Noise Trading and Illusory Correlations in U.S. Equity Markets

Abstract. This paper provides evidence that “illusory correlations” – a well-documented source of cognitive bias – lead some agents to be imperfectly rational noise traders. We focus on the head-and-shoulders chart pattern, considered by technical analysts to provide one of the most reliable trading signals. Our findings indicate that the pattern is associated with a substantial rise in trading volume even though it does not profitably predict directional movements. We further substantiate the connection between head-and-shoulders trading and imperfectly rational noise trading by showing that the pattern is associated with lower bid-ask spreads.

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1. Introduction

Psychologists have long documented a human tendency to create "illusory correlations," or equivalently, to believe in predictive relationships that don’t really exist (Chapman and Chapman, 1967; Bloomfield and Hales, 2002). This tendency has many apt illustrations from human history, including medieval medical treatments that compromised health. More recently, brain scientists have noted a strong physiological predilection to discover patterns in series that are consciously known to be random (De Bondt, 1993). Indeed, researchers have identified the part of the brain where subconscious pattern recognition occurs (Huettel et al., 2002).

We hypothesize that the human predilection to discover patterns, augmented by a strong desire to make money, leads some investors to believe in correlations between price patterns and future price movements that do not truly exist. If we are correct, such traders would be, in effect, noise traders.

Noise traders have been a key component of financial models since their introduction by Kyle (1985) and Glosten and Milgrom (1985); indeed, “[n]oise traders play a ubiquitous role in the finance literature” (Bloomfield, et al., 2009, p. 2275). Despite the conceptual importance of noise traders, there is no agreement about their nature in reality. For some researchers, noise traders must be rational optimizers who trade for hedging or liquidity reasons (e.g., Wang, 1994; Bacchetta and van Wincoop, 2006). But rational optimization has difficulty accounting for the massive amount of trading observed daily around the world. Others take the broader view that noise traders could be imperfectly rational. Black (1986, p. 531), for example, claims that “[p]eople who trade on noise are willing to trade even though from an objective point of view they would be better off not trading. Perhaps they think the noise they are trading on is information. Or perhaps they just like to trade.”
This paper provides evidence for the existence of imperfectly rational noise trading that is motivated by an illusory connection between equity returns and "head-and-shoulders" patterns. Technical analysts claim that these chart patterns – which involve a series of three price peaks, the highest of which is in the middle – produce a reliable signal of a coming downtrend; they likewise claim that the inverse patterns predict an uptrend. Our focus on technical trading is suggested by the historically dismissive attitude of mainstream economists towards this form of speculation. Malkiel (1990, p. 154), for example, asserts that “[t]echnical strategies are usually amusing, often comforting, but of no real value.”¹ This attitude persists despite studies providing theoretical and empirical support for the possibility that past prices carry information about future excess returns (Brown and Jennings, 1989; Lo et al., 2000; Osler, 2003). Since technical analysis is widely popular in practice, it could account for a substantial amount of trading volume if economists are correct in their suspicions.

We first provide evidence that head-and-shoulders patterns elicit a striking amount of trading. Our data include all NYSE and AMEX firms with daily data in the Center for Research in Security Prices (CRSP) database from 1962 to 2002 and all NASDAQ firms with CRSP data spanning five consecutive years. Our analysis finds that unusual trading around head-and-shoulders patterns averages over 60 percent of a day’s trading volume. Additional results show that this trading cannot be attributed to autocorrelation in volume, price volatility, or stale limit orders. These results are consistent across alternative parameterizations of the pattern, consistent across large and small firms, and consistent across the four decades of our sample.

We next provide evidence that head-and-shoulders trading is based on an illusory correlation by showing that the pattern does not predict directional price movements as claimed. Using bootstrapped significance tests we show that profits from trading as recommended by technical

¹ Note: If this comforting perspective is accurate, then some noise traders must be imperfectly rational.
analysts are negative – even before adjusting for transaction costs and risk. Returns in excess of the S&P 500 are also negative, consistent with results in Savin et al. (2007). (The observed negative profits, though generally significant, are insufficient to cover transactions costs if one trades in opposition to the advice of technical analysts.) These results are sustained for alternative parameterizations, for various subsamples, and when bootstrapped return distributions incorporate autocorrelated volatility.

We finish our analysis by providing evidence that head-and-shoulders trading is associated with relatively narrow spreads. If head-and-shoulders trading qualifies as uninformed noise trading, bid-ask spreads should narrow when such trading is active, other things equal (Glosten and Milgrom, 1985). Our analysis finds that spreads narrow by an average of 5 percent to 9 percent relative to normal levels on the days that head-and-shoulders traders should enter positions, which represents as much as 90 percent of the adverse-selection component of bid-ask spreads. Once again, the results are sustained across numerous robustness tests.

Since our study introduces the phenomenon of illusory correlations to finance research, the most closely related papers are not about this phenomenon per se but instead consider the evidence for imperfectly rational noise trading. The paper most closely related to ours, Greene and Smart (1999), identifies noise trading by focusing on the Wall Street Journal’s Dart Board column of the early 1990s. They show that the column was associated with elevated trading and narrower spreads even though its recommended trades were not profitable. Unlike head-and-shoulders trading, however, Dart-Board trading probably generated little noise trading in aggregate, since it involved just a handful of firms at infrequent intervals. Kalay and Wohl (2005) identify liquidity trading on the Tel Aviv Stock Exchange using the properties of the

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2 Subsequent to the initial circulation of this research (Osler, 1998), Kolev and Hogarth (2008) have independently suggested the influence of illusory correlations in CEO compensation.
order book, and present suggestive evidence that such trading is not profitable. Barber and Odean’s (2000) and Linainmaa’s (2010) evidence that retail equity trading is typically unprofitable implies that such trading serves as imperfectly rational noise trading. Kumar and Lee (2006) support this by showing that investor sentiment influences the returns for stocks with heavy retail ownership.

Existing studies of technical analysis are primarily concerned with market efficiency, so they examine profitability but not trading volume or bid-ask spreads. Studies of currency markets find that most technical strategies are profitable both before and after adjusting for transaction costs and risk (Menkhoff and Taylor, 2006). Studies of U.S. equity markets, by contrast, generally find that technical strategies are unprofitable after adjusting for transaction costs and risk (Fama and Blume, 1966; Murphy, 1986). Since some of the strategies studied most frequently by academics are rarely used in practice, those studies do not necessarily identify noise trading.

This paper proceeds as follows. Section 2 describes our data and our algorithm for identifying head-and-shoulders patterns. Section 3 shows that trading volume is exceptionally high when head-and-shoulders traders should open positions according to the recommendations of technical analysts. Section 4 shows that head-and-shoulders patterns do not profitably predict directional movements in U.S. equity markets and discusses how an illusory correlation could influence trading for decades. Section 5 shows that bid-ask spreads narrow contemporaneously with head-and-shoulders trading activity. Section 6 concludes.

2. Identifying Head-and-Shoulders Patterns

A head-and-shoulders pattern constitutes a series of three peaks, of which the highest is in the middle (see Figure 1). Technical analysts claim that a head-and-shoulders pattern after an up-trend predicts a down-trend. Likewise they claim that a pattern in which the roles of peaks and
troughs are reversed, called a “head-and-shoulders bottom,” predicts an up-trend if it follows a
downtrend. We construct a computer-based algorithm that identifies these patterns and simulates
associated speculative positions. To learn how these strategies are executed in practice, we had
numerous conversations with practicing technical analysts and consulted eight technical analysis
manuals. The sources agree to a striking extent on the following: (i) one should not enter a
position unless the pattern is "confirmed"; (ii) confirmation occurs if and when the price crosses
the "neckline"; (iii) the neckline is a straight line connecting the pattern’s two troughs and
extending forward in time; (iv) symmetric entry criteria apply to head-and-shoulders bottoms.
Our algorithm conforms to these requirements.

