IDENTIFYING NOISE TRADERS:

THE HEAD-AND-SHOULDERS PATTERN IN U.S. EQUITIES

ABSTRACT

This paper identifies a specific set of agents as noise traders in U.S. equity markets, and examines their effects on returns. These agents, who speculate using the "head-and-shoulders" chart pattern, are shown to qualify as noise traders because (1) trading volume is exceptionally high when they are active, and (2) their trading is unprofitable. Head-and-shoulders sales lower prices and vice versa, effects that disappear within two weeks.

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Since their introduction by Kyle (1985), noise traders have become fairly common actors in models of market microstructure. By now, we know a lot about what noise trading might be: It might be liquidity trading (Foster and Viswanathan 1990, 1993, Dow and Gorton 1993, Pagano and Roell 1996); it might be hedging (Dow and Gorton 1994a); or it might be speculation (De Long et a. 1990a,b). It might be rational (Dow and Gorton 1994a, 1994b); and it might not be rational (Black 1986; De Long et al. 1989, 1990, 1991; Kupiec 1994; Palomino 1996). Noise trading could even be undertaken by rational speculators themselves (Campbell et al. 1993; Wang 1994), so long as the trigger for noise trading is something besides the arrival of new information about asset value. In fact, noise trading takes so many forms in the theoretical literature that it can be defined most accurately by what it is not: noise trading is not rationally based on the arrival of new information about asset values.

By now, we also know a lot about the possible effects of noise trading. Among other things, we know that noise trading might permit securities markets to exist, by making information-gathering by rational speculators a profitable activity. That is, their presence could accommodate Grossman and Stiglitz's concern (1980) about "the impossibility of informationally efficient markets." Likewise, we know that noise trading might make market-making possible, by "provid[ing] camouflage which enables the insider to make profits at the [noise traders'] expense" (Kyle 1985, p. 1316). We know that noise trading might cause a permanent divergence between prices and fundamental values (De Long et al. 1990a).

Though we know a lot about what noise trading might be and how it might affect markets, as yet we have little direct evidence that it exists. The most suggestive evidence is provided by Kelly (1997), which finds that one-year U.S. stock returns tend to be smaller after periods of relatively high participation in the stock market by the general population, suggesting those without extremely high income may, as a group, serve the role of "uninformed" traders. The presence of a number of financial market puzzles that could be consistent with the presence of noise traders provides additional, indirect evidence for their existence. For example, the presence of noise trading could help explain the excess of equity returns over this century over those required to compensate investors for standard measures of risk (Mehra and Prescott 1985), the excess of stock market volatility over the amount implied by the behavior of dividends (Shiller 1981; Leroy and Porter 1981; Campbell and Shiller 1988a,b; Campbell and Kyle 1993), and the negative gap between the prices of closed end funds and the value of their component assets.

Unfortunately, these observations do not conclusively prove the existence of noise trading, because they might be explained by other factors. And even if one were to grant the existence of noise trading, one would still not know what motivates it, how it is carried out, or how common it is, since the empirical literature is essentially silent on these issues. This paper, however, provides direct evidence of the existence of noise traders, and simultaneously provides a preliminary identity to one group of them. Identification of noise traders permits further analysis, such as measuring the impact of these traders on stock returns, which the paper also undertakes.

In seeking to identify noise traders it seemed natural to begin with technical traders. These agents, who forecast financial price movements based on past prices and volumes, are mentioned frequently in the literature as candidates for noise traders (e.g., De Long et al. 1990b, Balduzzi et al. 1992). The absence of reasoned economic cause and effect in adherents' explanations for the supposed profitability of technical trading is one reason technical analysis comes to mind when discussing noise trading. Further, technical analysis is apparently an important input into decision-making for many, possibly the majority of financial market participants (see evidence discussed in Section I), so its impact could be proportionately large.

A third reason to look to technical analysis as a source of noise trading is the fact that technical trades associated with a given technical strategy will naturally tend to be correlated across agents. This is important in identifying noise trading because, as stressed by Shleifer and Summers (1990), noise trades "will only matter if they are correlated across noise traders. If all investors trade randomly, their trades cancel out ...[p. 23]." The correlation among certain technical trades arises from the fact that their analytical frameworks are widely shared, having been used for decades and taught at institutions like the New York Institute for Finance (Lukac et al. 1988). By contrast, some other types of noise trades, such as "liquidity" trades, are unlikely to be correlated across agents.

In equities markets, technical analysis is an especially likely candidate for noise trading because many other possible forms of noise trading seem unlikely either to exist or to be detectable. For example, it seems unlikely that there would be heavy liquidity trading in equities markets, since liquidity needs are generally satisfied in markets for securities such as cash and short-term securities, where transactions costs as well as returns are lower than in information-sensitive markets such as equities (Amihud and Mendelson 1986). One might also wonder about the extent to which equities markets would be used to hedge income flows, the form of noise trading modeled in Dow and Gorton (1994a). Other types of noise trading that might well be present in equities markets, such as portfolio rebalancing trades necessary to accommodate changing risk tolerances, may be difficult to identify statistically because they are unlikely to be correlated across agents.

The particular technical strategy examined here is based on the "head-and-shoulders" pattern, which involves three price peaks, the highest of which is in the middle. This nonlinear, visual chart pattern was chosen because it is widely familiar to market participants, having been in use at least since described by Shabacker in 1930, and it is considered by technical analysts to be one of the most reliable of all chart patterns. Moreover, the use of nonlinear chart patterns in U.S. equities markets has been the subject of very little research to date.[1] Its nonlinearity makes the head-and-shoulders pattern distinct from basic trend-following rules or momentum strategies (see Jegadeesh and Titman 1993, Carhart 1997). The nonlinearity of chart-based technical rules is also quite distinct from previously studies forms of nonlinearity, such as chaos or ARCH (Scheinkman and LeBaron 1989).

The identification of head-and-shoulders traders as noise traders is based on two empirical results. First, I show that the activity of head-and-shoulders traders substantially increases aggregate trading volume. In fact, the total trading generated by a given head-and-shoulders pattern amounts to one quarter of a days' trading volume. This is important, because a trading strategy cannot serve as noise trading unless people actively use it. Second, I show that head-and-shoulders trading is not profitable. Like all of the major results of this paper, these are supported by numerous sensitivity analyses.

Head-and-shoulders trading is shown to represent a *particular type* of noise trading: positive-feedback speculation in which noise is confused with information. Head-and-shoulders trading qualifies as positive-feedback speculation because sales are triggered by downward price movements and vice versa. Head-and-shoulders patterns qualify as noise because the associated trading strategy is unprofitable.

Though this paper identifies head-and-shoulders trading as type of noise trading, it does not claim to have identified all or even most noise trading. Many as-yet untested forms of technical analysis might also qualify as noise trading. Real-world noise trading probably also includes liquidity trades, fully rational portfolio rebalancing in response to changing preferences or opportunity sets, and, in some markets, rational hedging. Nonetheless, the fact that an unprofitable trading strategy apparently qualifies as noise trading suggests that noise trading in theoretical models can be realistically motivated by appealing to departures from rationality, as suggested by Shiller (1984), Shleifer and Summers (1990), and De Long et al. (1990b).

Having identified some real-world noise traders, I next examine their effect on returns. In perfect capital markets, noise traders do not affect returns because rational speculators immediately arbitrage away any divergence between the actual price and its “fundamental” value. If rational arbitrage is limited (Shleifer and Vishny 1997; De Long et al. 1990a), however, returns could be determined by the *level* of noise trading, as suggested by Black (1986) and by studies of block trades (Scholes 1972; Holthausen et al. 1987, 1990), or by *changes* in noise trading, as suggested by Kyle (1985) and De Long et al. (1990). The evidence presented here indicates that head-and-shoulders trading does affect returns and that it is the level of noise trading that matters, since the immediate effect of head-and-shoulders sales is to reduce prices, and vice versa. In contrast to the effects of block trades, which seem to be partially or completely permanent (Holthausen et al. 1990), the effect of head-and-shoulders trades begins to dissipate almost immediately, and disappears entirely within two weeks.

The analysis is based on a computer program that identifies head-and-shoulders patterns based on certain defining characteristics. These characteristics are described very consistently in the eight technical manuals consulted to ensure accuracy: [2] in a series of three peaks, the second (the “head”) must be higher than both the first or the third (the left and right “shoulders” respectively: see Figure 1). (In fact, the manuals agree on almost everything about head-and-shoulders patterns, a correlation which is striking given the absence of rigorous study of these patterns.) Head-and-shoulders patterns should signal a trend reversal. For example, the head-and-shoulders depicted in Figure 1 should indicate that prices have stopped rising and will soon begin a downtrend. Drawing a line from the left trough to the right trough, produces the "neckline," which is critical for determining when to enter. If the price drops below or "penetrates" the extension of this neckline after the third peak, then the pattern is "confirmed," and one should take a short position at this point. Head-and-shoulders can occur at the end of an up-trend, when they are called "tops," or at the end of a downtrend, when the role of peaks is taken by troughs, and vice versa, and they are called "bottoms. Further details of the head-and-shoulders identification algorithm are described in the Appendix.

The head-and-shoulders identification algorithm finds about 27 confirmed head-and-shoulders patterns per firm, slightly fewer than one per year, which is not inconsistent with the frequency described in the manuals. The data consist of prices and volume for 100 firms selected at random from the entire CRSP (Center for Research on Securities Prices) equities data set. To arrive at this set of firms I first identified all firms with price data spanning July 2, 1962, the starting date of the CRSP database, to December 31, 1993. This represents 31 ½ years, or 8220 daily observations.[3] Though this data set clearly has survivorship bias, I have unable to discover any reason to expect survivorship to undermine the paper's conclusions.[4] After eliminating redundancies associated with name changes and mergers, the data set included 528 firms, from which 100 were selected at random. All the tests here can be viewed as out-of-sample tests, since the belief in the predictive power of head-and-shoulders patterns developed prior to 1930 (Shabacker 1930).

The paper has four main sections and a conclusion. Sections I and II identify head-and-shoulders traders as noise traders by looking at trading volume and profitability, in turn. Implications of this identification are discussed at the end of Section II. Section III examines the impact of head-and-shoulders traders on returns. Section V summarizes the results and their implications.

I. IDENTIFYING NOISE TRADERS: AN ANALYSIS OF TRADING VOLUME

This section shows that trading based on head-and-shoulders signals is active in U.S. equities markets. It begins by surveying some readily available evidence on the prevalence of technical analysis in general.

A. Technical Trading Activity

Financial market participants are universally aware of technical trading, even if they are not practitioners themselves. Those who do practice it are sufficient in number to support an entire magazine devoted to the subject, *Technical Analysis of Stocks and Commodities*, circulation of which exceeds 50,000. Likewise, *Equis Monitor*, a quarterly information letter to subscribers of a particular brand of technical analysis software, has a circulation of about 40,000, and *Futures Magazine*, which devotes a substantial part of every issue to technical analysis, has circulation of around 65,000. There are, by now, myriad on-line sources of information on technical analysis, technical analysis software, and data sources for technical analysis. In addition to the existing pool of technical analysts, a new crop of 450 to 500 students learns the subject each year at The New York Institute of Finance.[5]

Formal evidence on the extent of technical analysis is not abundant. *Futures Magazine*, through a survey of its subscribers, found that over one third of respondents base their trading decisions exclusively on technical analysis, and half combine technical analysis with fundamental analysis. The few extant academic surveys support this general picture. Allen and Taylor (1990) find that, over short horizons, 96 percent of London foreign exchange traders rely on some form of technical analysis. Lui and Mole (1996) find that technical analysis is used by over 90 percent of foreign exchange traders in Hong Kong, Singapore, and Japan. Shiller (1989) documents that support and resistance levels were very important to traders during the 1987 stock market crash.

B. Head-and-Shoulders Trading Activity: Methodology

The available evidence on technical trading does not indicate whether head-and-shoulders trading, in particular, is active in U.S. equities markets. To investigate this question, it seems natural to examine trading volume data on the days when head-and-shoulders traders would be active. I narrow this focus more tightly to the days on which head-and-shoulders traders are likely to *enter* positions, because technical analysis manuals are quite specific about the criteria for entry but ambiguous about the criteria for exit.

The empirical strategy employed here is to test whether trading volume is unusually high on the days when, according to technical analysis manuals, head-and-shoulders traders are likely to open their positions. Since technical manuals strongly recommend that no positions be opened until the price crosses the neckline, it seems natural to look for head-and-shoulders trading activity on the days this takes place, which will henceforth be called "neckline-crossing days."

Unusual trading volume is calculated as the residuals from a regression of the log of daily volume on a constant, a linear trend, fifty of its own lags, ten lags of the daily absolute price change, and the log of the closing price.[6] This formulation has a number of advantages. First, it eliminates virtually all residual correlation for randomly selected test firms.[7] Further, it incorporates as the familiar positive relationship between volume and volatility in financial markets (e.g. Karpoff 1987). Finally, the trend and log price terms allow for the strong trends evident in volume for many firms.[8]

The next step is to calculate, for each firm, the average residual from neckline-crossing days. Under the null hypothesis that there is no active trading on head-and-shoulders patterns, volume on these days will be drawn from the same distribution as volume on other days. Under the alternative hypothesis that there is active trading on head-and-shoulders patterns, volume on neckline-crossing days should be drawn from a distribution with higher mean. As shown in Table 1A, unusual trading volume averages 11 percent of a day's trading volume on neckline-crossing days. A simple *t*-test would not reject the hypothesis that trading volume is drawn from the same distribution on neckline-crossing days than other days, since the average regression residuals themselves have a standard deviation of 16 percent across the 100 firms. However, based on the observation that average neckline-crossing day residuals are positive for 77 of the 100 firms, one might wonder whether a more powerful test, taking advantage of information implicit in the pattern of results across the 100 firms, would support the alternative hypothesis that regression residuals are unusually high on neckline-crossing days.[9]

The relatively powerful non-parametric test applied here can be summarized as follows: A variant of the bootstrap technique is used to determine, for each firm, the probability of achieving the actual level of average neckline-crossing day volume residuals under the null. From this test there will be 100 *p*-values, one for each firm, the distribution of which can be tested for consistency with the null. A more detailed description of this methodology is given below.

