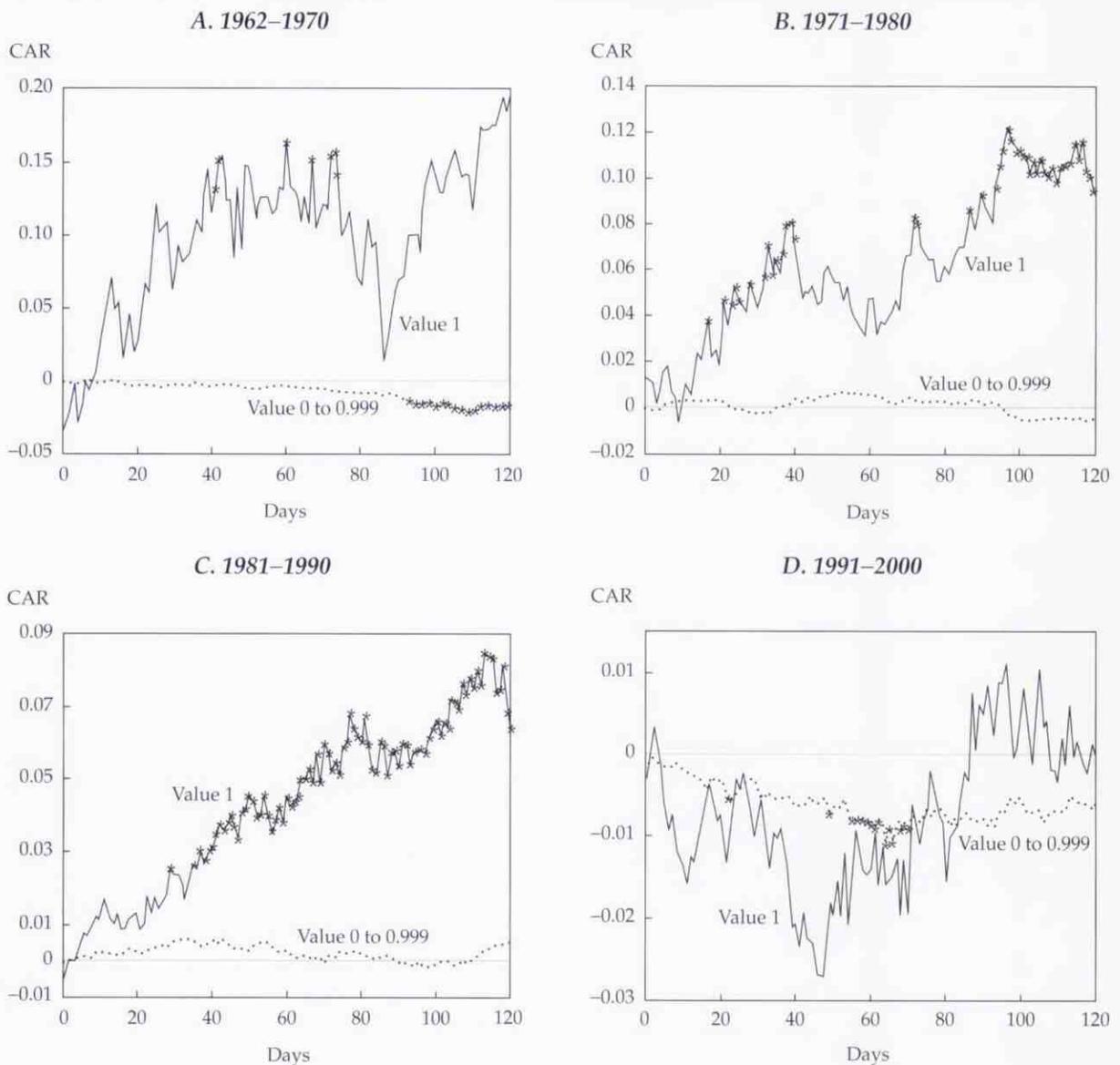
A. 1962–1970

B. 1971–1980

C. 1981–1990

D. 1991–2000

Note: Asterisks indicate CARs that are statistically significantly different from 0 at the 5 percent level.

More investors, including novice individual investors, became interested in technical analysis in the past decade, and more people with easy access to vast, free technical trading information on the Internet are aware of the RTOP pattern.

The inconsistent results in the subperiods may also be caused by the different number of patterns detected in the periods and, subsequently, different powers of the statistical tests. The results in certain subperiods are, therefore, not representative. For example, for RTOP, 3,274 stocks had a membership value less than 1 and 421 stocks had a membership value of 1 from 1991 through 2000. From 1962 through 1970, however, 914 stocks had a member-

ship value less than 1 and only 11 stocks had a membership value of 1.

We also computed CARs for the other patterns for the four subperiods already discussed and for subperiods of July 1962 through December 1980 and January 1981 through December 2000. In general, we found little in the way of consistently significant results. When we compared the results of subperiods during which a similar number of patterns were detected, the significance results were still inconsistent.