We use two samples of equity returns. The first sample comprises the 304 NYSE and AMEX
firms with data spanning July 2, 1962, (the starting date of CRSP) to December 31, 2002. This
represents 40.5 years, or about 10,200 daily observations, a period long enough to test whether
our results are consistent across time. Though this sample presumably over-weights large firms –
since they gravitate to the NYSE and since our selection criterion induces survivorship bias –
this should not bias the results. Technical analysts consistently assert that their predictions hold
equally for all financial assets; further, the reasons they cite for the predictive power of head-
and-shoulders patterns are social forces and behavioral biases unrelated to firm characteristics.
Nonetheless, we extend our analysis by creating a second sample that should display little
survivorship bias. The second sample comprises the 373 NASDAQ firms with 5 years of
consecutive data between December 14, 1972 (when NASDAQ firms were first included in
CRSP) and December 31, 2002. To abstract from price dynamics on ex-dividend dates, we

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(1985), Shabacker (1930), and Sklarew (1980). The methodology described here follows Chang and Osler (2000).
reconstruct each firm’s price series by applying historical dividend-adjusted returns to the initial price.

The manuals define head-and-shoulders patterns in terms of peaks and troughs, so the first step in identifying these patterns is to identify peaks and troughs in the dividend-adjusted price series. We require extrema to be separated from each other by a minimum vertical distance or “cutoff.” For a 5 percent cutoff, a local maximum (minimum) is identified as a peak once prices have declined (risen) by 5 percent from that point.

Given the sequence of peaks and troughs, the algorithm searches for sub-sequences that mirror the head-and-shoulders patterns depicted in the manuals. We constrain (i) the previous trend; (ii) the slope of the pattern; (iii) asymmetries between left and right shoulders; and (iv) the delay between the right shoulder and the neckline crossing (details in the Appendix). The parameters assigned to these constraints are necessarily somewhat arbitrary: in some cases, neither the manuals nor conversations with practicing technical analysts provided much guidance. Robustness tests show that the results are insensitive to wide variation in these choices.

We scan each firm’s data ten different times to capture head-and-shoulders patterns of different magnitudes. With each scan we impose a different cutoff. The minimum cutoff, at 1.5 standard deviations of actual daily returns, ensures the program distinguishes uptrends and downtrends from ordinary daily variation. The maximum cutoff, at 6.0 standard deviations, ensures a small but non-negligible chance of finding a large head-and-shoulders pattern for each firm. Each time the data are scanned with a new cutoff, duplicate head-and-shoulders signals are avoided by eliminating patterns entered within two days before or after a previously identified entry date. The results are invariant to the order in which the cutoffs are applied.
3. Trading Volume

To show that head-and-shoulders trading could provide an empirically significant source of noise trading it is necessary to demonstrate that people actually trade on this signal in meaningful amounts. We first consider the amount of technical trading in general and then examine the amount of trading associated with head-and-shoulders patterns in particular.

Casual empiricism points to substantial technical trading in equity markets. Technical traders are sufficient in number to support magazines largely devoted to the subject, including *Stocks and Commodities Magazine* and *Futures Magazine*, as well as online communities such as *MetaStock*. Myriad firms offer software and data for technical traders. Conferences, workshops, and seminars are held frequently in major cities. A new crop of 450 to 500 students learn the subject each year at The New York Institute of Finance. One can gain a Chartered Market Technician (CMT) certificate by passing three demanding tests. One can also join many professional associations and membership can be selective: one must have seven years of professional practice to join the American Association of Professional Technical Analysts.

Academic evidence confirms that technical trading is widespread. Shiller (1989), for example, documents that support and resistance levels were important during the 1987 stock market crash. Studies show that over 90 percent of currency traders in London (Allen and Taylor, 1990) and in Hong Kong, Singapore, and Japan (Lui and Mole, 1998) rely on technical analysis for short-term speculation.

To evaluate whether head-and-shoulders chart patterns influence trading activity, we focus on the days when technical traders are likely to open positions. We examine these “entry days,” rather than exit days, because the technical analysis manuals surveyed for this research explicitly and consistently delineate the same entry criterion – the price must decisively cross the neckline.
– while they leave implicit the criteria for existing positions. Our null hypothesis is that trading
volume is not unusual on head-and-shoulders entry days.

Unusual trading volume is measured as the residual from a regression of (log) daily volume,
\( \ln(\text{TradVol}_t) \), on a constant, 50 own lags, 10 lags of volatility, a linear trend, \( t \), and the log of the
closing price advanced 10 days, \( \ln(p_{t+10}) \):

\[
\ln(\text{TradVol}_t) = \alpha + \sum_{i=1}^{50} \beta_i \ln(\text{TradVol}_{t-i}) + \sum_{i=1}^{10} \chi_i \ln(\text{High}_{t-i} / \text{Low}_{t-i}) + \delta t + \phi \ln(p_{t+10}) + \epsilon_t. \tag{1}
\]

Volatility is measured as the proportionate gap between high and low prices, \( \ln(\text{High}_t / \text{Low}_t) \), as
recommended by Rogers and Satchell (1991). This controls for the familiar positive relationship
between volume and volatility. The trend and log price terms allow for the strong volume trends
evident for many firms: typically only one of these terms is significant. We advance the closing
price so that residuals on or before entry days for head-and-shoulders tops (bottoms) are not
artificially raised (lowered) by the known concurrent price decline (rise). Tests for randomly
selected firms show that residuals display no noticeable serial correlation.

For each firm we calculate average excess trading on entry days. This average has a normal
distribution according to the central limit theorem and zero mean according to the null. We treat
each firm as a single Bernoulli trial with probability one-half that average entry-day residuals are
positive. For the NYSE/AMEX (NASDAQ) sample, the number of firms with positive average
excess trading on entry days has a binomial distribution with parameters \( p = 0.5, n = 304 \) \( (n = 373) \) if observations are independent across firms.\(^4\)

The independence assumption deserves careful attention. Daily trading volume itself is
correlated across firms (Lo et al., 2000), but our focus is excess trading. More narrowly, our
focus is excess trading on entry days, which occur relatively infrequently; we identify about one

\(^4\) We exclude 13 NYSE/AMEX firms and 24 NASDAQ firms with incomplete volume data.
confirmed head-and-shoulders pattern per firm per year. We construct a time series for each firm, consisting of excess trading volume on entry dates and zeroes otherwise, and calculate correlations for each of the 46,056 NYSE/AMEX bilateral firm pairs. The vast majority of these correlations are tiny (under 5 percent in absolute value), and less than 2 percent of them have a t-value above unity. On this basis the independence assumption appears reasonable.

3.1 TRADING VOLUME: RESULTS

Our results indicate that equity trading is unusually active on head-and-shoulders entry days. Average entry-day excess trading is positive for 293 of the 304 NYSE/AMEX firms and for 350 of the 373 NASDAQ firms. These outcomes have vanishingly small likelihoods under the null. Excess entry-day trading volume averages a striking 40.3 percent of a day’s trading for NYSE/AMEX firms and 39.9 percent for NASDAQ firms.

Head-and-shoulders trading could also occur on other days. Extra-confident traders might enter before a “decisive” neckline crossing; less confident traders, or those who cannot monitor prices intraday, might enter later. Traders might choose different entry days if their data are sampled less frequently or represented with candlestick or point-and-figure charts.

As shown in Table 1, Panel A, unusual trading activity in NYSE/AMEX firms begins two days prior to our identified entry day, rises modestly, surges to a sharp peak on the entry day itself, falls rapidly the next day, then falls modestly for one more day, and disappears thereafter. In aggregate, such excess trading exceeds 65 percent of one day’s volume. As shown in Table 1, Panel B, the interval of significant excess trading is one day shorter for the NASDAQ sample but aggregate excess trading is larger, at 71 percent of a day’s volume.

These results suggest that head-and-shoulders patterns are associated with substantial trading. We note, however, that this trading could include more than technical trading. Since we show in
Section 4 that head-and-shoulders patterns have no predictive power, the extra trading could include informed trading attracted by the possibility of “camouflage” from uninformed traders. It could likewise include trading attracted by the narrower spreads documented in Section 5.