Evaluating Neckline-Crossing-Day Volume for an Individual Firm: The bootstrap methodology (Efron 1979, 1992) is currently the standard technique for evaluating technical trading strategies, in part because it requires no assumptions about unknown statistical distributions, such as the distribution of volume residuals under the null.[10] An empirical distribution of a firm's average neckline-crossing day residuals under the null is generated from residuals on other days according to the following recipe, which assumes k head-and-shoulders positions for the firm: Calculate the average of k residuals selected at random from non-neckline-crossing days; repeat this 10,000 times. This distribution is used to determine the p-value of that firm's actual average neckline-crossing-day residual.[11]

Evaluating Neckline-Crossing-Day Volume for 100 Firms: In a large group of firms for which the null of no head-and-shoulders trading is correct and for which the p-values are independently distributed across firms, roughly 5 percent will have a p-value below 0.05, roughly 10 percent will have a p-value below 0.10, etc. In fact, under the joint null hypothesis of no trading and independence across firms, the p-values should be distributed uniformly over [0,1]. By contrast, if the head-and-shoulders pattern is in fact a source of trading activity, then the p-values for average neckline-crossing day residuals will likely be concentrated at low levels: more than 5 percent of them will fall below 0.05, more than 10 percent of them will fall below 0.10, etc.

The Anderson-Darling test can be used to evaluate whether the observed distribution of *p*-values is statistically equal to the uniform [0,1]. To provide a graphical intuition of this test, Figure 2 contrasts the theoretical c.d.f. with a hypothetical observed c.d.f. The theoretical c.d.f., corresponding to the uniform [0,1], shows the share of firms one would observe with *p*-value at or below a given probability under the null hypothesis. This is a 45 degree line. The c.d.f. for the observed distribution shows the observed share of firms with *p*-value at or below a given probability. The actual and theoretical c.d.f.s, which both begin at (0,0) and end at (1,1), will generally diverge at intermediate points. As described in D'Agostino and Stephens (1986), the test uses a statistic (referred to as A^2) which is a weighted average of the vertical differences between actual and theoretical cumulative distribution functions (c.d.f.s).[12] The greater the vertical gap between these two c.d.f.'s, the more likely the Anderson-Darling test will reject the hypothesis that the actual data was drawn from the theoretical distribution.

Note that there are two tiers of marginal significance levels involved in the overall test procedure. In the first tier, 100 marginal significance levels are generated, one for each firm. In the second tier, the final test of the null, based on the distribution of the first 100 marginal significance levels, generates just one marginal significance level associated with the Anderson-Darling test. To minimize confusion, the significance levels in tier one will be referred to as "*p*-values," and those in tier two will be referred to as "marginal significance levels."

Under the alternative hypothesis that there is active head-and-shoulders trading, the observed c.d.f. will generally lie above the 45 degree line since, as mentioned earlier, the observed *p*-values will be concentrated at lower values. Conversely, if for some reason volume is unusually low around head-and-shoulders trading signals, the c.d.f. would generally fall below the 45 degree line. In both cases, though the Anderson-Darling test might reject the uniform density, it would not indicate the reason for the rejection. In fact, the Anderson-Darling test could reject the uniform density even if the actual *p*-values are not concentrated at high or low levels, if the source of the rejection is moments of the distribution higher than the first. To identify the source of a rejection it is critical to examine the actual *p*-values and to the actual volume residuals.

As mentioned above, the Anderson-Darling test is only valid if neckline-crossing-day residuals are distributed independently across firms. The reasonableness of this assumption is an empirical question. Trading volume itself is certainly correlated across firms (Lo and Wang 1997). However, residuals, not trading volume itself, are the focus here. Further, since the head-and-shoulders identification algorithm locates only about one confirmed pattern per year per firm, the residuals may well be effectively independent if neckline-crossing days differ noticeably across firms. To examine whether independence on neckline-crossing days is a reasonable assumption, I construct a time series for each firm consisting of volume residuals on identified entry dates and zeros otherwise. For each of the 4,950 pairs of firms I then calculate the bilateral correlation across these series. The vast majority of these correlations are extremely small: only 2, or 0.04 percent, have a *t*-value of unity or greater. On this basis, the independence assumption appears to be reasonable.

To recap this lengthy exposition of methodology, the null hypothesis is that head-and-shoulders trading is *no*t active in U.S. equities markets. For each firm, unusual trading volume is measured as the residual from a regression of volume on its own lags and other variables. A comparison of unusual trading volume on neckline-crossing days and the distribution of unusual trading on other days gives 100 *p*-values, one for each firm. The final test, based on the

Anderson-Darling statistic, looks at the distribution of these 100 *p*-values.

C. Results

The Anderson Darling test indicates rejection of the hypothesis that volume residuals on neckline-crossing days are distributed the same as residuals on other days, at a significance level lower than 1.0E-4 (Table 1A).[13] As just mentioned, this test does not indicate whether trading on these days is unusually high or unusually low. That trading is unusually high, consistent with the alternative hypothesis that head-and-shoulders traders are active on these days, was already suggested by the fact that average residual volume is around 11 percent. This alternative hypothesis gains further support from the fact that the 100 *p*-values associated with the test are concentrated at low values: 21 of them fall below 0.05 percent, and 32 of them fall below 0.10 (Figure 3). On this basis, the hypothesis of no head-and-shoulders trading on neckline-crossing days is rejected in favor of the alternative hypothesis of active trading.

Head-and-shoulders trading activity is not likely to fall exclusively on the neckline-crossing days identified here, for a number of reasons. First, not all technical traders base their decisions on the graphs used here, which rely only on closing prices. Some use daily high/low/close prices, some use weekly charts, some use point-and-figure charts, others use candlestick charts. Traders relying on different charting techniques could enter either before or after the neckline-crossing day determined by close prices. Further, anecdotal evidence suggests that some traders enter before a "decisive" crossing of the neckline. Finally, traders who cannot monitor prices on an intraday basis, or who require particularly decisive confirmation that the price has crossed the neckline, may enter later.

A Broader Window of Investigation: To gain further information about head-and-shoulders trading activity, I broadened the window of investigation to include the three days before and the three days following the neckline-crossing. Within this seven-day window, unusual trading activity begins at a slightly negative value, rises to a peak on the neckline-crossing day itself, and subsides monotonically thereafter (Table 1A). Unusual trading activity is positive and statistically significant on the neckline-crossing day itself and the two subsequent days (Table 1A). Altogether this suggests that head-and-shoulders traders generally wait patiently for a "decisive" penetration of the neckline, and then trade within a few days of observing the signal.

In aggregate, unusual trading on the neckline-crossing day and the two subsequent days amounts to one fifth of a day's volume, which seems, impressionistically, like a fairly substantial amount. About half of this head-and-shoulders trading occurs on the neckline-crossing day itself, suggesting that a substantial share of head-and-shoulders traders follow the market closely. Since these trades seem closely identified with head-and-shoulders patterns, it seems reasonable to assume that the trading identified as "unusual" is initiated by technical traders trading in the direction recommended by technical analysts--that is, that unusual trading following head-and-shoulders tops is initiated by sellers, and that unusual trading following head-and-shoulders bottoms is initiated by purchasers.

Double-Check: To verify further that the pattern of unusual trading volume just described is likely due to head-and-shoulders trading activity, I examine unusual trading volume on an arbitrary set of days. In particular, I consider a five-day window centered on sixty days following the head of the head-and-shoulders pattern. In this interval, the average residuals are uniformly quite small, never exceeding 2 percent of a day's trading volume in absolute value, and none are statistically significant.[14]

In short, the behavior of unusual trading around neckline-crossing days supports the hypothesis that head-and-shoulders based speculation is active in U.S. equities markets and potentially economically significant. In passing, it is worth noting that these results also support the reasonableness of the computer algorithm applied here. In particular, they suggest that the algorithm successfully selected the head-and-shoulders patterns that prompted trading during the sample period, and that it successfully selected the days on which such trading was most likely to occur.

Robustness: To examine the robustness of these results, I modify the tests above in a variety of ways. The first set of sensitivity analyses examine whether the empirical results are an artifact of the precise criteria used to identify the head-and-shoulders patterns. This is important because the parameter choices were necessarily somewhat arbitrary, since neither a close reading of the manuals and nor conversations with practicing technical analysts provided much guidance. Three of these sensitivity analyses change the restrictions on allowable asymmetries in the pattern, the fourth adds a volume criterion, and the fifth uses high-low-close prices, instead of close prices. In the second set of sensitivity analyses I split the sample in two ways, first according to a firm's average trading volume (large or small) and second according to time (first or second half of the sample period). These modifications are described more fully in the Appendix. Like the base case, all these sensitivity analyses indicate a resounding rejection of the null for days close to the neckline crossing but not otherwise, with unusual trading around the neckline-crossing totaling about one fifth of a day's volume (Table 1B).

D. Discussion

If a head-and-shoulders pattern is forming, other market participants could predict that some associated trading will take place. If such predictions were very accurate, then one might wonder whether head-and-shoulders trading would correctly be characterized as noise trading. This concern is addressed next.

Several considerations suggest that it is impossible to know the magnitude of head-and-shoulders trading, either before or after the price crosses the neckline. Before, there is an inescapable uncertainty about whether a given pattern of peaks and troughs will actually "cross the neckline," and thus trigger trading. Even after the price crosses the neckline on one's chart, one will not know the extent of head-and-shoulders trading for a number of reasons. First, the charts used by technical traders vary, as discussed above. Even among technical traders using the same chart, opinions vary on such issues as whether a pattern can be steep, how long one can wait before the neckline-crossing, and the like. Furthermore, many traders require separate, confirming buy or sell signals before they take a position. Finally, on any given day one cannot know how many individuals are watching a given firm, the resources are available to those individuals, and the individuals' other investment opportunities.[15]

Even if the magnitude of head-and-shoulders trading could be known, it could still qualify as noise trading. Consider first whether noise trading can be common knowledge *as* it occurs. Though the magnitude of current noise trading cannot be known in some models, such as Kyle (1985), it is common knowledge in models such as De Long et al. (1989) and Campbell et al.

(1993). Now consider whether the magnitude of noise trading can be partially or fully known *before* it occurs. Though noise trading is entirely unpredictable in most models, it is partially predictable in De Long et al. (1990) and Campbell et al. (1993), and some of it is fully predictable in Admati and Pfleiderer (1991). In sum, it seems that the amount of head-and-shoulders will be uncertain both before and as it occurs but, even if it is known, it could still qualify as noise trading.

II. PROFITABILITY OF HEAD-AND-SHOULDERS TRADING

This section evaluates the profitability of head-and-shoulders trading. Since the pattern is used as a signal for speculative trading, the goal of which is to make profits, a lack of profitability is sufficient to show that such trading does not qualify as rational speculation, and thus does qualify as noise trading.

Despite the skepticism about technical analysis common among economists, the literature provides both theoretical and empirical reasons to think that head-and-shoulders trading might be profitable. At the theoretical level, Brown and Jennings (1990) and Grundy and McNichols (1990) both show that historical prices might well provide valuable information in situations of asymmetric information. At the empirical level, studies of technical trading rules in foreign exchange markets consistently find them to be profitable, even after adjusting for transactions costs, opportunity costs, and risk (Chang and Osler 1997; LeBaron 1996; Levich and Thomas 1993; Sweeney 1986; Dooley and Shafer 1984). Studies of technical trading rules in equity markets generally find them to be profitable before transactions costs, opportunity costs, and risk, though profits often disappear once they are properly adjusted for these factors (Fama and Blume

1966; Brock et al. 1990; DeBondt and Thaler 1986; Jegadeesh and Titman 1993; Carhart 1997; Conrad et al. 1997; Murphy 1986).

A. Methodology

The first step in this analysis of profitability must be to measure the profits that would have been associated with head-and-shoulders trading in reality. For each position, profits are measured as cumulative percent returns between entry and exit dates, signed to reflect whether the trader would be long or short. (The Appendix provides further details on these hypothetical trades). Overall profitability for each firm is measured as the average percent profits per position. Adjustment for risk and other relevant factors is discussed below.

The null hypothesis is that the head-and-shoulders patterns are meaningless noise. This null is tested in two ways, each of which involves bootstrapping. In Test One, I bootstrap the distribution of the following measure: average profits per position across all 100 firms. Then the corresponding figure from the actual data is compared with this distribution. In Test Two, I use an approach that is similar to the testing strategy employed in Section I: First, I determine for each firm the probability of achieving the actual level of profits under the null, using the bootstrap technique. Then the distribution of *p*-values for the entire sample of 100 firms is compared to the uniform [0,1], which corresponds to the null hypothesis. Note that both tests focus on technical analysts' claim that the head-and-shoulders predicts trends and produce profits for *all* publicly traded U.S. firms.

Simulated Data: For each test I begin by generating 12,500 simulated price series by drawing randomly with replacement from the series of past returns. Then I run the head-and-shoulders identification and profit-taking algorithms on each artificial series.[16,17] Key characteristics of the simulated data, such as mean return and unconditional variance, are thus drawn from the same population as the original data. However, there is one important difference: by design, returns in the simulated data have no intertemporal dependence and cannot be predicted from past returns. Thus, by design, head-and-shoulders patterns in the artificial data are meaningless noise, consistent with the null.

To verify that the artificial data closely resemble the actual data, the mean, standard deviation, skewness, and kurtosis of returns were calculated on both the actual data and 1,000 simulated series for four firms chosen randomly from the 100 firms. The *p*-values of the actual mean, standard deviation, skewness, and kurtosis are shown in Table 2. *P*-values above 0.95 or below 0.05 would suggest that the simulation method introduces statistically significant bias. Reassuringly, the *p*-values in Table 2 are all between 0.4 and 0.6.

Test One: For this test, I use the simulated data to bootstrap the distribution of average profits per position, with the average taken across all firms. To begin, the profits from each firm's first round of simulated data are summed, and divided by the total number of positions in all those simulated data. A similar calculation is made for all subsequent rounds of simulated data, a process that creates a simulated distribution of overall average profits under the null. Overall average percent profits per position from the true data are then compared with this sample distribution.