These findings may provide another angle on the controversy about technical indicators. Three explanations seem to be possible regarding the

inconsistent subperiod results—different degrees of market efficiency in different periods, different numbers of patterns detected in different periods, and data snooping (as suggested by Sullivan, Timmermann, and White 1999).

Data snooping seems an unlikely explanation, however, for these findings on the effects of pattern membership values. The effects of technical trading rules may be spurious and driven by data snooping, especially when the trading rules are selected from a huge number of trading rules, which is not the case in our membership value effects. However, although the eight pattern templates used in this study are parts of a large number of possible visual patterns described in Figure 4, they were selected purely because they are the patterns most widely used by practitioners in the markets, as suggested by Lo et al. We did not select them because the trading signals from the eight patterns were the strongest among all the possible patterns. The criteria (definitions) used in building the pattern templates are exactly the same as those used by Lo et al. Thus, data snooping is not applicable in the postpattern performance of pattern templates. As for the parameters used in deciding membership thresholds, we made adjustments so the patterns with more symmetrical visual shapes would be assigned higher membership values (for example, the more symmetrical the two shoulders looked, the higher the membership value we set for HS). Because the tuning of parameters was not based on postpattern performance and the parameters that gave the best trading signals, the data snooping accusation does not apply in this case either.[7]

Conclusion

We have presented a fuzzy logic–based approach to measuring the degree of effectiveness of technical patterns. We believe there is still a long way to go, however, before computers will simulate human judgment. Nevertheless, by introducing fuzzy logic into the technical analysis domain, our approach incorporates human cognitive uncertainty into automatic pattern detection and analysis in a way that simulates human judgment significantly better than previously. Furthermore, we used the same method to measure the postpattern performance that is used in corporate event studies,

which allows a meaningfully comparison of technical analysis with fundamental analysis.

Our algorithm was able to detect subtle differences within a clearly defined pattern template. Such differences may not be apparent to average investors but only to certain experts. Thus, in comparison with visual technical pattern analysis, our approach offers superior precision in detecting and interpreting the technical patterns. In Chang and Osler's study, the head-and-shoulders pattern in foreign exchange markets could be profitable but it was not efficient because simpler trading rules dominated the trading strategy based on the HS pattern. Lo et al. concluded that the technical patterns are informative but do not provide the answer to the question: Is technical analysis profitable? Our approach can explain their results. If an investor excludes stocks showing the HS pattern but with a low membership value, the investor can improve the efficiency of the trading strategy based on the HS pattern. The results of our company-matching CAR tests suggest that forming portfolios with high membership value patterns can be profitable. Using our approach, investors can first examine the historical trading statistics, then use the proposed fuzzy logic–based approach to set their own variables and parameters, and finally, develop their own future winning strategies based on the fuzzy membership values.

In this study, we did not consider the situation in which more than one pattern shows up consecutively, which may affect postpattern performance. For instance, if the bearish indicator HS is followed by the bullish indicator IHS, how should the analyst or investor handle the situation? One possibility is to do as we did for overlapping patterns as discussed in our "Results" section. One would assign to the more recent pattern a new membership value that incorporates the membership value of both patterns.

Also, we studied only eight pattern templates in this study. Future research could include all the pattern templates described by Figure 4, although the effects of data snooping would need to be carefully examined.

Notes

1. See Neftci and Policano (1984); Treynor and Ferguson (1985); Pruit and White (1988); Brown and Jennings (1989); Jegadeesh and Titman (1993); Blume, Easley, and O'Hara (1994); Chan, Jegadeesh, and Lakonishok (1996); Campbell, Lo, and MacKinlay (1997); Lo and MacKinlay (1988, 1999); Goodacre and Bosher (1999); Goodacre and Kohn-Speyer (2001).

2. The Gaussian kernel is $(2\pi\sigma^2)^{-1/2}\exp[-(u^2/2)]$, where $u = (x - x_i/\sigma)$, σ is the window width, x_i values are the values of the independent variable in the data, and x is the value of the independent variable for which one seeks to smooth. Unlike most kernel functions, this one is unbounded on x; so, every data point will be brought into every smoothing, in theory, although outside three standard deviations, they make hardly any difference.

3. Chan et al. showed that companies with past-year stock return momentum and earnings surprise continue to experience the momentum over the next six months. They found that both return momentum and earnings surprises contribute to the momentum for up to six months.

4. We thank an anonymous referee for pointing out this issue.

5. We omit the figure for RBOT.

6. The Kruskal–Wallis test, a generalization of the Wilcoxon rank-sum test, is a nonparametric test for differences in means for two or more groups in the case of unequal sample sizes (Kruskal and Wallis 1952).

7. In the future, we would like to develop an algorithm to optimize the fuzzification procedure in which the variables and parameters would be selected according to the postpattern performance. The effects of data snooping as detailed in Sullivan et al. would then be tested.

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