3.2 TRADING VOLUME: ROBUSTNESS

We examine the robustness of these results with six sensitivity analyses, of which the first four vary the precise criteria used to identify head-and-shoulders patterns. Three greatly strengthen or relax the restrictions on allowable asymmetries in the pattern and the fourth adds a trading volume criterion commonly cited by technical analysts (details in the Appendix). The fifth test splits the sample into firms with high or low average trading volume, since research has found numerous differences in trading behavior across firms of different sizes. The last robustness test splits the NYSE/AMEX sample in July of 1982, about half-way through the sample period (a similar split is impossible for the NASDAQ firms because the sample period is shorter and because NASDAQ firms are only required to have 5 years of data). As shown in Table 1, Panels A and B, these tests consistently support our initial findings: statistically significant excess trading takes place on four or more days around the neckline crossing and totals 60 percent or more of a day’s volume.

To confirm that the results do not reflect a programming error, we examine excess trading on a five-day window centered on 60 trading days after the middle peak (or “head”) of each pattern. Unreported tests show that average excess trading for this arbitrary set of days is uniformly small – below 0.6 percent of daily volume in absolute value – and statistically insignificant.

Linnainmaa (2010) shows that the disposition effect and other striking properties of retail trading can be traced in part to the execution of stale retail limit orders during strong market moves. Since entry days will naturally tend to have large returns, we examine whether excess
trading on entry days can be attributed to this phenomenon. We compare excess trading on head- and-shoulder entry dates to the bootstrapped distribution of excess trading under the null that any excess trading is due to stale limit orders. The bootstrap methodology (Efron, 1979) is attractive because it requires no assumptions about the statistical distribution of excess volume.

The methodology involves 10,000 simulated samples of excess entry-day trading volume for each firm. For a given firm $i$ we first divide each daily return by that firm’s overall standard deviation of returns and partition these standardized returns, $r_{st}^i$, into seven buckets: $r_{st}^i < 1$, $r_{st}^i \in [1, 2)$, ..., $r_{st}^i \geq 6$. Denote the number of firm $i$’s standardized entry-day returns in bucket $b$ as $x_{ib}$. To create a single simulated sample for firm $i$, for each bucket $b$ we randomly select $x_{ib}$ entries from firm $i$’s bucket-$b$ standardized returns. If firm 1 has four entry-day returns in bucket 2, for example, we randomly select four of firm 1’s bucket-2 standardized returns. For each randomly-selected return we note the date and find the excess volume for that date. From these excess volumes we then calculate the mean. The distribution of these means across the 10,000 simulated samples represents the distribution of average excess trading due to stale limit orders.

The results indicate that the execution of stale limit orders accounts for less than half of excess entry-day trading. Averaging across all NYSE/AMEX firms, mean simulated excess entry-day trading is 10.5 percent, only about one quarter of the observed average of 40.4 percent. For NASDAQ firms, mean simulated entry-day excess trading is 18.1 percent while the observed average is 41.4 percent. To evaluate the statistical significance of these results we find, for each firm, the fraction of its 10,000 simulated samples for which mean excess trading exceeds the observed average. These $p$-values are distributed U[0,1] under the null and will be concentrated at low levels under the alternative hypothesis that head-and-shoulders patterns bring high trading volume. Informal evidence that the $p$-values are not distributed U[0,1] comes from their average,
which is well below 0.10 for both the NYSE/AMEX firms and the NASDAQ firms. We test this formally using the Anderson-Darling statistic, $A^2$, which is a weighted average of the vertical differences between actual and theoretical c.d.f.s. This test incorporates more information – and is thus more powerful – than the more familiar Kolmogorov-Smirnov test, which relies solely on the largest vertical difference between two c.d.f.s (D’Agostino and Stephens, 1986). The Anderson-Darling statistics are 755.5 for the NYSE/AMEX sample and 114.4 for the NASDAQ sample – well above the critical value of 3.9 for 1-percent significance.

4. Predictive Power

Though the results so far suggest that head-and-shoulders patterns are associated with substantial excess trading, trading on these patterns would not represent an illusory correlation if, as claimed by technical analysts, these patterns profitably predict directional price movements.

We analyze the patterns’ profitability by simulating the positions of head-and-shoulders traders. As described in detail in the Appendix, simulated positions are opened at the closing price on the neckline-crossing day. The positions are exited when any profitable trend has clearly ended. Small deviations from the predicted trend are ignored, as recommended by the manuals. Since technical traders generally use stop-loss orders to limit downside risk, we exit automatically if the position incurs a loss of 1 percent or more. Profits are measured as cumulative percentage returns between entry and exit dates, signed to reflect whether the position is long or short. Overall profitability for each firm is measured as average percentage profits per position. Adjustment for transaction costs is discussed below. Adjustment for risk proved unnecessary because patterns were not sufficiently profitable.

We once again rely on bootstrap tests, since the distribution of equity returns is known to differ from the normal but there is no consensus alternative. Our null hypothesis is that head-and-
shoulders patterns have no predictive power for returns – that is, the patterns are noise. To simulate the distribution of a firm’s profits under this null, we generate 10,000 simulated price series by drawing randomly with replacement from the firm’s historical (dividend-adjusted) daily returns. Key characteristics of the simulated data, such as mean return and unconditional variance, should be drawn from the same population as the original data. However, returns in the simulated data have no intertemporal dependence. We verify that the statistical properties of the artificial data closely resemble those of the actual data using eight randomly chosen firms – four each from the NYSE/AMEX and the NASDAQ. For each firm we compare the first four central moments of the actual return series and with same moments from 1,000 simulated series. Reassuringly, the $p$-values of the central moments from the actual data are all fairly close to 0.50 (Table 2, Panels A and B).

For each NYSE/AMEX firm, we run the head-and-shoulders identification and profit-taking algorithms on that firm’s original (dividend-adjusted) price series and on each of that firm’s 10,000 simulated price series. We then use the distribution of average profits from the firm’s simulated series to calculate the $p$-value for observed average profits under the null. Finally, we compare the distribution of the resulting 304 $p$-values to the $U[0,1]$ distribution using the Anderson-Darling statistic. We apply this same procedure to the 373 NASDAQ firms.

Once again the assumption that $p$-values are generated independently deserves scrutiny, given the known correlations of daily returns across firms. Despite these correlations, the $p$-values may effectively be independent because head-and-shoulders patterns arise infrequently and holding periods average only about two weeks. To test for independence we examine the pair-wise correlations of head-and-shoulders returns. For each firm, we create a vector with zero on any day the trading algorithm indicates no position and that day’s return to head-and-
shoulders trading otherwise. The associated $t$-statistic is less than 1.0 for 90 percent of the 46,056 pair-wise correlations among NYSE/AMEX firms. Likewise, the associated $t$-statistics is less than 1.0 for 92 percent of the 69,378 pair-wise correlations among NASDAQ firms. We conclude that it is reasonable to view these $p$-values as independent across firms.

4.1 PREDICTIVE POWER: RESULTS

Our tests consistently indicate that head-and-shoulders patterns do not profitably predict directional price moves in U.S. equities. In the NYSE/AMEX sample, average profits are -0.08 percent on positions held for an average of 10 business days. Negative profits, though inconsistent with the claims of technical analysis manuals, might indicate that the pattern could be profitable when used in reverse – that is, by buying (selling) after head-and-shoulders tops (bottoms). But this would not be advisable, either, since the profits are not significantly below the -0.19 percent average in the simulated data. Figure 2 shows the c.d.f. for the 304 NYSE/AMEX $p$-values, which stays quite close to the c.d.f. associated with the null, i.e., the 45-degree line. If technical analysts were correct, the $p$-values would be concentrated at low values and the observed c.d.f. would lie above the 45-degree line. The Anderson-Darling statistic of 2.27 is below the 2.5 critical value for 5 percent significance, confirming that the observed distribution of $p$-values is not significantly different from U[0,1]. We conclude that head-and-shoulders patterns do not profitably predict directional price moves for NYSE/AMEX firms.