Test Two: For this test I use all 10,000 simulated data sets for firm one to calculate the statistical significance of average profits for that firm under the null. This calculation is then repeated for each of the other 100 firms separately, a process that creates 100 *p*-values. These *p*-values should be concentrated at low values if the pattern is useful at predicting trend reversals. Under the broad null hypothesis that the true data are generated by the same process used to create the simulated data, these *p*-values should be distributed uniformly.

In examining the actual distribution of *p*-values, the implicit assumption that the *p*-values are generated independently might be questioned based on the known correlations of daily returns across U.S. firms. However, since the positions signaled by the head-and-shoulders trading rule are relatively brief and infrequent, the *p*-values may be effectively independent. Once again, a natural test for this independence is based on the pair-wise correlations of daily head-and-shoulders returns across firms.[18] For all but one of these 4950 pair-wise correlations, the *t*-statistic is below one, suggesting that technical buy-sell signals are not highly correlated across firms, and that it is reasonable to interpret these *p*-values as independent.

B. Results

The results uniformly suggests that head-and-shoulders trading is not profitable. Average profits per position are actually negative, at -0.24 percent (on positions held for an average of 10 business days). Average profits in the simulated data are -0.03 percent. By itself, this suggests that actual profits might actually be lower than those one would expect under the null hypothesis. According to Test One, this difference is not statistically significant, as can be seen from the twotailed 95-percent confidence interval based on the simulated average profits (Figure 4). The marginal significance of the actual profit value, shown in Table 3, is 0.12.

The results from Test Two broadly corroborate the conclusion that head-and-shoulders trading is not profitable. As shown in Figure 5, the set of 100 *p*-values generated for this test are not concentrated at low values, as they would be if the pattern successfully predicts trend reversals. If the pattern tends to produce excessive losses, the *p*-values would be concentrated at high values and, as indicated in Table 3, there is a very modest tendency for profits to be concentrated at high levels. The Anderson-Darling statistic of 2.6 has marginal significance of 0.045 percent, suggesting that this difference is statistically significant, in contrast to the conclusion of Test One. The statistical significance of this result could also reflect a modest tendency for *p*-values to be concentrated away from values towards the center of the distribution, as can be seen in Figure 5. In any case, the difference between the actual distribution and the uniform is not great, and there is no suggestion here that the pattern produces positive profits if used according to the recommendations of technical analysts.[19]

As in the previous section, the robustness of this result is examined by modifying the baseline profitability test in a variety of ways. In addition to the seven modifications already described, three more are added. Two of these involve modifying the model of equity price behavior associated with the null, first to incorporate the possibility that the return process is AR(1), and second to incorporate the possibility that price levels are AR(1) and return volatility follows a GARCH(1,1) process (Bollerslev 1987; see Appendix for further details). The remaining sensitivity analysis modifies the exit strategy to allow a quicker exit if losses begin to accrue. In each case profits are recalculated on both the original and the 12,500 simulated series. These modifications leave the central results essentially unchanged (Table 3).[20]

Some of these sensitivity analyses provide information beyond their general support for the central hypothesis. For example, theoretical models presented in Frankel and Froot (1990) and De Long et al. (1990b) suggest that the pattern might be more profitable for firms with high trading volume, since the extra volume could stem from trend-following technical trading which would be more likely to generate self-fulfilling profits when carried out in greater volume. This hypothesis does not receive support: at standard significance levels the results indicate that trading volume is unimportant for the profitability of head-and-shoulders patterns. This suggests, in turn, that any self-fulfilling profits from these positive-feedback traders must be quite small, further evidence for which is provided below. It also suggests that positive-feedback trading of this type may induce offsetting trades by other agents, as predicted by De Long et al. (1990b). (These alternatives are not mutually exclusive.)

As noted earlier, that average profits in the *simulated* data are slightly negative, at -0.03 percent. In fact, average simulated profits are negative about 80 percent of the time, a proportion that would be extremely unlikely in such a large sample if the probability of negative profits were 50 percent. Though this may seem surprising, since the pattern is necessarily meaningless in these data, it reflects two additional facts: (i) the share of head-and-shoulders tops, which produce sell signals, exceeds 50 percent of all positions for 80 of the 100 firms; and (ii) prices rise on average over the sample period for all but five firms. This implies that head-and-shoulders traders tend to lose money with respect to any long-run prevailing trend, because they tend to sell stocks which generally trend upward.

Though measured average profits in the *actual* data are also negative, they are not statistically different from zero. This conclusion is based on an appropriate confidence interval, constructed by taking a centered 95 percent confidence interval relative to the simulated mean and shifting it laterally. Nonetheless, true average profits would likely be negative when adjusted for transactions costs, opportunity costs, and risk.

C. Discussion

It is possible to be more specific about the type of noise traders represented by head-and-shoulders traders. First, they confuse noise with information, consistent with the description provided in Black (1986): "People sometimes trade on noise as if it were information. If they expect to make profits from noise trading, they are incorrect. ... People who trade on noise are willing to trade even though from an objective point of view they would be better off not trading." (pp. 530-31). This distinguishes head-and-shoulders traders from the imperfectly rational speculators of De Long et al. (1990a, 1991), who generally understand the price process but mis-perceive one aspect of it, and who earn positive profits. Second, head-and-shoulders traders are positive-feedback traders, since the trigger for a sale is a declining price, and vice versa. Some possible effects of positive-feedback trading are examined in Frankel and Froot (1990) and De Long et al. (1990b).

The rest of this subsection contrasts the results just presented with those of other research, and discusses some of their implications.

Other Research on Technical Analysis: The finding that head-and-shoulders trading is unprofitable contrasts with most previous research on technical analysis in this and other markets. This difference could well reflect differences among technical strategies: earlier studies generally test filter rules, moving-average cross-over rules, and momentum or contrarian strategies, all of which are fairly easy to calculate. Chart-based technical strategies, which rely on recognition of nonlinear patterns, have only rarely been the subject of close scrutiny.

One exception to this is Chang and Osler (1997), which tests the rationality of using head-and-shoulders patterns for speculating in six major currencies vis-a-vis the dollar. Though that study agrees with the present study that head-and-shoulders trading is not rational, the results of the two papers contrast in an important way. Chang and Osler (1997) shows that the pattern is profitable for two dollar-based exchange rates, those with the mark and the yen. Using the pattern in the foreign exchange market is not rational, however, because is dominated by other technical strategies. By contrast, the present study of equities markets concludes that head-and-shoulders trading is not rational because it does not produce profits at all.

Origins of an Unprofitable Trading Strategy: It is natural to inquire how an unprofitable strategy could become trusted initially. One possibility is that the strategy was actually profitable in the period when it was first noted. During that initial period, prior to 1930, insider trading and market manipulation were reportedly rampant (Sobel 1965). However remote the possibility, such practices could conceivably have generated nonlinear price patterns. Legislation in the 1930s made such practices illegal, and the behavior of prices may have changed, eliminating the predictive power of the patterns, as the trading practices became relatively rare.

Head-and-shoulders trading may always have been unprofitable. Even so, it is not difficult to compile a list of well-documented forms of imperfectly rational human cognition that might have led traders to believe it was actually profitable. Such a list would include the following: (i) value-based biases: “people tend to think that positively valued events have a greater chance of occurring than negatively valued events,” (Yates 1990, p. 202); (ii) “illusory correlations:”

"people have a tendency to find connections among groups of events that do not exist" (Yates 1990, p. 171); (iii) overconfidence in one's judgement: "if a person feels that his or her actions are capable of influencing a situation, then the judged likelihood that the resulting outcome will be positive tends to be unduly high" (Yates 1990, p. 203); and (iv) distorted recollections: people have a greater tendency to remember pleasant or successful experiences (such as profitable trades) than unpleasant ones (Yates 1990, p. 201). Each of these tendencies has been extensively documented by well-specified experiments in the field of cognitive psychology. Some of them, such as a tendency towards overconfidence, are also supported by evidence from economists (Golec and Tamarkin 1995).

Survival of an Unprofitable Trading Strategy: Since head-and-shoulders trading has not been profitable over the past few decades, economists will naturally wonder why the strategy's use has not died out during that time. Theoretical results in the finance literature can help address this question. First, it has been shown that a lack of risk-adjusted profitability does not ensure that a trading strategy will disappear from the marketplace in the long run. In De Long et al. (1991), noise traders hold incorrect expectations about the return variances that lead them to take positions overweighted in the risky asset. If the risky asset has a relatively high expected return, the noise traders earn positive profits on average. Further, because market returns have some randomness, and funds gravitate to agents with successful histories (Shleifer and Vishny 1997), some noise traders could have sufficient luck to survive in the market indefinitely even if their strategy is not, on average, profitable (Gruen and Gyzicki, 1993). The surviving agents will be visible to and may encourage potential new entrants, especially those with certain value-based biases or overconfidence in their own judgement. Kyle and Wang (1997) show that, in certain market structures, overconfidence can be a dominant strategy and can survive indefinitely.

Evidence bearing on the survival of unprofitable strategies also comes from other disciplines. For example, social psychologists have conducted well-designed studies showing that social forces can be quite powerful when there is little objective information to confirm an individual's own opinion (Sherif 1937, cited in Shiller 1984). It could be argued that the absence of a consensus among finance professionals regarding the determination of stock prices leaves ordinary investors in such a situation. Similarly, cognitive psychologists have shown through their experiments that beliefs and behaviors are difficult to "extinguish" when they are randomly reinforced (Carlson and Buskist 1997). Thus the randomness of profits from technical trading could leave investors with a belief in the profitability of technical trading that is not easily dispelled by evidence to the contrary.

Departures From Rationality and Financial Markets: There is a divergence of opinion among finance academics regarding whether noise traders should be modeled as optimizing agents. Originally, noise trades were modeled very as simple random disturbances (Kyle 1985). More recently, however, it has become common to model noise traders as explicit utility maximizers (Wang 1993, 1994). The present paper's conclusion that some real-world noise trading does not qualify as the outcome of an optimizing decision by market participants indicates that noise traders in theoretical models need not be utility maximizers to be realistic.

The results here provide a possible explanation for the strong empirical relationship between trading volume and volatility. In particular, it has been observed in a number of settings that this relationship holds even when the flow of publicly-available information remains unchanged (French and Roll 1986; Ito et al. 1998). This paper suggests the possibility that traders create their own volatility by misinterpreting noise as information.

III. IMPACT OF HEAD-AND-SHOULDERS TRADING ON RETURNS

So far this paper has identified head-and-shoulders traders as real-world noise traders in U.S. equities markets. It has shown that there is active trading on the pattern, and that such trading is not profitable. This section turns from identifying noise traders to identifying their effects on returns, looking first at their initial impact on returns as they open positions and second at whether that impact effect is temporary or permanent. Throughout this section, a price rise represents a positive "return" if head-and-shoulders traders would be long the stock, and a negative return if they would be short.

A. Initial Impact of Head-and-Shoulders Trading

There are a number of competing hypotheses about how noise trading should affect returns as it occurs. In perfect capital markets, unlimited arbitrage ensures that prices are invariant to noise trading. However, in reality there may be limits to rational arbitrage (De Long et al. 1990a; Shleifer and Vishny 1997), in the presence of which noise trading will affect returns. In some theoretical noise trading models, such as Kyle (1985) and De Long et al. (1990a), the difference between a stock's "fundamental value," that is, the value it would have in the absence of noise trading, and its current value includes an additive term that is proportional to the current level of net purchases by noise traders. In this case, returns are determined by *changes* in the level of these net purchases from period to period.

It is also possible that returns are determined by the *level* of net purchases by noise traders in a given period, as suggested by Black (1986, page 532): "The noise that noise traders put into stock prices will be cumulative, in the same sense that a drunk tends to wander farther and farther from his starting point." A number of alternative hypotheses could explain such an effect. The market could interpret noise trades as containing some important information. However, unlike block trades, where similar immediate price effects have been documented (Dann et al. 1977; Holthausen et al. 1987, 1990), there is no reason to presume that the information associated with head-and-shoulders trades would be related to the size of the trades.

Returns could be affected by the level of net purchases by noise traders if the demand curve for stocks is downward sloping (Shleifer 1986). Such a demand curve could be observed in a market with limited substitutes for a firm's securities, or a market where agents or their beliefs are heterogeneous (Mikkelson and Partch 1985; Bagwell 1992). Alternatively, it could be observed if there is non-zero price elasticity of demand among non-speculative agents, as suggested by Dow and Gorton (1993). Finally, returns could be affected by the level of net purchases by noise traders if there are substantial liquidity costs associated with the difficulty of identifying potential buyers and sellers. For example, market makers might require a premium to take shares on the books for which they do not have an immediate purchaser (Kraus and Stoll 1972).

To evaluate the immediate effects of head-and-shoulders trading on returns, one would ideally examine returns on neckline-crossing days, when head-and-shoulders trading is generally heaviest (Section I). Unfortunately, the results of such analysis would be unreliable because of an important selection bias: by definition, on a neckline-crossing day the price falls beyond a certain point (for a head-and-shoulders top) or rises above a certain point (for a head-and-shoulders bottom), so price movements on neckline-crossing days will tend to be larger than average (in absolute value) and in the direction consistent with profitability for head-and-shoulders traders. In consequence, this analysis concentrates on returns from the closing price on the neckline-crossing day to the closing price on the next day. For convenience, these later days will be referred to as "days after," and these returns will be referred to as "day-after returns."

It has already been shown (Section I) that trading volume is unusually high on days after, though it is lower than the unusual volume on the immediately preceding (neckline-crossing) day. As discussed earlier, it will be assumed that measured unusual trading represents a response to desired sales from head-and-shoulders trading following head-and-shoulders tops, and vice versa. That is, average unusual trading volume will be interpreted as a measure of *net* noise trading, and the direction of that trading will be assumed consistent with the recommendations of technical analysts.