The NASDAQ sample paints a similar picture. Trading profits in the original series are -.2.79 percent below their mean in the simulated data. As shown in Figure 2, the $p$-values are concentrated at high values or equivalently the c.d.f. falls below the 45-degree line, consistent with the alternative hypothesis that profits are negative. For the NASDAQ sample the tendency towards negative profits is confirmed by the Anderson-Darling test, suggesting again the
possibility that one could profit by reversing the recommended technical trading strategy. However, transactions costs would wipe out any potential profits from the reverse strategy. Keim and Madhavan (1997) find that technical traders on NASDAQ paid between 1.4 percent and 1.7 percent per trade during much of our sample period. This implies a total round-trip cost of roughly 3.0 percent, matching the expected profits from head-and-shoulders trading. Since an investor must also consider risk – which makes any strategy less attractive – the reverse strategy would seem inadvisable.

We confirm the robustness of these test results with nine sensitivity analyses (Table 3). The first six involve modifying the parameters of the head-and-shoulders identification algorithm, splitting the sample according to a firm’s average trading volume, or splitting the NYSE/AMEX sample into two sub-periods of roughly equal length. The next two robustness tests incorporate AR(1) and GARCH(1,1) dependencies in the simulated return process to verify that the results are unaffected by autocorrelation in volatility. In the final robustness test, positions are automatically closed if losses reach only 0.5 percent, rather than 1 percent.

Although these robustness tests confirm the lack of profitability from head-and-shoulders trading, they reveal subtle differences. When we modify the head-and-shoulders identification algorithm, the negative profits (losses) in the full NYSE/AMEX sample generally become statistically significant, though not necessarily larger than in the base case. Overall losses are larger, as well as significant, in the second half of the sample period, suggesting that the technical analysts’ claims for this pattern have become more incorrect over time. Consistent with earlier results, profits seem to be more significantly negative for firms with lower trading volume. They are negative but not significant for NYSE firms with high trading volume but significantly negative for all other firms.
4.2 PREDICTIVE POWER: RELATION TO THE LITERATURE

Our conclusion that head-and-shoulders patterns do not profitably predict directional price movements in U.S. equity markets is consistent with the common finding that simple trend-following technical trading strategies are not profitable in these markets (Fama and Blume, 1966; Murphy, 1986; Brock et al., 1992). Not all studies support this conclusion, however. Lo et al. (2000) arrive at a conclusion more supportive of technical analysis. Their study, spanning a variety of chart patterns including the head-and-shoulders, finds that the distribution of one-day returns conditional on the observation of a pattern differs statistically from the unconditional distribution. They also find that head-and-shoulders patterns are associated with positive absolute one-day returns and lower volatility, which raises questions about the risk-return relation.

Lo et al.’s (2000) approach to identifying head-and-shoulders patterns and taking positions is not closely aligned with the recommendations of technical analysis manuals. Lo et al. impose few constraints on peaks and troughs, they do not require patterns to be confirmed by a neckline crossing, and they scan the data only once and thus only find patterns of a certain size. Lo et al. enter positions three days after a pattern is identified, rather than immediately afterwards as recommended, because they smooth the data using kernel regressions. Finally, Lo et al. hold positions for fixed time horizons (e.g., 1 day) rather than conditioning exits on market dynamics.

We reexamine the conclusions of Lo et al. (2000) using the methodology outlined here for identifying patterns and entering positions. Like Lo et al., we then calculate returns on fixed-length positions and compare these returns to quantiles of the unconditional returns. This exercise confirms Lo et al.’s finding that the conditional distribution of returns after head-and-shoulders patterns differ statistically from the unconditional distribution.

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5 The lack of profits distinguishes head-and-shoulders trading from the imperfectly rational speculation in certain models, such as DeLong et al. (1990, 1991), which produces positive profits.
shoulders patterns differs from the unconditional distribution of returns. Figure 3 shows the share of conditional returns within each of 20 unconditional-return quantiles for 1-, 3-, 5-, and 10-day holding periods. At the 1-day horizon, returns near the mean are overrepresented; at longer horizons, extreme adverse returns are overrepresented. Anderson-Darling statistics confirm that these differences are significant.\(^6\)

Unlike Lo et al. (2000), however, we find no puzzle with respect to risk and return. As shown in Table 4, Panels A and B, the average return after head-and-shoulders patterns is statistically the same as or below its unconditional counterpart at all horizons while the corresponding standard deviation of returns consistently exceeds its unconditional counterpart.

Savin et al. (2007), who also examine the profitability of head-and-shoulders patterns, follow Lo et al. (2000) in smoothing the equity-price data with kernel regressions but impose more constraints on the patterns and scan the data repeatedly to identify patterns of varying sizes. Rather than testing directional predictive power, however, Savin et al. evaluate excess returns relative to a market index. They find no excess returns, which we confirm by comparing head-and-shoulders returns relative to concurrent parallel positions in the S&P 500. For NYSE/AMEX firms the average excess return per position is negative, at -0.62 percent, and significant at the 1 percent level. For NASDAQ firms this measure of excess returns, at -0.89 percent, is also negative and significant.

Although trend-following technical trading strategies do not seem profitable in U.S. equity markets, they do generally prove profitable when applied to currencies – even after adjusting for transaction costs and risk (Menkhoff and Taylor, 2006). Using the methodology applied here, Chang and Osler (2000) find that head-and-shoulders patterns were profitable in two major

\(^6\) For the 1-, 3-, 5-, and 10-day horizons the Anderson-Darling statistics are 37.7, 39.1, 39.3, and 39.2, respectively.
currency pairs over the period 1973 to 1994 and trace that to the profitability of simpler trend-following trading signals. The lack of predictive power associated with technical analysis in equities may thus reflect the greater difficulty of predicting trends in those markets.

4.3 ILLUSORY CORRELATIONS

There is a striking contrast between technical analysts’ claims about head-and-shoulders patterns and the patterns’ apparent lack of predictive power in U.S. equities. To highlight this contrast, we reproduce a representative description of head-and-shoulders patterns (Ferri, 2009, p. 322):

The head-and-shoulders top is a signal that a security's price is set to fall, once the pattern is complete, and is usually formed at the peak of an upward trend. The second version, the head-and-shoulders bottom (also known as inverse head and shoulders), signals that a security's price is set to rise and usually forms during a downward trend.

This contrast suggests that the technical analysts’ claims about head-and-shoulders patterns reflect an “illusory correlation.” Among economists this finding might be surprising, because it does not support the general preference for agent rationality, or it might equally well be unsurprising, given their general distrust of technical analysis. Among psychologists, however, this finding would definitely not be surprising.

Extensive experimental evidence shows that people often identify correlations among entities or events that do not, in fact, exist. For example, in laboratory experiments naïve subjects found nonexistent correlations between randomly matched pairs of words and between randomly matched psychological symptoms and patient drawings (Chapman and Chapman, 1967). This tendency is apparent throughout human history. Egyptians and Mesopotamians believed that evil demons were often responsible for disease; medieval Europeans blamed cats for the bubonic plague (and the extermination of cats favored the rats, who were really to blame); the Romans believed that livers from sacrificial animals provided omens. A prominent psychology text highlights the relevance of illusory correlations to our maintained hypothesis about noise traders:
“[i]llusory correlations .. imply ... that people can easily maintain beliefs in and make judgments on the basis of dependencies between events that are assumed to exist but actually do not. The effect would be to introduce ‘noise’ into the person’s opinions” (Yates, 1990, p. 173).

Although the phenomenon of illusory correlations has not previously been discussed in behavioral finance, existing experimental studies support its relevance. Kroll et al. (1988), whose subjects choose among assets with returns drawn from normal distributions, find that “even ... where the subjects were instructed and could actually verify that the stock price changes were random, many of them still developed, maintained for a while, discarded, and generated new hypothesis about nonexistent trends” (p. 409). Similarly, De Bondt (1993), whose subjects forecast stock prices and exchange rates in a “technical analysis game,” concludes that “people are prone to discover ‘trends’ in past prices and to expect their continuation,” even when “price changes are highly unpredictable” (p. 357).

Neurologists would be no more surprised than psychologists to learn that traders sometimes make illusory correlations between chart patterns and returns, since brain science highlights a neurological predilection to find patterns. Huettel et al. (2002) show that subjects, when shown a sequence of observations they know to be random, react more swiftly to entries that continue a pattern than to other entries. The authors trace pattern-seeking activity to the prefrontal cortex using functional magnetic resonance imaging. They conclude that humans are programmed to find patterns automatically: “[t]he recognition of patterns is an obligatory dynamic process that includes the extraction of local structure from even random series” (p. 489).

Given a natural tendency to focus on patterns, an illusory correlation from price patterns to future returns could be fostered by three more familiar psychological tendencies. First, wishful thinking: “[p]eople tend to think that positively valued events have a greater chance of occurring
than negatively valued events” (Yates, 1990, p. 202). Second, overconfidence: “[i]f 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). Strong tendencies towards overconfidence have been documented even among experienced financial-market professionals (Oberlechner and Osler, 2011). Third, selective memory: people are more likely to remember their successes than their failures (Yates, 1990).

Our results suggest that head-and-shoulders traders have not been driven from U.S. equity markets even though the patterns lacked predictive power throughout our forty-year sample period. This is consistent with the empirical finding in Oberlechner and Osler (2011) that overconfident currency traders survive even as they gather decades of experience. Our result also conforms to extensive evidence from psychology showing that beliefs and behaviors, once established, are difficult to “extinguish” if they are randomly reinforced (Carlson and Buskist, 1997). The randomness of returns to head-and-shoulders trading could make it difficult to dispel a belief in its overall profitability.

Theory highlights a number of reasons why imperfectly rational trading might survive. Trading on strategies that are unprofitable in expectation could still earn positive profits for a lucky few, and funds gravitate to traders with successful histories (Shleifer and Vishny, 1997). The success of surviving agents could encourage new traders to adopt the unprofitable strategy. Hirshleifer (2010) provides a formal model of how the social transmission mechanism favors the transmission of active strategies – like technical analysis – relative to passive strategies, even when the active strategies are not necessarily more profitable. Humans tend to over-generalize from small samples and to overweight “salient” information (Yates, 1990), so new traders may not sufficiently discount the boasts of a few lucky noise traders. Psychologists have shown that
social forces are especially powerful when there is little objective information (Sherif, 1937, cited in Shiller, 1989). There may indeed be a shortage of objective information in equity markets, since finance professionals often disagree about fundamentally correct prices and since there is little rigorous evidence on most technical trading strategies. DeLong et al. (1991) show that imperfectly rational traders with on-average unprofitable strategies could even come to dominate a market.

Since our evidence suggests that imperfectly rational noise trading can survive for decades, it’s worth considering the influence of such trading on market quality. Theory suggests that it brings excess trading, higher volatility, and lower pricing efficiency (Odean, 1998; Daniel et al., 1998; 2001). Theory also suggests, however, that noise trading can be beneficial. It can provide camouflage for informed traders; it can help exchanges achieve economies of scale and lower costs for all traders; and it can help markets avoid no-trade equilibria. Bloomfield et al. (2009) confirm, in an experimental setting, that uninformed noise trading brings higher overall trading volume and lower spreads. Thus it would be incorrect to assume that imperfectly rational noise trading necessarily undermines market quality.

5. Bid-Ask Spreads

If head-and-shoulders trading is indeed based on an illusory correlation, then it is by definition uninformed noise trading. According to microstructure theory (Glosten and Milgrom, 1985) and evidence (Lei and Wu, 2003), bid-ask spreads should narrow contemporaneously with uninformed noise trading. To test whether head-and-shoulders trading is associated with

---

7 Head-and-shoulders trading would qualify as imperfectly rational noise trading even if it is predictable. Noise trading can be common knowledge as it occurs (DeLong et al., 1989) or before it occurs (DeLong et al., 1990).

8 If technical traders are uninformed, their presence should bring narrower spreads even if they tend to be liquidity
narrower bid-ask spreads we examine the behavior of spreads on entry days. Spreads for NYSE/AMEX firms come from the Trade and Quote (TAQ) data, which begin in 1994; we take the average spread during the final 15 minutes of the day’s trading. Data for NASDAQ firms are closing bid and ask quotes provided by CRSP.

Our null hypothesis is that the distribution of spreads is the same on head-and-shoulders entry days as on other days. For each firm we estimate the following econometric model of bid-ask spreads and then examine spread residuals (“excess spreads”) on entry days

\[ \text{Spread}_t = \phi + \sum_{j=1}^{50} \lambda_j \text{Spread}_{t-j} + \sum_{j=1}^{10} \mu_j \ln(\text{High}_{t-j} / \text{Low}_{t-j}) + \theta + \rho \ln(p_{t,10}) + \eta_t. \]  

(2)

The variables not defined previously are the bid-ask spread, \(\text{Spread}_t\), which is calculated as the difference between bid and ask quotes relative to the mid-quote, and \(\eta_t\), the residual.

This model can capture all three of the key drivers of equity spreads suggested by microstructure theory: inventory risk, adverse selection, and operating costs. As is common in the literature, we capture inventory risk by price volatility. Adverse-selection risk depends on the probability of informed trading, which tends to be lower for more actively traded stocks (Easley et al., 1996) and in other ways varies systematically across firms. The constant term captures this cross-sectional variation as well as variation in operating costs. Since our sample is relatively long and operating costs have declined over time, we include a trend as well as the constant. During most of our sample period, spreads were constrained by minimum tick sizes of one-eighth (later one-sixteenth and finally one penny), which raised average spreads for firms with low prices (Easley et al., 1996). We therefore include the (log) closing price (though we use the “takers,” as suggested by Keim and Madhavan (1997). Mechanically, aggressive traders can bring wider bid-ask spreads, but this effect is transitory. As shown in Glosten and Milgrom (1985), when the share of uninformed traders rises adverse selection risk declines and average spreads should narrow even if the uninformed are liquidity takers.
price 10 days ahead to avoid simultaneity bias). Any remaining influences on spreads are captured by lagged spreads.

Under the null, a firm’s average entry-day spread residual has probability one-half of being negative. Each firm is effectively a Bernoulli trial of this outcome, so the number of NYSE/AMEX (NASDAQ) firms with negative average spread residuals has a binomial distribution with \( p = 0.5 \) and \( n = 304 \) (\( n = 373 \)).

Consistent with the hypothesis that head-and-shoulders trading is uninformed noise trading, bid-ask spreads appear to be unusually low on head-and-shoulders entry days. Average entry-day spread residuals are negative for 215 (71 percent) of our 304 NYSE/AMEX firms (Table 5, Panel A) and for 234 (63 percent) of our 373 NASDAQ firms (Table 5, Panel B). Both results are very highly significant. Excess entry-day spreads average -0.32 percent for the NYSE/AMEX firms and -0.24 percent for the NASDAQ firms. Entry-day spreads are, on average, 8.9 percent below their unconditional mean of 3.6 percent for the NYSE/AMEX firms and 4.9 percent below the unconditional mean of 4.9 percent for the NASDAQ firms.

As shown in Table 5, Panels A and B, this qualitative conclusion is robust to our four different parameterizations of the head-and-shoulders pattern. This conclusion is also sustained across firms with high and low trading volume, though we note that spreads narrow most on entry days for firms with low trading volume. As a final check we verify that the results are unchanged if NYSE/AMEX bid-ask spreads are calculated as the average over the last hour of the day rather than over the last quarter hour.

Following our earlier investigation of excess trading, we also consider a window of seven days surrounding the entry day. As shown in Table 5, Panels A and B, excess spreads decline
sharply on the entry day and rise rapidly shortly thereafter. Figure 4 shows how this pattern mirrors the up-down pattern of excess trading.