If the *level* of head-and-shoulders trading affects returns, then day-after returns should be relatively large: sales would depress prices after head-and-shoulders tops, and vice versa, so returns from positions opened on the neckline-crossing day would be higher. If the *change* in head-and-shoulders trading affects returns, day-after returns then, because unusual trading volume on days after is lower than unusual volume on neckline-crossing days (Table 1), day-after returns should be relatively small.

The two tests examined here correspond to the two tests used in Section II, and are based on the same simulated data. Test One examines average day-after returns across all 100 firms taken simultaneously. Test Two examines the pattern of *p*-values of day-after returns for each firm. The null hypothesis is that actual day-after returns are no different than they are in the simulated data, which, in turn, corresponds to the hypothesis that head-and-shoulders traders have no effect on prices. Under the hypothesis that day-after returns are unusually low, the *p*-values would be concentrated at high levels. Under the hypothesis that day-after returns are unusually high, the *p*-

values would be concentrated at low levels.

Actual day-after returns average 0.014 percent per position across all firms. According to Test One, this is statistically significantly higher than the average return of -0.035 percent in the simulated data, with marginal significance of 1 percent.[21] The results of Test Two corroborate this overall conclusion, and show that it is not driven by any small subset of firms. As shown in Figure 6, the 100 *p*-values for observed day-after returns are heavily concentrated at low levels: 19 of them fall below 0.05, and 61 of them fall below 0.5. This is consistent with the hypothesis that day-after returns are unusually high. The statistical significance of this result, according to the Anderson-Darling test, is lower than 1.0E-4.

Because the actual day-after returns would be dwarfed by transactions costs (Chan and Lakonishok 1997), one could not trade profitably on the information that head-and-shoulders traders are active on days-after. To measure the total effect of head-and-shoulders trading on day-after prices, one must compare actual day-after returns with simulated day-after returns, rather than looking at their absolute magnitude. The incremental effect of head-and-shoulders traders on day-after prices is about 0.06 percent.

Results across the various sensitivity analyses uniformly concur that head-and-shoulders sales tend to push prices downward, and purchases to push prices upward (Table 4). The effect is most clearly apparent for large firms, and for the first half of the sample.

That bid-ask bounce could not be the source of this result can be ascertained from the following reasoning: Suppose one has observed a head-and-shoulders top. The trading algorithm would lead one to assume a short position when the closing price drops across the neckline. Such a price decline, all else equal, is more likely to occur when the close is at the bid price rather than at the ask. No such bias exists for the next day's close, which is equally likely to be at the bid or the ask. Thus, absent any movement in the underlying price, the expected close the next day is slightly higher, implying a *negative* return to the short position. To further examine the possible role of bid-ask bounce, AR(1) coefficients were estimated for each firm's daily returns. Of these, 30 were negative and statistically significant while a much larger number, 48, were positive and statistically significant.

In short, the results presented here do not support certain predictions from the noise trader models of Kyle (1985) and De Long et al. (1990), indicating that changes in the level of net noise trades should affect returns. Instead these results are consistent with models indicating that the level of noise trades themselves should affect returns. As discussed above, there are a number of plausible reasons why the level of noise trades could affect returns. It may be possible to ascertain more precisely which of these reasons are relevant by examining the duration of these effects.

B. Permanent or Temporary?

If the initial effect of head-and-shoulders trades is due to perceived information asymmetries, as could be true for block trades, then it is likely to be permanent. If it reflects a downward demand curve for stocks then the effect could be either permanent or temporary. A permanent effect would occur if the downward slope is due to heterogeneity in the preferences or beliefs of rational speculators, as suggested by Shleifer (1986). The downward slope might, instead, reflect a non-zero price elasticity of demand among non-speculative agents, as suggested by Dow and Gorton (1993). In this case, Osler (1998) indicates that the effects would die out gradually after being extended over time by rational but non-informative speculative trading. The initial effect of noise trading would also be temporary if it is due to liquidity costs.

To examine whether the effects of head-and-shoulders trades are temporary or permanent, I examine returns corresponding to selected intervals. Only the second of the two tests applied to day-after returns will be used here, since the overall results of the two tests do not differ substantially and the first test is somewhat less powerful. Taking the neckline-crossing day as “zero,” I examine returns through days three, five, and ten (see Table 5). The results indicate that by the third day after the neckline-crossing, the effects of head-and-shoulders trading have begun to be reversed but they are still detectable. In fact, returns over days two-three are 0.08 percent lower than would be expected under the null. The reversal continues through the end of the first week, with returns over days four-five 0.02 percent lower than would be expected under the null. By the end of the second week cumulative returns are statistically indistinguishable from the values they would have had under the null, and there seems to be no statistically distinguishable effect of head-and-shoulders trading on returns thereafter.

These results suggest that the price effects of head-and-shoulders traders disappear slowly but completely. This is consistent with the possibility that the initial effects are caused by liquidity costs (Kraus and Stoll 1972). It is also consistent with the predictions of Osler (1998), if the initial effects are due to non-zero price elasticity of demand from non-speculative agents. The temporary nature of the effect is not consistent with the hypothesis that the initial effect is due to heterogeneity among investors' risk preferences or beliefs (Shleifer 1986). The apparent absence of any permanent effect contrasts with the fairly common result that some or most of the effect of block trades is permanent (e.g., Holthausen et al. 1990).

Most of the sensitivity analyses confirm the general pattern portrayed above. However, there are some differences among the sensitivity analyses worthy of note. First, the initial price effect seems to have disappeared much more rapidly in the second half of the sample period than in the first. This is consistent with the possibility, noted earlier, that profitability of this pattern may have been exceptionally low since 1977. The price dynamics are also more pronounced for firms with relatively high trading volume. Second, the results from the simulation involving high, low and close prices are statistically significant at all horizons. A closer look at the results suggests that this is more a reflection of the high concentration of p-values at both extremes than a reflection of stronger price movements. Finally, results for the stronger-horizontal-symmetry sensitivity and for the GARCH simulation are ambiguous, suggesting a lack of power. In particular, they imply the following three inconsistent conclusions: (i) head-and-shoulders trades significantly affect returns on day one; (ii) there is no difference between actual and simulated returns between days zero and three; (iii) there is no difference between actual and simulated returns between days one and three.

Taken together, the price results of this section and the volume results of Section I suggest that, when head-and-shoulders traders are active, unusually high trading volume should presage return reversals. This is consistent with predictions from the theoretical model of Campbell et al. (1993, p. 906), as well as that paper's empirical results showing that daily stock returns can be better predicted when lagged trading volume is taken into account, and that higher trading volume is associated with lower ensuing autocorrelation. This result is also consistent with Conrad et al. (1994), who show that return autocovariances are negative for securities traded unusually heavily in a previous period.

V. SUMMARY

This paper identifies a source of noise trading in U.S. equities markets: speculation based on the visual price pattern called a head-and-shoulders. This identification is based on two empirical results. First, head-and-shoulders trading is fairly active. On average, head-and-shoulders entry trades following the confirmation of a given pattern aggregate about one quarter of a day's trading volume, spread out over three days. Second, head-and-shoulders trading is not profitable. The data set comprises daily trading volume and prices over 1962-1993 for 100 firms chosen randomly from the CRSP database.

Having identified a source of noise trading, the paper proceeds to examine how such trading affects returns. The results indicate that sales in response to head-and-shoulders patterns tend to reduce prices, and vice versa. This is inconsistent with the predictions of some noise trader models, such as Kyle (1985) and De Long et al. (1990), but is similar to the effect of block trades. It could represent the effects of asymmetric information, liquidity costs, downward sloping demand curves based on heterogeneous agents, or downward sloping demand curves based on non-zero elasticity of demand among non-speculative agents. The immediate price effect of head-and-shoulders trades disappears slowly but completely over the subsequent two weeks. This slow decay is consistent with the presence of liquidity costs and with a downward sloping demand curves based on non-zero elasticity of demand among non-speculative agents. It is not consistent with asymmetric information or with a down-ward sloping demand curves based on heterogeneous agents.

The finding that an unprofitable strategy for speculation is the source of active trading has implications for modeling of financial markets. In particular, it suggests that it is not necessarily unrealistic to model noise traders without including an explicit maximizing motivation for their trades. Since this form of noise trading is apparently not rational, trading that does not conform to the standards of rationality could potentially have the first-order effects on financial markets attributed to noise traders.

The paper intends only to provide positive identification for one source of noise trading, not to identify all or even most noise trading. There are likely to be multiple sources of noise trading in any financial market. Possible additional sources of noise trading could include other unprofitable technical strategies, liquidity trading, and hedging. Further research identifying and quantifying the sources of noise trading could improve our understanding of market microstructure.

REFERENCES

Admati, Anat, and Paul Pfleiderer, “Sunshine Trading and Financial Market Equilibrium,” *The Review of Financial Studies* 4 (1991): 443-81.

Allen, H. Linda and Mark P. Taylor, "Charts, Noise, and Fundamentals in the Foreign Exchange Market," *Economic Journal* 29, (1990): 49-59.

Allen, Franklin, and Risto Karjalainen, “Using Genetic Algorithms to Find Technical Trading Rules,” Rodney L. White Working Paper No. 20-93 (Wharton School, 1993).

Amihud, Yakov, and Haim Mendelson, “Asset Pricing and the Bid-Ask Spread,” *Journal of Financial Economics* 17 (1986): 233-49.

Arnold, C., and D. Rahfeldt, *Timing the Market: How to Profit in Bull and Bear Markets with Technical Analysis* (Chicago: Probus Publishing, 1986).

Bagwell, Laurie S., “Dutch Auction Repurchases: an Analysis of Shareholder Heterogeneity.” *Journal of Finance* 47 (March 1992): 71-105.

Balduzzi, Pierluigi, Guiseppe Bertola, and Silverio Foresi, “Nonlinearities in Asset Prices and Infrequent Noise Trading,” Mimeo (March 1992).

Black, Fischer, "Presidential Address: Noise," *Journal of Finance* vol. 41, (1986): 529-544.

Blume, Lawrence, and David Easley and Maureen O'Hara, "Market Statistics and Technical Analysis: The Role of Volume," *Journal of Finance* Vol. 49, (1994): 153-181.

Bollerslev, T., "A Conditionally Heteroskedastic Time Series Model for Speculative Prices and Rates of Return," *Review of Economics and Statistics,* (1987): 542-47.

Brock, W., J. Lakonishok, and B. LeBaron, "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns," *Journal of Finance* Vol. 48, No. 5 (December 1992): 1731-64.

Brooks, John N. *Once in Golconga: A True Drama of Wall Street 1920-1938* (Publishing info??)

Brown, David P., and Robert H. Jennings, "On Technical Analysis," *The Review of Financial Studies,* Vol. 2, No. 4 (1990): 527-51.

Campbell, John Y., Sanford J. Grossman and Jiang Wang, “Trading Volume and Serial Correlation in Stock Returns,” *The Quarterly Journal of Economics*, Vol. (November 1993): 905-39.

Campbell, John Y., and Albert S. Kyle, “Smart Money, Noise Trading and Stock Price Behavior,” *Review of Economic Studies* 60 (1993): 1-34.

Campbell, John Y., and Robert Shiller, “ The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors,” *Review of Financial Studies* 1 (1988a): 195-228.

Campbell, John Y., and Robert Shiller, “Stock Prices, Earnings and Expected Dividends,” *Journal of Finance* 43 (1988b): 661-676.

Carhart, Mark M., "On Persistence in Mutual Fund Performance," *Journal of Finance* Vol. 52 (1997): 57-82.

Carlson, Neil, and William Buskist, “Psychology: The Science of Behavior,” Fifth Edition (Allyn and Bacon, Boston: 1997).

Chan, Louis, and Josef Lakonishok, “Institutional Equity Trading Costs: NYSE Versus Nasdaq,” *The Journal of Finance*, Vol. 52 (June 1997): 713-34.

Chang, P.H. Kevin and Carol L. Osler, "Technical Trading as a Source of Market Irrationality: The Head-and-Shoulders Pattern in Foreign Exchange," Federal Reserve Bank of New York, Mimeo, 1997.

Chapman, L. J., and J.P. Chapman, “Genesis of Popular but Erroneous Psychodiagnostic Observations,” *Journal of Abnormal Psychology* Vol. 72, (1967): 193-204.

Conrad, Jennifer, Allaudeen Hameed, and Cathy Niden, “Volume and Autocovariances in Short-Horizon Individual Security Returns,” *The Journal of Finance*, Vol. 49 (September 1994): 1305-29.

Conrad, Jennifer, and Gautam Kaul, “An Anatomy of Trading Strategies,” Mimeo, University of North Carolina (1997).

Cutler, David, James M. Poterba, and Lawrence H. Summers, “Speculative Dynamics,” *Review of Economic Studies* Vol. 58 (1991): 529-46.

D'Agostino, Ralph B. and Michael A. Stephens, *Goodness-of-Fit Techniques* (New York: Marcel Dekker, Inc., 1986).

Dann, Larry Y., David Mayers, and Robert Raab, Jr., "Trading Rules, Large Blocks and the Speed of Price Adjustment," *Journal of Financial Economics* Vol. 4 (1977): 3-22.

De Bondt, Werner, and Richard Thaler, "Does the Stock Market Overreact?" *Journal of Finance,* Vol. 40 (1985): 793-805.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, "The Size and Incidence of Losses From Noise Trading," *The Journal of Finance*, Vol. 44 (July 1989): 681-96.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, "Noise Trader Risk in Financial Markets," *Journal of Political Economy* Vol. 98, (1990a): 703-738.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, "Positive Feedback Investment Strategies and Destabilizing Rational Speculation," *Journal of Finance,* Vol. 45, No. 2 (1990b): 379-95.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, "The Survival of Noise Traders in Financial Markets," *Journal of Business* Vol. 64, (1991): 1-19.

Dooley, Michael P., and Jeffrey Shafer, "Analysis of Short-Run Exchange Rate Behavior: March 1973 to November 1981," in Floating Exchange Rates and the State of World Trade and Payments, Bigman and Taya, eds. (Ballinger Publishing Company, Cambridge , MA: 1984): pp. 43-70.

Dow, James, and Gary Gorton, "Trading, Communication and the Response of Asset Prices to News," *The Economic Journal* Vol. 103 (May 1993): 639-46.