According to established theory, it is the adverse selection component of spreads that declines when uninformed trading intensifies. Prominent studies estimate this component to be 43 percent of equity spreads (Stoll, 1989), 20.3 percent (Glosten and Harris, 1988), or 9.6 percent (Huang and Stoll, 1997). For the NYSE/AMEX sample, the 8.9 percent decline in spreads on entry days represents 21 percent, 44 percent, and 93 percent, respectively, of the estimated adverse-selection component. For the NASDAQ sample the 4.9 percent decline in the spread on entry days represents 11 percent, 24 percent, and 50 percent of the estimated adverse-selection component. In short, our estimates imply an economically substantial compression of the adverse-selection component of bid-ask spreads on head-and-shoulders entry days.

6. Conclusion

This paper provides evidence that “illusory correlations” leads some U.S. equity traders to serve as imperfectly rational noise traders. Cognitive psychologists have long recognized in human beings a tendency to imagine correlations among phenomena that don’t really exist (Chapman and Chapman, 1967). Brain science confirms a biological proclivity to search for patterns and even identifies the regions of the brain in which that activity takes place (Huettel et al., 2002).

To identify an illusory correlation in financial markets, the paper focuses on the head-and-shoulders chart pattern, one of the most familiar and trusted technical trading signals. Our analysis first provides evidence that these patterns are associated with substantial trading, using daily data for 304 NYSE/AMEX firms and 373 NASDAQ firms. Trading volume is over 60 percent higher than normal around the days that traders would typically enter positions signaled by head-and-shoulders patterns. Tests show that this excess trading cannot be explained by
concurrent volatility or the execution of stale limit orders. We then provide evidence that trading on these signals is not profitable, which implies that the correlation between head-and-shoulders patterns and future U.S. equity returns asserted by technical analysts is “illusory.” All results are supported by numerous robustness tests.

Our evidence suggests that head-and-shoulders trading fits Black’s (1986) description of noise traders: “people sometimes trade on noise as if it were information. If they expect to make profits from noise trading, they are incorrect” (p. 529). We further support the connection between head-and-shoulders trading and noise trading by showing that bid-ask spreads narrow on head-and-shoulders entry days. The narrowing amounts to between 5 and 9 percent of average spreads and could represent up to 90 percent of the adverse-selection component of spreads.

Our results raise the possibility that technical analysis, in aggregate, contributes substantial noise trading. Since the head and shoulders pattern is just one among dozens of chart patterns, and since charting itself represents just one among myriad approaches to technical analysis, there could be over a thousand technical trading signals. If only a fraction of these signals represent “illusory correlations,” technical analysis could be an important source of noise trading.

The connection we document between imperfectly rational trading and bid-ask spreads suggests that imperfect rationality could be a relevant topic of market microstructure research. As noted by Barberis and Thaler (2003), behavioral finance has primarily focused elsewhere, most notably individual trading behavior, equity returns, and corporate finance. In future research it could be appropriate to investigate more closely the possible influence of imperfect rationality on market quality dimensions such as price discovery, volatility, and liquidity.
Appendices

A1. Identifying Head-and-Shoulders Patterns

As discussed in Section 2, we first reduce the data to a series of peaks and troughs and find subsequences of peaks with the highest in the middle. Since technical analysts claim the pattern portends a trend reversal, we require that any head-and-shoulders top represent the culmination of an upward movement. The peak preceding the beginning of a head-and-shoulders top must be lower than the left shoulder, and the trough preceding the pattern must be lower than the pattern’s first 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 about equal in height. To prevent the head-and-shoulders patterns detected by our algorithm from differing too greatly from this paradigm, we constrain the patterns further. Our “horizontal symmetry” requirement says that the number of days between the left shoulder and head should not differ too much from the number of days between the head and the right shoulder. The “horizontal symmetry” parameter for the base case is 2.5: neither should be more than 2.5 times the other. Our “vertical symmetry” requirement says that the pattern as a whole should not be too steeply sloped. For the base case we constrain the right side as follows: the shoulder must exceed, and the trough cannot exceed, the midpoint between the left shoulder and left trough. A symmetric constraint applies to the left side.

A2. Profits from a Head-and-Shoulders Pattern

Entering a position: As described in the text, we enter a position at the closing price on the neckline-crossing day. If prices move adversely, positions are exited automatically on the day losses reach 1 percent.

Exiting a Position: In general, we close positions once the price stops moving in the predicted direction. Following a head-and-shoulders top, the short position is maintained until the price has risen by at least a “cutoff” percent above its local minimum so the first new trough is confirmed. Technical analysis manuals consistently emphasize that the price may temporarily revert towards the neckline before continuing in the predicted direction (we refer to this as a “bounce”). In our parameterization, if the first trough after entry occurs before the price has declined by 25 percent of the distance between the head and the neckline (known to technical analysts as the “measuring objective”), we keep the position open. The position is closed when the next trough is identified.

A3. Robustness Tests

Even with guidance from market participants and technical manuals, some of our parameter choices are inevitably somewhat arbitrary. To verify that these choices are not critical to the results, we carry out the following sensitivity analyses.

1. **Horizontal Symmetry Relaxed**: The horizontal symmetry parameter is raised to 3.5.

2. **Horizontal Symmetry Intensified**: The horizontal symmetry parameter is lowered to 1.5.

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9 The requirements for head-and-shoulders patterns are illustrated for a top; the requirements for a head-and-shoulders bottom replace “peaks” with “troughs” and vice-versa.
3. **Vertical Symmetry Relaxed:** The right shoulder must exceed the left trough, and the left shoulder must exceed the right trough.

4. **Volume Criterion Added:** We add the following criterion, which is common to all the technical manuals we consulted: there should be greater trading volume at the left shoulder than at the head.\(^{10}\) When using the estimates of Equation (1) to construct simulated volumes, volume residuals are taken from the same day as the random price change in the simulated price series.

Additional robustness tests:

5. **Split Sample by Trading Volume:** The sample is partitioned into equal numbers of firms with low and high trading volume.

6. **Split Sample Across Time:** The NYSE/AMEX sample is split in July of 1982.

7. **An AR(1) Process for Returns:** Each firm’s simulated prices are generated from a firm-specific AR(1) regression for returns.

8. **A GARCH(1,1) Process for Returns:** Each firm’s simulated prices are generated from a firm-specific GARCH(1,1) system for returns.

9. **Stop-loss Reduced:** The maximum tolerated loss is reduced from 1.0% to 0.5%.

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\(^{10}\) A few manuals indicate additional volume criteria, but there is no consistency among these criteria.
References


Table 1. Trading volume around head-and-shoulders entry days

The table shows average excess trading volume around head-and-shoulders entry days, as percent of a day’s volume. A firm’s excess volume is the residual from this model of trading volume (TradVol):

$$\ln(TradVol_t) = \alpha + \sum \beta_i \ln(TradVol_{t-1}) + \sum \chi_i \ln(High_{t-1}/Low_{t-1}) + \delta t + \phi \ln(p_{t+10}) + \epsilon_t.$$  

Here, \(p_t\) is day \(t\)'s closing price; \(High_t\) and \(Low_t\) are day \(t\)'s extrema. Under the null that entry days are not unusual, each firm is a Bernoulli trial for which positive average entry-day excess volume occurs with probability 0.5 and the number of positive-average firms has a binomial distribution. NYSE/AMEX sample includes the 304 firms for which CRSP volume data exist from July 2, 1962 through December 31, 2002. NASDAQ sample includes the 373 firms with CRSP volume data for five consecutive years. Bold implies statistical significance. Robustness tests are detailed in the Appendix.