Dow, James, and Gary Gorton, "Arbitrage Chains," *Journal of Finance,* Vol. 49 (1994a): 819-49.

Dow, James, and Gary Gorton, "Noise Trading, Delegated Portfolio Management, and Economic Welfare," NBER *Working Paper* 4858 (September 1994b).

Edwards and Magee, *Technical Analysis of Stock Trends,* Fifth edition (Boston: John Magee Inc: 1966).

Efron, B., "Bootstrap Methods: Another Look at the Jackknife," *Annals of Statistics,* Vol 7, No. 1 (1979): 1-26

________ *The Jackknife, the Bootstrap, and Other Resampling Plans,* (Philadelphia: Society for Industrial and Applied Mathematics, 1982).

Fama, Eugene F. and Marshall E. Blume, "Filter Rules and Stock Market Trading," *Journal of Business* Vol. 39, (1966): 226-241.

Foster, F. Douglas, and S. Viswanathan, “A Theory of the Interday Variations in Volume, Variance, and Trading Costs in Securities Markets,” *Review of Financial Studies*, Vol. 3 (1990): 593-694.

Foster, F. Douglas, and S. Viswanathan, “The Effect of Public Information and Competition on Trading Volume and Price Volatility,” *Review of Financial Studies*, Vol. 6 (1993): 23-56.

Frankel, Jeffrey, and Kenneth Froot, "Explaining the Demand for Dollars: International Rates of Return and the Expectations of Chartists and Fundamentalists," in R. Chambers and P. Parlberg, eds.: *Agriculture, Macroeconomics and the Exchange Rate* (Westfield Press, Boulder, CO: 1990).

French, Kenneth, and Richard Roll, “Stock Return Variance: The Arrival of Information and the Reaction of Traders,” *Journal of Financial Economics* 17 (1986): 99-117.

Golec, Joseph, Maurry Tamarkin, “Do Bettors Prefer Long Shots Because They Are Risk-Lovers, or Are They Just Overconfident?” *Journal of Risk and Uncertainty* Vol. 11 (1995): 51-64.

Grossman, S. J., and J.E. Stiglitz, “On the Impossibility of Informationally Efficient Markets,” *American Economic Review*, Vol. 70 (1980): 393-408.

Gruen, D., and M. Gizycki, “Forward Discount Bias: Is It Anchoring?” Mimeo, Reserve Bank of Australia (1994).

Grundy, Bruce, and Maureen McNichols, “Trade and the Revelation of Information Through Prices and Direct Disclosure,” *The Review of Financial Studies* Vol. 2, No. 4 (1989): 495-526.

Hardy, C. Colburn, *The Investor's Guide to Technical Analysis* (New York: McGraw Hill, 1978).

Holthausen, Robert W., Richard W. Leftwich, and David Mayers, “Large-Block Transactions, the Speed of Response, and Temporary and Permanent Stock-Price Effects,” *Journal of Financial Economics* Vol. 26 (1990): 71-95.

________________________, “The Effect of large Block Transactions on Security Prices: A Cross-Sectional

Analysis," *Journal of Financial Economics* Vol. 19 (1987): 237-67.

Ito, Takatoshi, Richard K. Lyons, and Michael T. Melvin, "Is There Private Information in the FX Market? The Tokyo Experiment," *The Journal of Finance* 53 (June 1998): 1111-1130.

Jegadeesh, Narasimhan and Sheridan Titman, "Returns to Buying Winners and Selling Losers: Implications for Stock Market, *Journal of Finance*, Vol.48 (1993): 65-91.

Karpoff, Jonathan M., "The Relation Between Price Change and Trading Volume: A Survey," *Journal of Financial Quantitative Analysis* Vol. 22, (1987): 109-126.

Kaufman, P., *Commodity Trading Systems and Methods* (New York: Ronald Press, 1978).

Kelly, Morgan, “Do Noise Traders Influence Stock Prices?” *Journal of Money, Credit, and Banking*, Vol. 29 (August 1997): 351-63.

Kraus, Alan, and Hans R. Stoll, “Price Impacts of Block trading on the New York Stock Exchange,” *Journal of Finance* Vol. 27 (1972): 569-88.

Kupiec, Paul, “Noise Traders, Excess Volatility, and a Securities Transactions Tax,” Mimeo, Board of Governors of the Federal Reserve System (September 1994).

Kyle, A.S., "Continuous Auctions and Insider Trading," *Econometrica* Vol. 53, (1985): 1315-1336.

Kyle, A.S., and F. Albert Wang, “Speculation Duopoly with Agreement to Disagree: Can Overconfidence Survive the Market Test?” *The Journal of Finance* Vol. 52 (December 1997): 2073-90.

LeBaron, Blake, "Technical Trading Rule Profitability and Foreign Exchange Intervention," NBER Working Paper (March 1996).

Leroy, S.F., and R.D. Porter, “The Present-Value Relation: Test Based on Implied Variance Bounds,” *Econometrica* Vol. 49 (1981): 555-74.

Levich, R., and L. Thomas, "The Significance of Technical Trading-Rule Profits in The Foreign Exchange Market: A Bootstrap Approach," *Journal of International Money and Finance* Vol. 12, No. 5 (October 1993): 451-474.

Levy, R.A., "The Predictive Significance of Five-Point Chart Patterns," *Journal of Business*, Vol. 44, No 3 (July 1971): 316-323.

Lo, Andrew, and Jiang Wang, “Trading Volume: Definitions, Data Analysis, and Implications of Portfolio Theory,” Mimeo, Sloan School of Management MIT (January 1997).

Lui, Yu-Hon, and David Mole, “The Use of Fundamental and Technical Analyses by foreign Exchange Dealers: Hong Kong Evidence,” Mimeo, City University of Hong Kong.

Lukac, Louis P., B. Wade Brorsen, and Scott H. Irwin, “Similarity of Computer Guided Technical Trading Systems,” *The Journal of Futures Markets* Vol. 8 (1988): 1-13.

Mehra, Rajneesh, and Edward C. Prescott, "The Equity Premium: a Puzzle," *Journal of Monetary Economics*, Vol. 15 (February 1985): 145-72.

Mikkelson, Wayne, and Megan Partch, "Stock Price Effects and the Costs of Secondary Distributions," *Journal of Financial Economics*, Vol. 59 (June 1985): 165-94.

Modigliani, F., and M.H. Miller, "Corporate Income Taxes and the Cost of Capital: A Correction," *American Economic Review* Vol. 53 (June 1963): 433-43.

Murphy, J. Austin, "Futures Fund Performance: A Test of the Effectiveness of Technical Analysis," *The Journal of Futures Markets* Vol. 6 (1986): 175-85.

Murphy, John J., *Technical Analysis of the Futures Market: A Comprehensive Guide to Trading Methods and Applications* (Prentice Hall, New York: 1986).

Osler, C., "Short-Term Speculators and the Puzzling Behavior of Exchange Rates," Forthcoming, *Journal of International Economics.*

Pagano, Marco, and Ailsa Roell, "Transparency and Liquidity: A Comparison of Auction and Dealer Markets With Informed Trading," *The Journal of Finance* Vol. 51 (June 1996): 579-611.

Palomino, Frederic, "Noise Trading in Small Markets," *The Journal of Finance*, Vol. 51 (September 1996): 1537-50.

Pring, M., *Technical Analysis Explained: The Successful Investor's Guide to Spotting Investment Trends and Turning Points*, Third Edition (New York: McGraw-Hill, 1985).

Scheinkman, Jose, and Blake LeBaron, "Nonlinear Dynamics and Stock Returns," *Journal of Business* Vol. 62 (1989): 311-37.

Scholes, Myron S., "The Market for Securities: Substitution Versus Price Pressure and the Effects of Information on Share Price," *Journal of Business* Vol. 45 (1972): 179-211.

Shabacker, R.W., *Stock Market Theory and Practice* (B.C. Forbes Publishing Company, New York: 1930).

Sherif, Muzafer, "An Experimental Approach to the Study of Attitudes," *Sociometry* Vol. 1 (1937): 90-98.

Shiller, Robert, “Do Stock Prices Move Too Much to Be Justified by Subsequent Changes in Dividends?” *American Economic Review* Vol. 71 (1981): 421-435.

Shiller, Robert, “Stock Prices and Social Dynamics,” *Brookings Papers on Economic Activity* 2 (1984): 457-98.

Shiller, Robert J., *Market Volatility*, (Cambridge, MA: MIT Press, 1989).

Shleifer, Andrei, “Do Demand Curves Slope Down?” *The Journal of Finance* Vol. 41 (1986): 579-90.

Shleifer, Andrei, and Lawrence Summers, “The Noise Trader Approach to Finance,” *Journal of Economic Perspectives* Vol. 4 (Spring 1990): 19-33.

Shleifer, Andrei, and Robert W. Vishny, “The Limits to Arbitrage,” *The Journal of Finance* Vol. 52 (March 1997): 35-55.

Sklarew, Arthur, *Techniques of a Professional Commodity Chart Analyst* (New York: Commodity Research Bureau, 1980).

Sobel, Robert, *The Big Board* (New York: The Free Press, 1965).

Sweeney, R. J., "Beating the Foreign Exchange Market," *Journal of Finance* Vol 41, No. 1 (March 1986): 163-82.

Wang, Jiang, “A Model of Intertemporal Asset Prices Under Asymmetric Information,” *Review of Economic Studies* Vol. 60 (1993): 249-82.

Wang, Jiang, “A Model of Competitive Stock Trading Volume,” *Journal of Political Economy*, Vol. 102 (1994):127-68.

Yates, J. Frank, *Judgement and Decision Making* (New Jersey: Prentice Hall, 1990).

APPENDIX: Structuring Trades Based on Head-and-Shoulders Trading Signals

I. Identifying Head-and-Shoulders Patterns.

The algorithm first transforms the price series into a zig-zag pattern, which comprises a series of peaks and troughs separated by a minimum required movement or "cutoff." For example, if the "cutoff" is 5 percent , then a local maximum is labeled a peak once prices have declined by 5 percent from that local maximum. Similarly, a local minimum is labeled a trough once prices have risen by 5 percent from that local minimum.

After creating the zig-zag pattern, the algorithm searches for sequences of peaks and troughs that satisfy a list of requirements.[22] It is first required that, in a series of three consecutive peaks, the second peak must be higher than either the first or third. Since head-and-shoulders is a reversal pattern, it is also required that any head-and-shoulders top represent the culmination of an upward movement. More specifically, it is required that the peak preceding a head-and-shoulders top (LL peak in Figure 1) be lower than the left shoulder, and the trough preceding the pattern (LL trough) be lower than the first trough (left trough).

In the idealized head-and-shoulders pattern depicted in the technical manuals, the three main peaks (left shoulder, head, and right shoulder) are about equally spaced in time, and the two shoulders are approximately equal in height. To prevent the head-and-shoulders patterns that detect by the algorithm from differing too greatly from this paradigm, additional requirements are imposed corresponding to horizontal and vertical symmetry. For horizontal symmetry, the number of days between the left shoulder and head is required to fall between 2.5 and 1 /2.5 times the number of days between the head and right shoulder. For vertical symmetry, it is required that the head-and-shoulders pattern be only moderately sloped. Thus, the right shoulder must exceed, and the right trough must not exceed, the midpoint between the left shoulder and left trough. Similarly, the left shoulder must exceed, and the left trough must not exceed, the midpoint between the right shoulder and right trough.

Multiple cutoffs are used to capture head-and-shoulders of differing magnitudes. Specifically, “cutoffs” used equal 6.0, 5.5, 5.0, 4.5, 4.0, 3.5, 3.0, 2.5, 2.0, and 1.5 times the standard deviation of actual daily returns. The top limit was chosen to ensure that there was a small but not negligible chance of finding a head-and-shoulders pattern of that size for each firm. The bottom limit was chosen to exceed the daily standard deviation of returns to ensure that upward and downward trends would be distinguished from ordinary daily variation. Each time the data are scanned with a new cutoff, duplicate head-and-shoulders signals are eliminated. In particular, if a head-and-shoulders pattern using one cutoff implied entering a position two days before or after a previously identified entry date, the new position was not included.

II. Taking Profits After Identifying a Head-and-Shoulders Pattern

Once a head-and-shoulders pattern has been identified, the algorithm enters and exits hypothetical trading positions according to recommendations of the technical manuals.

Entering a Position: Technical analysis manuals clearly state that, following a head-and-shoulders pattern, one enters into a position only after the price has crossed the neckline. Given the data’s daily frequency, entry is identified on the same day that the closing price crosses the neckline, and that day’s closing price is assigned as the trader’s entry price. It is assumed that there are no limits on short sales.

Exiting a Position: The technical analysis manuals provide few specific criteria by which to time exit trades. Nonetheless, a few principles were consistently emphasized in all the manuals consulted. Most importantly, the manuals stress that the head-and-shoulders indicates that a new trend should be forming. I infer from the word "trend" that one should expect to hold positions for at least a few days. The directive to hold positions rather than exit a day or two later is also reflected in the manuals' emphasis that the vertical distance from the neckline to the head represents a “price objective,” or “minimum probable” magnitude of the anticipated price reversal once the price has crossed the neckline. Finally, the manuals also stress that, before reaching the objective, the price may temporarily revert back towards the neckline before continuing its trend away from the neckline (this temporary reversion is referred to here as a “bounce”).

These general guidelines are incorporated into the trading algorithm by the requirement that positions be held until the price stops moving in the predicted direction, unless it appears that the price is in a bounce. Thus, following a head-and-shoulders top, if the price declines, the short position is maintained until the first new trough is identified. At this point, the price will have risen at least “cutoff” percent above its local minimum, suggesting that the predicted price decline has ended.

To incorporate the bounce possibility, this general exit strategy is modified. Following a head-and-shoulders top, the short position is maintained even after the first trough has been identified, if that trough occurs before the price has declined by at least 25 percent of the measuring objective. The position is maintained until a second trough has been identified (regardless of the magnitude), or when a stop loss limit is reached (defined in the next paragraph), whichever occurs first.

One further caveat applies to this basic exit rule. A "stop loss" of one percent is established, consistent with general market practice. That is, if prices move in the “wrong” direction, positions are exited automatically on the day losses reach or surpass one percent. This limits traders’ potential losses in case the strategy doesn’t work.

III. Robustness Checks

Many of the choices made in establishing a base case were somewhat arbitrary, even though I sought guidance from many technical manuals and from market participants. To verify that these choices are not critical, a number of sensitivity analyses were carried out. These are described below.[23]

(i) *Horizontal Symmetry Relaxed*: The horizontal symmetry requirement is parameterized by the maximum and minimum value of the following fraction: the number of days between left shoulder and the head, in the numerator, and the number of days between the head and the right shoulders in the denominator. These maximum and minimum fractions are changed from their base values of (2.5, 1/2.5) to (3.5 1/3.5.

(ii) *Horizontal Symmetry Intensified*: The critical fractions listed above are changed from (2.5, 1/2.5) to (1.5 , 1/1.5).

(iii) *Vertical Symmetry Relaxed:* The vertical symmetry requirement, which concerns the height of the left and right shoulders and left and right troughs relative to each other, is relaxed. More specifically, the right shoulder is now required to exceed the left trough (and the left shoulder to exceed the right trough).

(iv) *Volume Criterion Added*: According to technical manuals, the prototypical head-and-shoulders pattern is characterized by greater trading volume at the left shoulder than at the head.[24] (A few manuals, such as Arnold and Rahfeldt (1986), Hardy (1978), Pring (1985), and Sklarew (1980), indicate additional volume criteria, but there is no consistency among these additional criteria.) This single volume criterion is added in the identification of head-and-shoulders patterns.

As is well known, daily volume data are strongly autocorrelated, an attribute that is taken into account when creating the simulated volume series. Regressing the log of daily volume on its own lagged values, a trend, and a constant indicates that forty lags is sufficient to eliminate autocorrelation among the residuals. These regressions are then used to construct the simulated series, which are based on lagged simulated volume, and randomly drawn residuals corresponding to the same day as the randomly drawn price change.

(v) *High/Low/Close Prices*: The effects of using high and low prices to identify head-and-shoulders patterns is also explored. This is important because many market participants use charts based on high/low/close data rather than simple close data. To identify head-and-shoulders tops the basic algorithm is modified to require that the peaks in the pattern be found in the highs, and that between each peak in the highs there be at least one trough in the lows. The neckline is constructed from the troughs in the lows. Head-and-shoulders bottom positions are identified similarly. Since intraday data are not available, and since entry is predicated on the level of the closing price, it is assumed that all positions are entered at the *close*.

To simulate the highs and lows for the artificial series, two variables must be constructed from the original three series. The first, “spread,” is the difference between the day’s high and low expressed as a fraction of the day’s close. The second, “location,” is the difference between the close and the low as a fraction of the difference between the high and the low. Location is sampled using exactly the same random variables as are used to create the artificial close series. This preserves the fact that, on days when prices rise overall, the close is generally nearer the high than the low, and vice versa. To sample the spread, its autoregressive structure is first captured with an autoregression on forty lags. The simulated spread value for a given day, say day *t*, is the sum of (i) a spread residual sample from the same day used in constructing the daily closing price for that day, and (ii) an “expected” value calculated as the product of the regression coefficients and forty lags of the simulated data.

(vi) *Split Sample Across Time*: The sample is split at 30 June 1977, roughly the midpoint of the entire sample period, and each segment is examined separately.

(vii) *Split Sample by Trading Volume*: The sample is split into two subsets of 50 firms each, according to average trading volume over the entire sample period (large and small).

(viii) *Stop loss Reduced*: The stoploss limit, the minimum loss necessary for us to close out a losing position, is reduced from 1 percent to 0.5 percent.

(ix) *An AR(1) Process for Returns*: For each firm, an estimated AR(1) coefficient for returns, and residuals from the AR(1) regression on actual prices, is used to create the 12,500 simulated series.

(x) *A GARCH(1,1) Process:* For each firm, an estimated GARCH (1,1) model for prices is used to create the 12,500 simulated series. To ensure that residual variances are always positive in the simulated series, the standard GARCH model was slightly modified: the standard deviation of residuals, rather than their variance, was explicitly estimated. In particular, the standard deviation was estimated as a linear function of its own first lag and the absolute value of the lagged regression residual. Otherwise the procedure follows that in Brock et. al (1992).

Table 1: Trading Volume is Unusually High Around Head-and-Shoulders Entry Days

For each firm *I*, the following regression is run: $Log(Volume_t) = \alpha + \sum_{j=1}^{50} \beta_i Log(Volume_{t-1}) + \sum_{j=0}^{10} \gamma_i |p_{t-j} - p_{t-j-1}| + \theta t + \mu\ splitdummy + \varepsilon_t$

where closing prices are labeled p. Using an objective pattern identification algorithm on 100 firms, days when head-and-shoulders pattern crosses the neckline are identified and the average residuals from those days, ε_i are computed. Suppose the number of neckline-crossing days is n. The distribution of these average residuals under the null is derived by calculating 10,000 averages of n residuals from other days for the same firm *I*. Under the null hypothesis that there is no head-and-shoulders related trading, the associated *p*-values should be distributed uniformly over [0,1]. The Anderson-Darling statistic, A^2, is used to evaluate this hypothesis. As a rule of thumb, A^2 above 2.5 implies statistical significance at the 5 percent level. If the marginal significance of this statistic falls below 0.05 the null hypothesis is rejected. The same process is repeated for each of the three days prior and subsequent to the neckline-crossing days. Average unusual trading volume per position across all firms is shown as a percent of daily trading volume. The data consist of daily stock prices from July 2, 1962 to December 31, 1993 on 100 randomly selected firms from the CRSP database.

Table 1A: The Base Case	**Entry - 3**	**Entry - 2**	**Entry - 1**	**Entry**	**Entry + 1**	**Entry + 2**	**Entry + 3**
Average Residual (%)	**-1.25**	**-0.68**	**1.40**	**11.99**	**5.02**	**3.36**	**1.91**
A^2	**0.64**	**0.53**	**1.14**	**37.22****	**7.77****	**3.46***	**1.69**

Table 1B: Sensitivity Analysis Average Residuals (%)	**Entry - 3**	**Entry - 2**	**Entry - 1**	**Entry**	**Entry + 1**	**Entry + 2**	**Entry + 3**
Modified Identification Algorithm:							
1. Horiz. Sym. Stronger	-0.80	0.98	2.78	13.04**	6.02**	3.16	0.83
2. Horiz. Sym. Relaxed	-1.54	-1.14	1.47	11.37**	4.66**	2.51*	2.18
3. Vert. Symmetry Relaxed	-2.20	-1.11	0.15	10.68**	4.03**	2.53*	0.63
4. Volume Criterion Added	-2.41	-2.29	-0.34	15.21**	6.03**	2.94	2.67
5. High/Low/Close Data	-1.66	1.09	2.40	12.44**	4.16**	2.62	-0.71
Split Sample:							
6a. First Half	-3.09	-1.80	4.16	9.94**	2.21	1.94	0.85

6b. Second Half	-3.75	-2.54	4.06	14.49**	9.26**	
7a. High Trad. Vol.	1.52	-1.51	2.28	9.89**	5.77**	
7b. Low Trad. Vol.	-4.21	0.20	0.45	14.23**	4.21*	

*Significant at the 5 percent level. ** Significant at the 1 percent level.

Table 2. *P*-Values of Actual Data Compared with 1,000 Simulated Series, for 4 firms
Simulated data are created by drawing randomly with replacement from daily returns. The table reports the marginal significance of actual moments relative to those of the simulated series. The data consist of daily closing prices from July 2, 1962 to December 31, 1993 for 100 firms selected at random from the CRSP database.

% Change in Daily Close	**Mean**	**Std. Deviation**	**Skewness**	**Kurtosis**
Firm I	0.512	0.491	0.487	0.486
Firm II	0.530	0.476	0.528	0.468
Firm III	0.478	0.521	0.473	0.520
Firm IV	0.544	0.444	0.581	0.466

Table 3: Head-and-Shoulders Trading is Not Profitable.

Using an objective pattern identification algorithm on 100 firms, we compute average percent profits from head-and-shoulders based speculation on both the actual data and 10,000 series simulated by drawing randomly with replacement from daily returns. The first column shows the results of Test One, in which the actual average of profits, taken across all firms and positions, is compared with the distribution of its 10,000 corresponding simulated values. The second and third columns show the results of Test Two, in which profits for each firm are first compared with the distribution of simulated profits for that firm. Under the null hypothesis that head-and-shoulders trading is not profitable, the 100 associated *p*-values (shown in Figure 5) should be distributed uniformly over [0,1]. The table reports the percent of firms with *p*-values below 0.05, and the percent with *p*-values below 0.50, for the base case and for various sensitivity analyses. It also reports the Anderson-Darling statistics (A^2). As a rule of thumb, statistics above 2.5 are statistically significant at the 0.05 level. If profits in the actual data were higher than those in the simulated data, the percent of firms with *p*-values below 0.05 would tend to exceed 5, and the percent with *p*-values above 0.5 would tend to exceed 50. The data consist of daily prices from July 2, 1962 to December 31, 1993 for 100 firms selected randomly from the CRSP database.

Case	Marginal Significance (Test One)	Effect on Average Profits	A^2 (Test Two)	Percent *p*-Values < 0.05	Percent *p*-Values < 0.50	Percent *p*-Values > 0.95
Base	**0.12**	**-0.21**	**2.6***	**5**	**48**	**8**
Modified Identification Algorithm:						
1. Horiz. Sym. Stronger	**0.13**	**-0.06**	**0.8**	**4**	**46**	**7**
2. Horiz. Sym. Relaxed	**0.22**	**-0.30**	**1.4**	**4**	**48**	**8**
3. Vert. Sym. Relaxed	**0.04**	**-0.29**	**4.4****	**5**	**48**	**17**
4. Volume Criterion Added	**0.49**	**-0.10**	**0.3**	**6**	**49**	**6**
5. High/Low/Close Data	**0.01**	**-0.38**	**4.0****	**5**	**43**	**14**
Split Sample:						
6a. First Half	**0.47**	**-0.01**	**1.4**	**7**	**45**	**8**
6b. Second Half	**0.07**	**-0.52**	**1.2**	**3**	**45**	**9**
7a. High Trading Vol.	**0.09**	**-0.43**	**1.8**	**0**	**46**	**6**
7b. Low Trading Vol.	**0.39**	**-0.12**	**3.2***	**10**	**50**	**10**
Modified Assumed Returns Process:						

8. AR(1)	**0.13**	**-0.26**	**2.0**	**2**	**48**	**7**
9. GARCH(1,1)	**0.03**	**-0.26**	**1.4**	**4**	**47**	**7**
Modified Exit Strategy:						
10. Stop loss Reduced	**0.33**	**-0.15**	**2.8***	**6**	**54**	**8**

* Significant at the 5 percent level. ** Significant at the 1 percent level.

Table 4: Head-and-Shoulders Returns Are Unusually High On the Days After the Neckline Crossing

Using an objective pattern identification algorithm on 100 firms, we compute average signed returns following days on which head-and-shoulders patterns are confirmed (neckline-crossing days) on both the actual data and 10,000 series simulated by drawing randomly with replacement from daily returns. The third column shows the results of a test in which the actual average of returns, taken across all firms and positions, is compared with the distribution of its 10,000 corresponding simulated values. Under the null hypothesis that head-and-shoulders trading does not affect returns, the 100 associated *p*-values (shown in Figure 6) should be distributed uniformly over [0,1]. The fourth column reports Anderson-Darling statistics (A^2) for this null, and the fifth reports the percent of firms with *p*-values below 0.05.† If returns in the actual data are higher than those in the simulated data, the percent of firms with *p*-values below 0.05 will should exceed 5. The data consist of daily prices from July 2, 1962 to December 31, 1993 for 100 firms selected randomly from the CRSP database.

Case	**Average Returns**	**Average Effect**	**Marginal Significance (Test One)**	**A^2 (Test Two)**	**Percent Firms with *p*-Values < 0.05**
Base	0.01	0.06	0.01	13.9**	19
Modified Identification Algorithm:					
1. Horiz. Sym. Stronger	0.08	0.12	0.00	12.05**	20
2. Horiz. Sym. Relaxed	0.01	0.05	0.00	12.60**	17
3. Vert. Sym. Relaxed	0.01	0.07	0.00	30.98**	28
4. Volume Criterion Added	0.04	0.09	0.01	3.46*	0
5. High/Low/Close Data	-0.01	0.05	0.05	7.90**	18

Split Sample:					
6a. First Half	0.05	0.10	0.02	8.49**	16
6b. Second Half	0.01	0.08	0.07	4.00**	9
7a. High Trading Vol.	0.10	0.12	0.01	12.11**	22
7b. Low Trading Vol.	-0.06	0.01	0.53	6.12**	18
Modified Assumed Returns Process:					
8. AR(1)	0.01	0.11	0.01	4.86**	16
9. GARCH(1,1)	0.01	0.06	0.07	6.19**	13

* Statistically significant at the 5 percent level.

** Statistically significant at the 1 percent level.

† The sensitivity analysis with modified stoploss is not reported because the results for this table are identical to the base case.

Table 5: The Price Effects of Head-and-Shoulders Traders Disappears Completely Within Two Weeks

For each of the 100 firms, average signed returns are computed for over various periods after the neckline crossing. Actual signed returns are compared with those from 10,000 artificial series simulated by drawing randomly with replacement from daily returns. The columns provides the measured difference between the actual returns and those in the simulated data. Under the null hypothesis that head-and-shoulders trading has no effect on returns, the 100 associated *p*-values will be distributed uniformly over [0,1]. The Anderson-Darling statistic is used to test the equivalence of their actual distribution with this theoretical benchmark. The data consist of daily stock prices from July 2, 1962 to December 31, 1993 on 100 randomly selected firms from the CRSP database.