### Panel A: NYSE/AMEX

<table>
<thead>
<tr>
<th>Days relative to entry</th>
<th>– 3</th>
<th>- 2</th>
<th>– 1</th>
<th>0</th>
<th>+ 1</th>
<th>+ 2</th>
<th>+ 3</th>
<th>Total Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base case: Excess volume</td>
<td>0.54</td>
<td>3.73</td>
<td>8.51</td>
<td>40.28</td>
<td>11.61</td>
<td>0.91</td>
<td>0.34</td>
<td>65.04</td>
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<td>Marginal significance</td>
<td>0.71</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.14</td>
<td>0.98</td>
<td></td>
</tr>
</tbody>
</table>

Modified identification of head-and-shoulders

1. Horizontal symmetry stronger
   - 0.51 | 3.16 | 8.64 | 36.24 | 13.69 | 2.93 | 2.09 | 61.73 |
2. Horizontal symmetry relaxed
   - 0.18 | 3.46 | 8.77 | 40.03 | 11.09 | 1.27 | 0.11 | 63.35 |
3. Vertical symmetry relaxed
   - 0.54 | 3.73 | 8.51 | 40.28 | 11.65 | 0.91 | 0.34 | 64.17 |
4. Add volume criterion
   - 0.54 | 3.74 | 8.51 | 40.28 | 11.65 | 0.91 | 0.34 | 64.18 |

Split sample

5a. High trading volume
   - 2.03 | 1.95 | 9.33 | 35.29 | 10.11 | 1.10 | -2.52 | 57.78 |
5b. Low trading volume
   - 0.85 | 5.92 | 7.70 | 45.82 | 12.80 | 0.12 | 3.58 | 72.24 |
6a. 1962-1982
   - 0.13 | 4.22 | 8.25 | 37.66 | 10.34 | 1.48 | 0.20 | 60.47 |
6b. 1982-2002
   - 1.03 | 4.73 | 9.36 | 42.32 | 11.57 | -2.35 | 0.71 | 67.98 |

### Panel B: NASDAQ

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<th>Days relative to entry</th>
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<th>- 2</th>
<th>– 1</th>
<th>0</th>
<th>+ 1</th>
<th>+ 2</th>
<th>+ 3</th>
<th>Total Sig.</th>
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<td>0.00</td>
<td>0.12</td>
<td>0.48</td>
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</table>

Modified identification of head-and-shoulders

1. Horizontal symmetry stronger
   - 4.43 | 7.60 | 15.78 | 44.86 | 10.43 | 1.40 | -0.21 | 71.07 |
2. Horizontal symmetry relaxed
   - 0.06 | 7.39 | 13.68 | 48.77 | 11.12 | -0.88 | -1.97 | 80.96 |
3. Vertical symmetry relaxed
   - 0.02 | 7.52 | 13.20 | 47.11 | 12.34 | -0.54 | -2.41 | 80.17 |
4. Add volume criterion
   - 3.11 | 11.85 | 9.63 | 47.03 | 10.71 | -3.12 | 1.31 | 67.37 |

Split sample

5a. High trading volume
   - 4.31 | 5.95 | 13.36 | 47.80 | 15.14 | 0.87 | 1.87 | 82.25 |
5b. Low trading volume
   - 5.08 | 12.66 | 12.93 | 43.21 | 13.32 | 4.39 | 0.11 | 69.46 |
Table 2. Simulated return series compared with original series

The table reports $p$-values of original data relative to 1,000 simulated series created by drawing randomly with replacement from own-firm daily dividend-adjusted returns. Firms are selected at random. NYSE/AMEX sample includes the 304 firms for which CRSP price data exist from July 2, 1962 through December 31, 2002. NASDAQ sample includes the 373 firms with CRSP price data for five consecutive years. **Bold** implies statistical significance.

<table>
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<th>Std. deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
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<td>0.539</td>
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<td><strong>Panel B: NASDAQ</strong></td>
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<td>0.476</td>
<td>0.511</td>
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<tr>
<td>Firm 4</td>
<td>0.513</td>
<td>0.556</td>
<td>0.579</td>
<td>0.588</td>
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Table 3. Profitability of head-and-shoulders patterns

We compute average percent profits from head-and-shoulders trading using original dividend-adjusted returns and 10,000 simulated return series. The first column of each pair reports the average across firms of the difference between each firm’s observed profits and its average simulated profits. Under the null hypothesis that head-and-shoulders trading is not profitable, each firm’s $p$-values for realized profits relative to the distribution of simulated profits should be distributed $U[0,1]$. The second column reports Anderson-Darling statistics ($A^2$) for the test of the uniform distribution. Values over 2.5 (3.9) are significant at the 5 (1) percent level and are highlighted in **bold**. NYSE/AMEX sample includes the 304 firms for which CRSP data exist from July 2, 1962 through December 31, 2002. NASDAQ sample includes the 373 firms with CRSP data for five consecutive years. Robustness tests are detailed in the Appendix.

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<td>5b. Low trading volume</td>
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<td></td>
<td></td>
<td>NA</td>
<td>NA</td>
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<td>6b. 1982-2002</td>
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<td>2.63</td>
<td></td>
<td></td>
<td>NA</td>
<td>NA</td>
<td></td>
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</tr>
<tr>
<td>Autocorrelated volatility</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. AR(1)</td>
<td>-0.29</td>
<td>1.65</td>
<td></td>
<td></td>
<td>-3.41</td>
<td>53.2</td>
<td></td>
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<tr>
<td>8. GARCH(1,1)</td>
<td>-0.27</td>
<td>1.85</td>
<td></td>
<td></td>
<td>-3.03</td>
<td>403.3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Modified exit strategy</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9. Stop-loss at 0.5%</td>
<td>-0.17</td>
<td>1.37</td>
<td></td>
<td></td>
<td>-2.98</td>
<td>170.6</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 4. Head-and-shoulders fixed-horizon returns vs. unconditional returns

The table presents moments of average returns after head-and-shoulders patterns and average unconditional returns for non-overlapping fixed time horizons of 1, 3, 5, and 10 days. Under the null hypothesis that the distribution of returns following head-and-shoulders patterns is the same as the unconditional distribution, the two should not differ. NYSE/AMEX sample includes the 304 firms for which CRSP data exist from July 2, 1962 through December 31, 2002. NASDAQ sample includes the 373 firms with CRSP data for five consecutive years. Differences between results in **bold** are significant at the 5% level.

<table>
<thead>
<tr>
<th>Return horizon</th>
<th>1 day</th>
<th>3 days</th>
<th>5 days</th>
<th>10 days</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: NYSE/AMEX</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Mean (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head-and-shoulders</td>
<td>0.13</td>
<td>0.15</td>
<td>0.22</td>
<td><strong>0.23</strong></td>
</tr>
<tr>
<td>Unconditional</td>
<td>0.11</td>
<td>0.18</td>
<td>0.30</td>
<td><strong>0.59</strong></td>
</tr>
<tr>
<td><strong>Standard deviation (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head-and-shoulders</td>
<td>0.59</td>
<td>0.92</td>
<td>1.16</td>
<td>1.57</td>
</tr>
<tr>
<td>Unconditional</td>
<td>0.03</td>
<td>0.05</td>
<td>0.08</td>
<td>0.16</td>
</tr>
<tr>
<td><strong>Skewness</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head-and-shoulders</td>
<td>0.57</td>
<td>-0.42</td>
<td>-0.30</td>
<td>-0.25</td>
</tr>
<tr>
<td>Unconditional</td>
<td>6.17</td>
<td>1.53</td>
<td>0.63</td>
<td>0.18</td>
</tr>
<tr>
<td><strong>Kurtosis</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head-and-shoulders</td>
<td>8.52</td>
<td>8.08</td>
<td>7.02</td>
<td>7.79</td>
</tr>
<tr>
<td>Unconditional</td>
<td>57.58</td>
<td>4.55</td>
<td>4.55</td>
<td>3.42</td>
</tr>
<tr>
<td><strong>Panel B: NASDAQ</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Mean (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head-and-shoulders</td>
<td>-1.53</td>
<td>-1.36</td>
<td>-1.53</td>
<td>-1.63</td>
</tr>
<tr>
<td>Unconditional</td>
<td>0.11</td>
<td>0.22</td>
<td>0.34</td>
<td>0.63</td>
</tr>
<tr>
<td><strong>Standard deviation (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head-and-shoulders</td>
<td>2.86</td>
<td>3.59</td>
<td>3.96</td>
<td>4.88</td>
</tr>
<tr>
<td>Unconditional</td>
<td>0.10</td>
<td>0.23</td>
<td>0.36</td>
<td>0.72</td>
</tr>
<tr>
<td><strong>Skewness</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head-and-shoulders</td>
<td>-0.59</td>
<td>1.12</td>
<td>-0.96</td>
<td>-0.20</td>
</tr>
<tr>
<td>Unconditional</td>
<td>4.10</td>
<td>3.61</td>
<td>3.17</td>
<td>3.55</td>
</tr>
<tr>
<td><strong>Kurtosis</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head-and-shoulders</td>
<td>18.45</td>
<td>12.36</td>
<td>7.75</td>
<td>6.85</td>
</tr>
<tr>
<td>Unconditional</td>
<td>35.50</td>
<td>26.76</td>
<td>19.98</td>
<td>23.03</td>
</tr>
</tbody>
</table>
Table 5. Spreads on head-and-shoulders entry days

The table shows average excess spreads around head-and-shoulders entry days estimated from this model:

\[
\text{Spread}_t = \varphi + \sum_{j=1}^{50} \lambda_j \text{Spread}_{t-j} + \sum_{j=1}^{10} \mu_j \ln\left(\frac{\text{High}_{t-j}}{\text{Low}_{t-j}}\right) + \theta_t + \rho \ln(p_{t+10}) + \eta_t,
\]

Spread\(_t\) is measured as \((\text{ask}_t - \text{bid}_t) / \text{mid}_t\); \(p_t\) is day \(t\)’s closing mid-price; High\(_t\) and Low\(_t\) are day \(t\)’s extrema.

Under the null that entry days are not unusual, each firm is a Bernoulli trial for which negative average entry-day excess spreads occur with probability 0.5 and the number of negative-average firms has a binomial distribution. NYSE/AMEX sample includes the 304 firms with CRSP price data from July 2, 1962 through December 31, 2002. NASDAQ sample includes the 373 firms with CRSP price data for five consecutive years. **Bold** implies statistical significance. Robustness tests are detailed in the Appendix.

### Panel A: NYSE/AMEX

<table>
<thead>
<tr>
<th>Days relative to entry</th>
<th>-3</th>
<th>-2</th>
<th>-1</th>
<th>0</th>
<th>+1</th>
<th>+2</th>
<th>+3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base case: Excess spread</td>
<td>-0.43</td>
<td>-0.09</td>
<td>0.34</td>
<td>-0.32</td>
<td>-0.41</td>
<td>-0.10</td>
<td><strong>-0.05</strong></td>
</tr>
<tr>
<td>Marginal significance</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.96</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**Modified identification of head-and-shoulders**

1. Horizontal symmetry stronger  
   -0.31  -0.15  0.01  -0.18  0.05  -0.06  -0.01
2. Horizontal symmetry relaxed  
   -0.25  -0.04  -0.04  -0.28  -0.32  -0.15  **-0.08**
3. Vertical symmetry relaxed  
   -0.15  -0.01  0.15  -0.35  -0.23  -0.05  0.02
4. Add volume criterion  
   0.04  -0.04  0.02  -0.09  0.02  -0.01  -0.02

**Split sample**

5a. High trading volume  
   -0.38  0.06  0.50  -0.25  -0.22  -0.01  -0.03
5b. Low trading volume  
   **-0.46**  -0.12  0.15  -0.37  -0.46  -0.14  **-0.08**

**Different measure of spreads**

6. Spread over last hour  
   -0.12  0.01  0.02  -0.14  -0.10  -0.03  **-0.01**

### Panel B: NASDAQ

<table>
<thead>
<tr>
<th>Days relative to entry</th>
<th>-3</th>
<th>-2</th>
<th>-1</th>
<th>0</th>
<th>+1</th>
<th>+2</th>
<th>+3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base case: Excess spread</td>
<td>0.16</td>
<td>0.03</td>
<td>0.04</td>
<td><strong>-0.24</strong></td>
<td>0.03</td>
<td>-0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Marginal significance</td>
<td>0.81</td>
<td>0.08</td>
<td>0.28</td>
<td><strong>0.00</strong></td>
<td>0.52</td>
<td>1.00</td>
<td>0.52</td>
</tr>
</tbody>
</table>

**Modified identification of head-and-shoulders**

1. Horizontal symmetry stronger  
   0.08  -0.02  -0.05  **-0.23**  0.09  0.00  **-0.09**
2. Horizontal symmetry relaxed  
   0.12  0.00  0.00  **-0.22**  0.05  -0.02  0.03
3. Vertical symmetry relaxed  
   0.05  -0.01  0.04  **-0.14**  0.03  0.05  0.00
4. Add volume criterion  
   0.06  0.01  0.00  **-0.16**  0.10  -0.07  0.02

**Split sample**

5a. High trading volume  
   0.11  0.02  -0.02  **-0.07**  0.11  -0.11  0.02
5b. Low trading volume  
   0.19  0.02  0.07  **-0.44**  -0.14  0.08  **-0.01**
Figure 1. Hypothetical head-and-shoulders pattern
Figure 2. Cumulative distribution functions for average percent profits

The figure shows the theoretical and observed c.d.f.’s for the \( p \)-values associated with average profitability of head-and-shoulders positions. Samples include 304 NYSE/AMEX firms and 373 NASDAQ firms. Each firm’s dividend-adjusted returns are bootstrapped to create 10,000 simulated series. Each firm’s \( p \)-value reflects a comparison of average profits per position in the original data to the distribution of average profits in the simulated data. The distribution of the resulting \( p \)-values should be \( U[0,1] \) under the null hypothesis of no profitability, in which case the estimated c.d.f. will lie close to the 45-degree line. If technical analysts are correct that the patterns predict trend reversals, the observed c.d.f. should lie above the theoretical c.d.f.
Figure 3. Distribution of conditional and unconditional returns

The figure shows the number of returns following head-and-shoulders trading signals that fall in each of twenty quantiles of the unconditional distribution of returns. Under the null hypothesis that the conditional and unconditional distributions are the same, the number in each quantile should be roughly the same. NYSE/AMEX data comprise daily returns and trading volumes for all 304 firms for which data exist from July 2, 1962 through December 31, 2002. NASDAQ data comprise daily prices and trading volumes for all 373 firms for which such data exist in CRSP for five consecutive years. Anderson-Darling statistics, reported in the text, confirm that the distributions differ statistically.
Figure 4. Excess trading and excess spreads around head-and-shoulders entry days

The table shows average excess trading volume and average excess spreads around head-and-shoulders entry days for NASDAQ firms in our base case. For each firm we run two regressions:

\[ \ln(\text{TradVol}_t) = \alpha + \sum_{i=1}^{50} \beta_i \ln(\text{TradVol}_{t-i}) + \sum_{i=1}^{10} \chi_i \ln(\text{High}_{t-i} / \text{Low}_{t-i}) + \delta + \phi \ln(p_{t+10}) + \epsilon_t, \]

\[ \text{Spread}_t = \varphi + \sum_{j=1}^{50} \lambda_j \text{Spread}_{t-j} + \sum_{j=1}^{10} \mu_j \ln(\text{High}_{t-j} / \text{Low}_{t-j}) + \theta + \rho \ln(p_{t+10}) + \eta_t. \]

Spread\(_t\) is measured as (ask\(_t\)-bid\(_t\))/mid\(_t\); \(p_t\) is day \(t\)'s closing mid-price; \(\text{High}_t\) and \(\text{Low}_t\) are day \(t\)'s extrema.

The sample for volume (spreads) includes 349 (373) NASDAQ firms with five or more consecutive years of volume (price) data in the CRSP database.