Case	**1-3**	**3-5**	**5-10**	**0-3**	**0-5**	**0-10**
Base	**-0.06***	**-0.04***	**0.06**	**-0.05***	**-0.09***	**-0.04**
Modified Identification Algorithm:						
1. Horiz. Sym. Stronger	**-0.11**	**-0.08**	**-0.06**	**-0.08**	**-0.15**	**-0.22**
2. Horiz. Sym. Relaxed	**-0.06***	**-0.04**	**0.06**	**-0.08**	**-0.12**	**-0.05**
3. Vert. Sym. Relaxed	**-0.01****	**0.06**	**-0.04**	**-0.01****	**0.05**	**0.01**
4. Volume Criterion Added	**-0.11***	**0.03**	**-0.12**	**-0.04***	**-0.01**	**-0.13**
5. High/Low/Close Data	**-0.19***	**0.09***	**-0.03****	**-0.14****	**-0.05****	**-0.08****
Split Sample:						
6a. First Half	**-0.00**	**-0.14**	**0.10**	**0.09**	**-0.05**	**0.05**
6b. Second Half	**-0.27****	**0.09**	**0.00**	**-0.19***	**-0.10**	**-0.10**
7a. High Trading Vol.	**-0.06***	**-0.13***	**0.10**	**-0.01**	**-0.14***	**-0.03**
7b. Low Trading Vol.	**-0.04**	**0.09**	**-0.00**	**-0.03***	**0.06**	**0.06**
Modified Assumed Returns Process:						
8. AR(1)	**-0.15****	**-0.04**	**0.05**	**-0.04***	**-0.08**	**-0.03**
9. GARCH(1,1)	**-0.14**	**-0.04**	**-0.04**	**-0.08**	**-0.10**	**-0.10**

* Statistically significant at the 5 percent level. ** Statistically significant at the 1 percent level.
† The sensitivity analysis with modified stoploss is not reported because it provides results identical to the base case.

Figure 1: Hypothetical Head-and-Shoulders Pattern

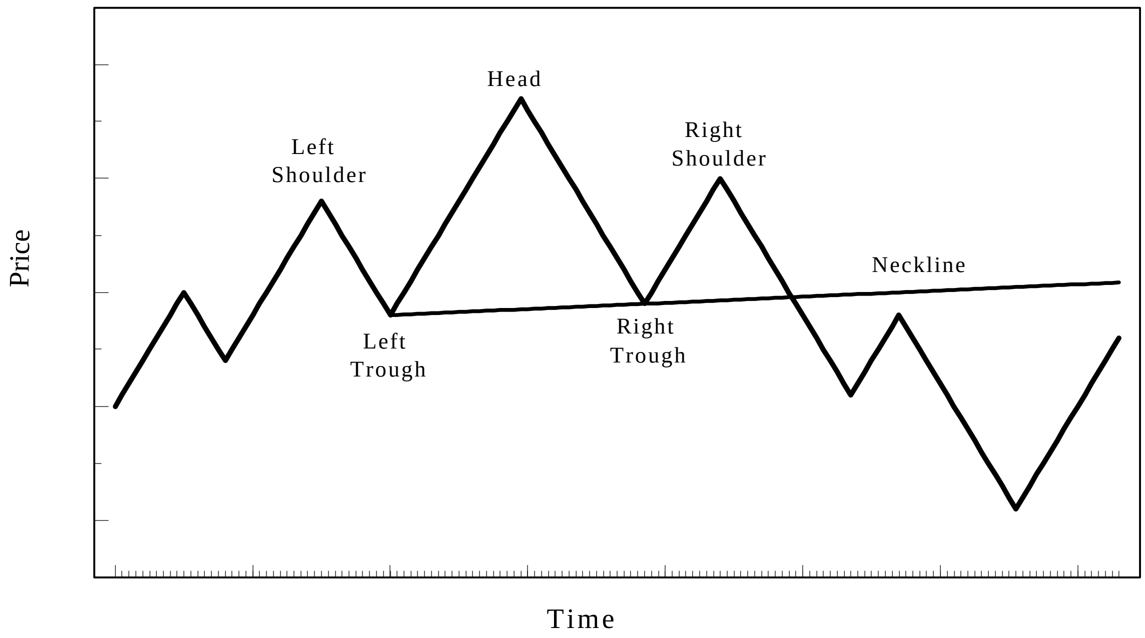


Figure 2: Theoretical Distributions of P-Values

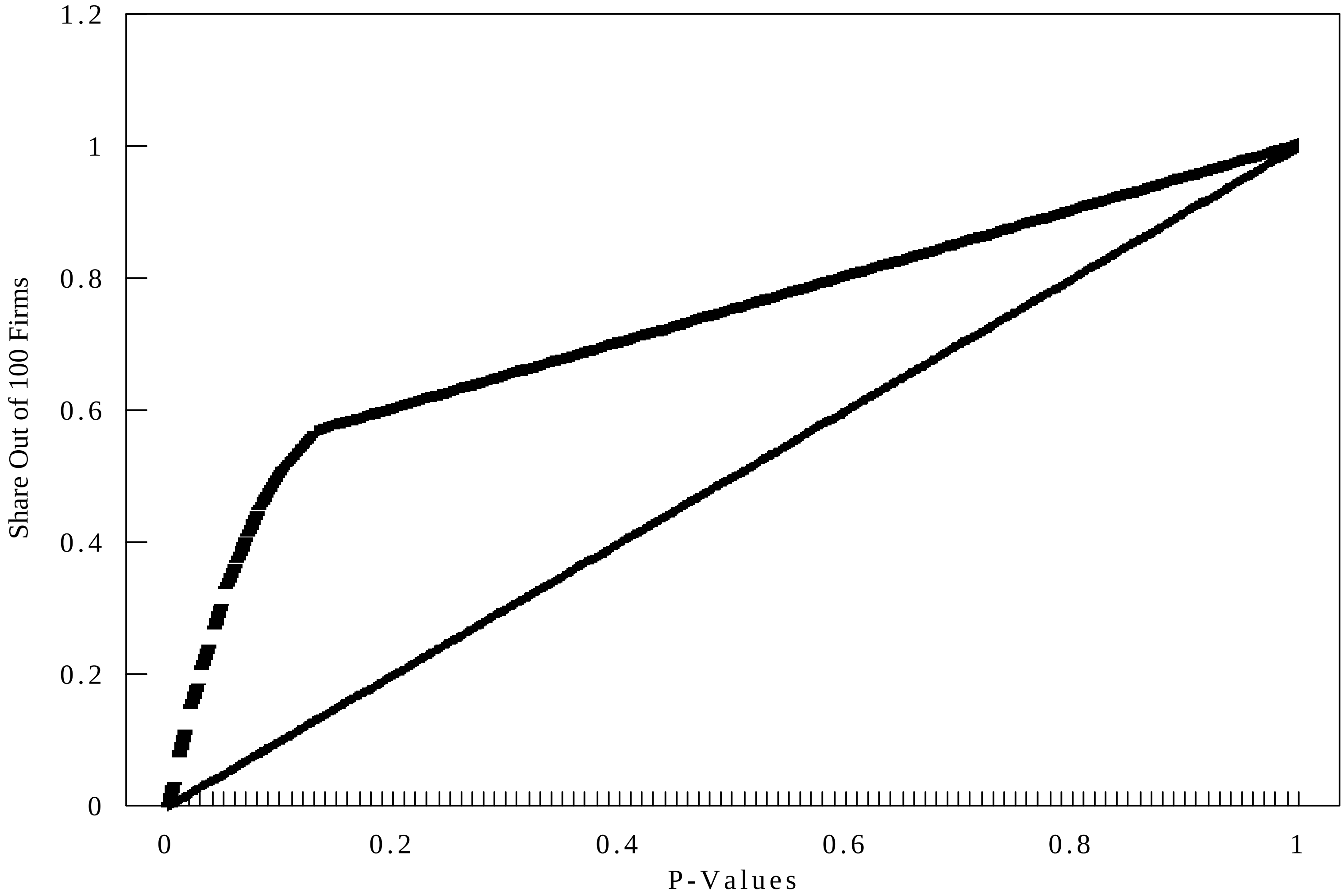


Figure 3: Trading Volume is Unusually High on Neckline-Crossing Days

Base Case: Cumulative Distribution, p-Values for Unusual Trading Volume

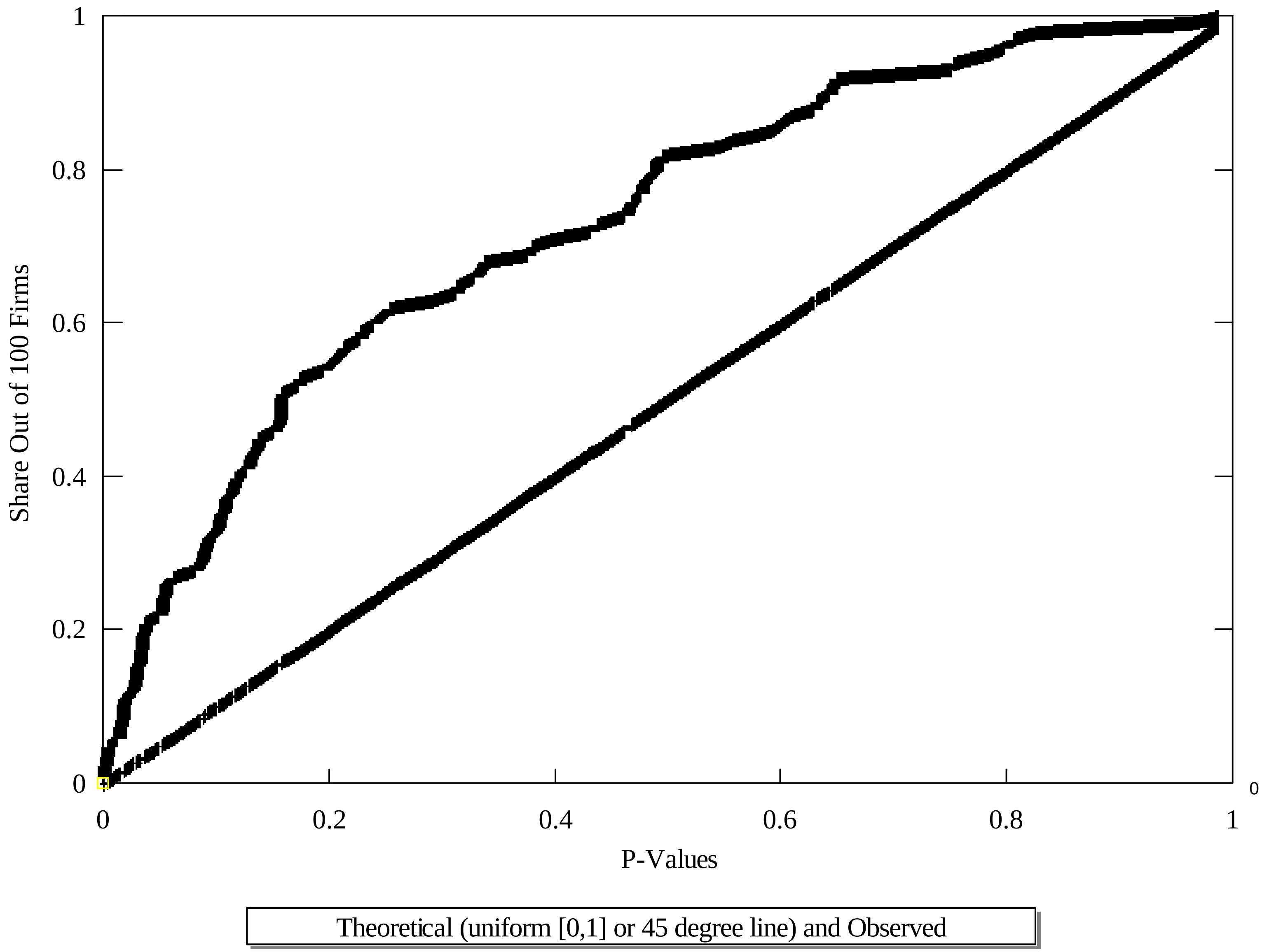


Figure 4: Frequency Distribution of Average Percent Profits

Average Over All Positions and All Firms for Base Case

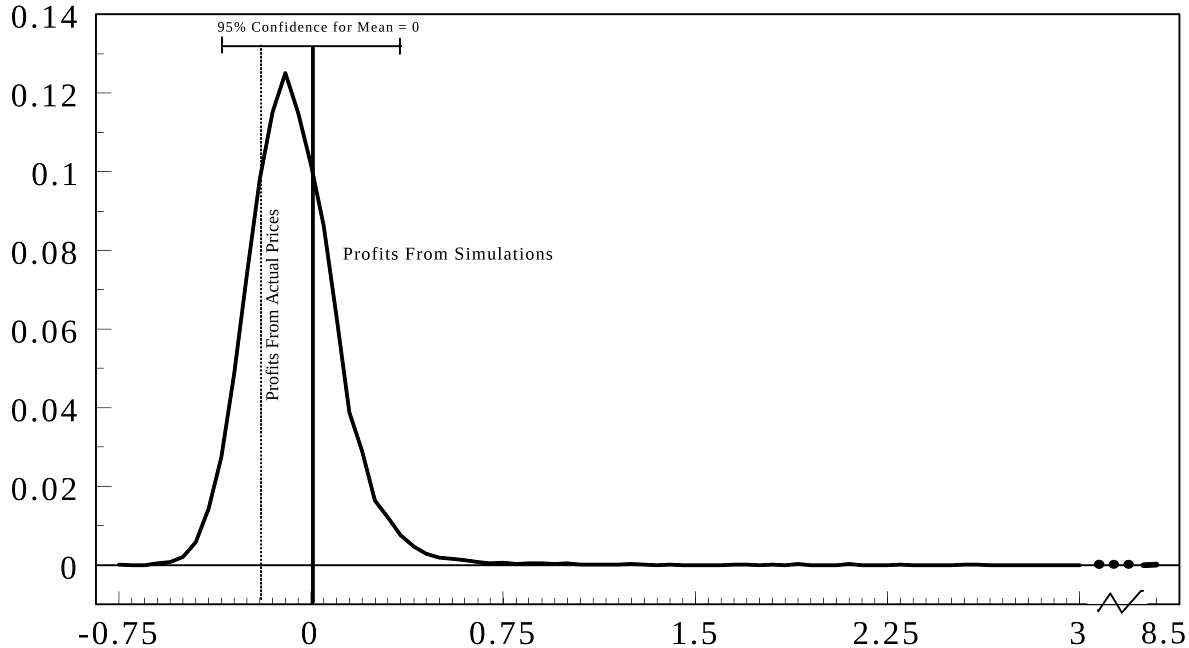
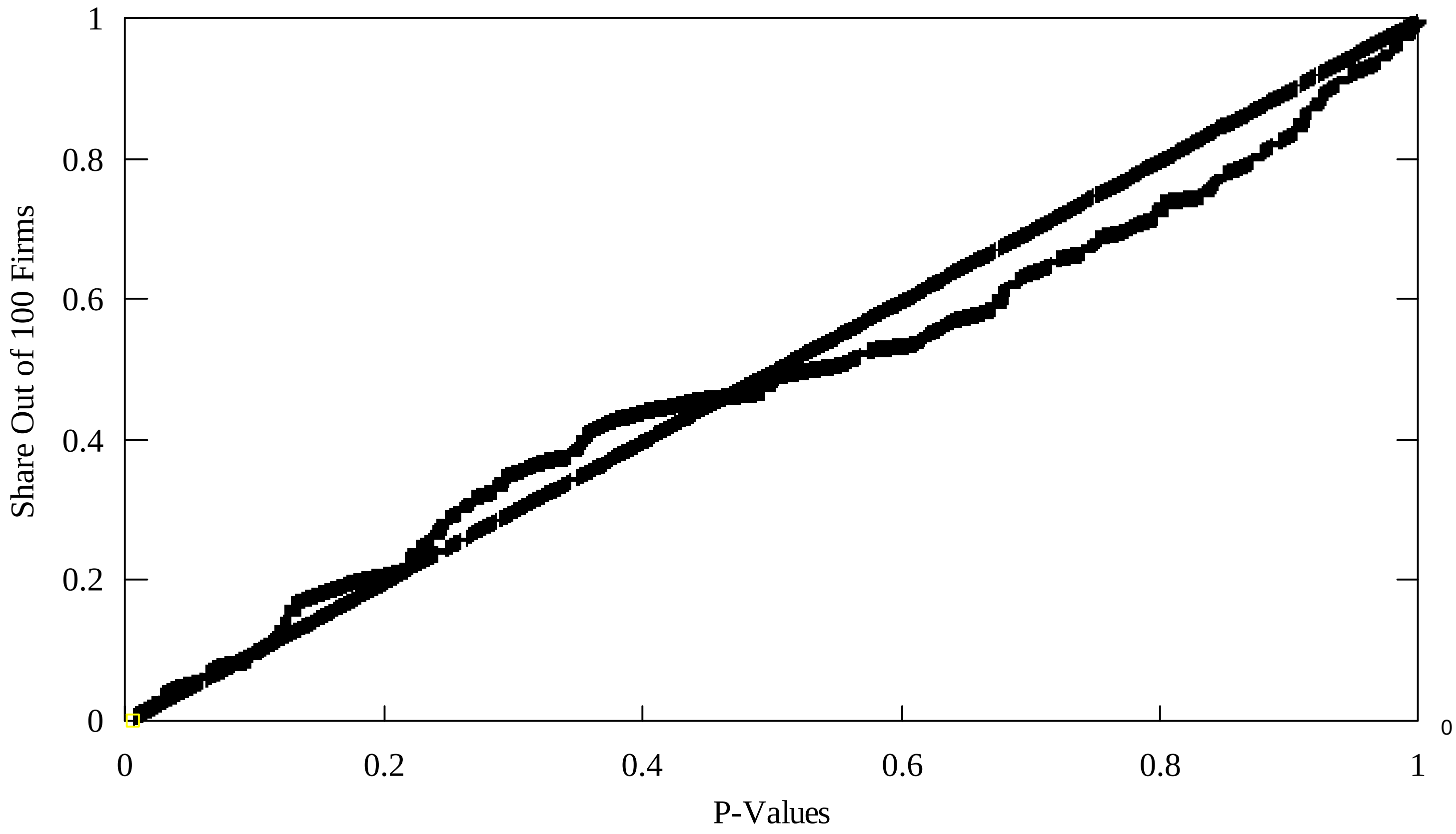


Figure 5: Head-and-Shoulders Trading is Not Profitable

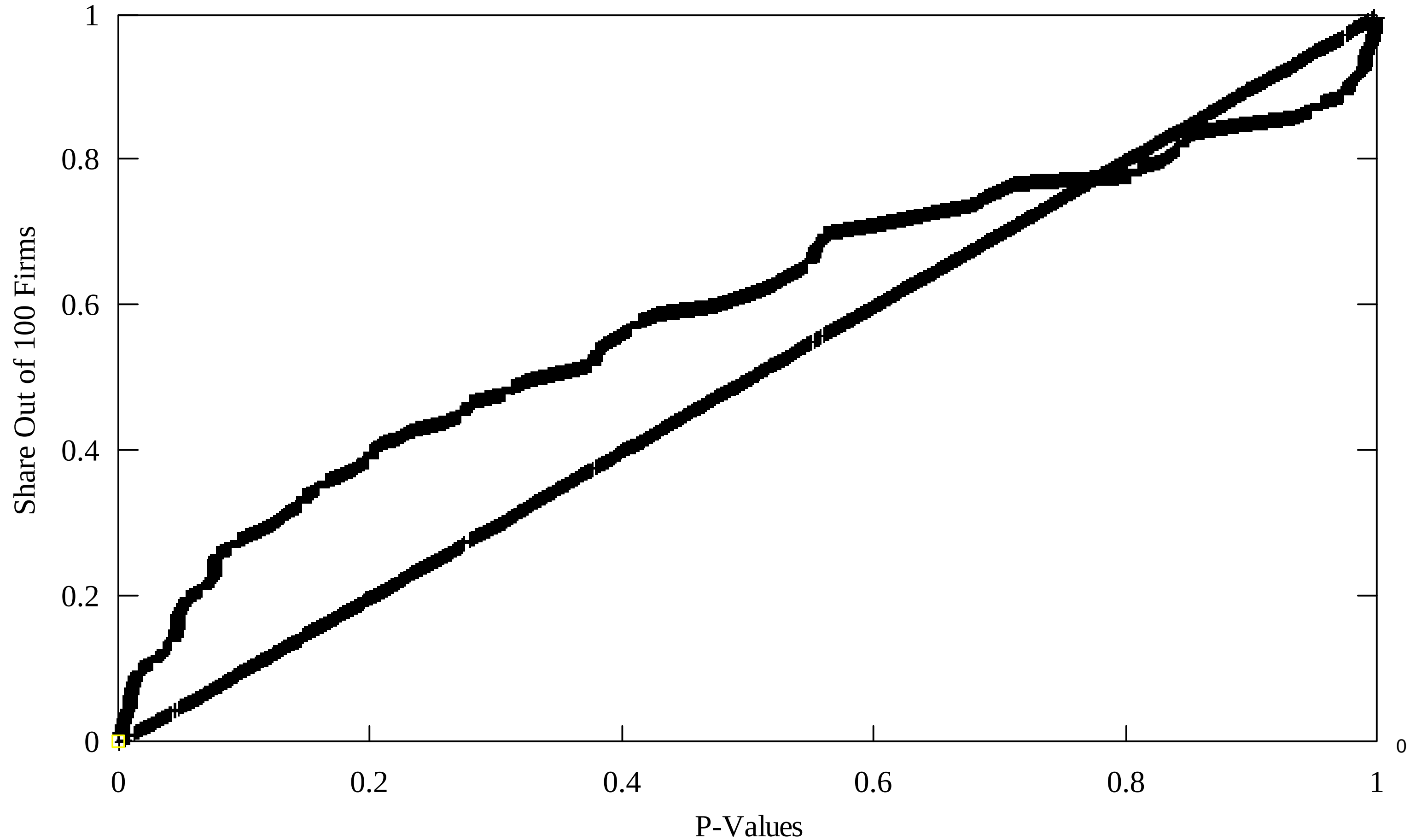
Base Case: Cumulative Distribution, p-Values for Profits



Theoretical (uniform [0,1], or 45 degree line) and Observed

Figure 6: H&S Sales Tend to Reduce Prices, and Vice Versa

Base Case: Cumulative Distribution, p-Values for Day-After H&S Returns



Theoretical (uniform [0,1] or 45 degree line) and Observed

NOTES

1. Though Levy (1971) examines the head-and-shoulders, the study does not carefully incorporate technical analysts' specific rules about entry and does not allow for flexible exit dates, so its results may not be relevant to the actual practice of technical analysis.

5. Those manuals are Arnold and Rahfeldt (1986), Edwards and Magee (1966), Hardy (1978), Kaufman (1978), Murphy (1986), Pring (1985), Shabacker (1930) and Sklarew (1980).

3. Most firms have discrete price declines on ex-dividend days. To prevent the identification algorithm from misinterpreting these largely predictable price declines as technical signals, dividends are re-incorporated into all stock prices. Specifically, the closing price series labeled "actual" is obtained by applying CRSP's dividend-adjusted return series to the initial closing price. We adjust the return series to ensure that we always deal with 5-day weeks, as recommended by charting manuals.

4. It has been suggested that, since surviving firms will tend to be relatively large, there may be less volatility and therefore less technical trading in their securities. Results presented later indicate that the volume of trading around head-and-shoulders signals does not differ meaningfully according to the size of the firm.

5. Figures on subscriptions and enrollment come from personal communications with representatives of the institutions mentioned.

6. To avoid biasing the residuals on the days before and including the neckline-crossing, the tenth lead of the log closing price is used instead of the concurrent one. This has only trivial effects on the regression results, since the log price is essentially capturing trends, but it means that residuals on or before neckline-crossing days for head-and-shoulders tops (bottoms) are not artificially inflated (deflated) by the known concurrent price decline (rise).

7. For all four randomly-selected firms, the marginal significance of the Q-statistic for residual autocorrelation was 1.00.

8. Regression results for randomly sampled firms indicate that either the trend or the log price is statistically and economically important, but not both.

9. It would be possible to use this observation directly in a parametric test of the null hypothesis that entry-day trading is not unusual. Such a test would involve assuming that average entry-day residuals would be independent across firms and evenly distributed around zero, in which case they would be distributed as a binomial (n,p) with $n = 100$ and $p = 0.5$. The results of such a test indicate that trading volume on neckline-crossing days is, indeed, unusually high. However, these results are not reliable, since average entry-day residuals are not evenly distributed around zero.

10. See, for example, Brock, Lakonishok, and LeBaron (1992), Levich and Thomas (1993), Allen and Karjalainen (1993), LeBaron (1991), and LeBaron (1996).

11. This approach is described as a "variant" of the bootstrap because the distribution under the null is derived without simulating any data series.

12. The Anderson-Darling statistic for this particular case is calculated from the c.d.f. of the ranked p-values (denoted $F_n(x)$) and the c.d.f. of the uniform distribution (denoted $F(x)$) as

follows:

$$A^2 = \sum_{i=1}^{100} \frac{[F_n(x) - F(x)]^2}{F(x)(1-F(x))} \quad .$$

As described in D'Agostino and Stephens (1986), this is equivalent to the following calculation:

$$A^2 = -100 - \frac{1}{100}\sum_{i=1}^{100}(2i-1)[\log F_n(i) + \log(1-F_n(101-i))] \quad .$$

13. The *p*-values reported in the tables and the text are linear interpolations or extrapolations of levels provided in D'Agostino and Stephens (1986), Table 4.3, p. 108.

14. There was nothing special about the choice of these days. Detailed results, suppressed to save space, are available from the author.

15. The statistical significance of the result that head-and-shoulders trading volume is unusually high around neckline-crossing days is conceptually unrelated to the predictability of trading volume.

16. For example, beginning with an artificially generated closing price for day *t*, one constructs the corresponding price for day *t*+1 by randomly selecting a day from the sample, say day *x*, and adjusting the day-*t* price upwards or downwards by the actual gross return associated with day *x*.

17. The number of simulations per stock series was set at 12,500 because experiments with the random subsample of four firms showed that 12,500 simulations were necessary to obtain convergence in the *p*-values in one of the sensitivity analyses.

18. That is, for each firm I create a vector in which each day is represented by a zero if head-and-shoulders traders were out of the market or their actual daily return if they were in the market. It is the correlations among these vectors that are discussed in the text.

19. It is possible that the difference between the observed and theoretical distributions is unrelated to the first moment of profits. In particular, one can see in Figure 5 that the distribution of observed *p*-values is more concentrated in the mid-range, between 0.2 and 0.8, than would be predicted under the null. Again, there is no information here to suggest that the pattern is profitable if used in the manner recommended by technical analysts.

20. I also examine but do not report a case in which the bounce parameter is increased. Specifically, the analysis increases the vertical distance from the neckline that constitutes an incomplete or temporary "pullback" on the way to an ultimately larger trend reversal. More specifically, the bounce parameter, expressed as a fraction of the "price objective" (the predicted magnitude of price reversal after entering a position), is raised from 0.25 to 0.5. So few cases of "bounce" were observed in practice that this had only trivial effects on the results.

21. The negative sign of simulated day-after returns is presumably related to the above-mentioned tendency of head-and-shoulders traders to sell upwardly trending stocks.

22. These requirements are illustrated for a head-and-shoulders top; in the requirements for a head-and-shoulders bottom, “peaks” replace “troughs,” and vice-versa.

23. I also examine but do not report a case in which the bounce parameter expressed as a fraction of the “price objective” (the predicted magnitude of price reversal after entering a position), was raised from 0.25 to 0.50. Few cases of “bounce” were observed in practice, so it is not surprising that this modification had only trivial effects on the results.

24. Blume, Easley, and O'Hara (1994) present a theoretical model in which a volume criterion is justified in technical analysis because it adds information on the "quality of information" beyond that already incorporated in price.