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

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Abstract. This paper provides evidence that "illusory correlations," a well-documented source of cognitive bias, leads some agents to be imperfectly rational noise traders. We identify illusory correlations by focusing on the head-and-shoulders chart pattern. Though this is considered one of the most reliable technical trading signals, our evidence indicates that the signal does not profitably predict directional movements as claimed. We connect this illusory correlation to noise trading by showing that the pattern is associated with a significant rise in trading volume and a substantial reduction in bid-ask spreads.

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I. Introduction

This paper provides evidence that "illusory correlations," a well-documented source of cognitive bias, leads some agents to be imperfectly rational noise traders. We identify illusory correlations by focusing on the head-and-shoulders chart pattern. Though this is considered one of the most reliable technical trading signals, our evidence indicates that the signal does not profitably predict directional movements as claimed. We connect this illusory correlation to noise trading by showing that the pattern is associated with a significant rise in trading volume and a substantial reduction in bid-ask spreads.

Psychologists long ago documented a human tendency to create "illusory correlations," or equivalently, to believe in relationships that don't truly exist among real-world variables (Chapman and Chapman, 1967; Bloomfield and Hales, 2001). This tendency has many apt illustrations from human history, including ancient beliefs in pantheons of gods and medieval medical treatments now known to be counterproductive. More recently, brain scientists have noted a strong physiological predilection to discover patterns in series that are consciously known to be random and have identified where subconscious pattern recognition occurs in the brain (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 connections 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) because they help markets avoid no-trade equilibria (Milgrom and Stokey, 1982, Morris, 1994), Bloomfield, et al. (2005) asserts that "noise traders play a ubiquitous role in the finance literature”; Kalay and Wohl (2005) describe them as “an integral part of modern microstructure theory”.

There is no agreement, however about how noise traders should be modeled. Many researchers assert that noise traders must be rational optimizers (e.g., Ross 1989, Spiegel and Subrahmanyam, 1992, Wang 1994, Dow and Gorton, 1995, Bacchetta and van Wincoop, 2006). Others are open to the possibility that some real-world noise trading reflects imperfect rationality. Black (1986), for example, claims that “People 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 that a common, active form of speculation amounts to imperfectly rational noise trading. We examine one of the market’s most familiar and trusted chart patterns, the "head-and-shoulders" pattern. This involves a series of three price peaks, the highest of which is in the middle. Technical analysts claim that a head-and-shoulders pattern predicts a downtrend and that the inverse pattern predicts and uptrend. Our focus on technical trading is suggested by economists' historically dismissive attitude towards this form of speculation.[1] Malkiel (1990), for example, asserts that “[t]echnical strategies are usually amusing, often comforting, but of no real value.” This attitude persists despite studies providing both theoretical and empirical reasons why past prices might signal future prices (Brown and Jennings, 1989, Osler, 2003, Kavajecz and Odders-White, 2004). Our analysis is based daily data from the Center for Research on Securities Prices (CRSP) and intraday data from the Trades and Quotes database. All results are consistent across samples and subsamples and are supported by numerous sensitivity analyses.

[1] This perception may stem from the absence of reasoned economic analysis associated with technical trading signals, which are derived exclusively from information on past prices and volumes.

We first provide evidence for illusory correlations by showing that head-and-shoulders trading signals do not profitably predict directional price moves. Raw profits from trading on this pattern as recommended by technical analysts are statistically insignificant, even before adjusting for transaction costs and risk. Even returns in excess of the S&P 500 are significantly negative, consistent with results in Savin et al. (2007).

We next provide evidence that this apparently illusory correlation does influence trading. We show unusual trading upon the completion of a head-and-shoulders pattern averages over 40 percent of a day's trading volume. This trading cannot be attributed to volatility, autocorrelation in volume, or stale limit orders (Linnainmaa, 2010). We find no diminution in the high excess trading volume over time, despite the pattern's consistent lack of profitability.

If head-and-shoulders trading qualifies as uninformed noise trading then bid-ask spreads should narrow when such traders are active, other things equal (Glosten and Milgrom, 1985). We provide evidence that head-and-shoulders trading is indeed associated with relatively narrow spreads. On average, spreads narrow by five percent on the days that head-and-shoulders traders should be opening positions, a figure that could represent over half of the asymmetric information component of spreads.

Few papers consider empirical evidence for noise trading. Greene and Smart (1999) show that, in the early 1990s, real-world noise traders included agents who traded on the *Wall Street Journal's* Dart Board column. Like head-and-shoulders patterns, these columns were associated with high levels of trading even though their recommended trades were not profitable. Consistent with the hypothesis that these were noise traders, spreads tended to narrow with the associated trading. Dart-Board trading seems unlikely to have generated substantial noise trading even in the 1990s, since it involved just a handful of firms at infrequent intervals. Other studies find more indirect evidence of noise trading. Kumar and Lee (2005) provide indirect evidence of noise trading by showing that retail investor sentiment is a significant influence on returns for stocks with relatively heavy retail ownership. Kalay and Wohl (2005) identify liquidity trading on the Tel Aviv Stock Exchange using the properties of the order book.

Most existing research on technical analysis is concerned with market efficiency and thus focuses exclusively on profitability. Studies of equity markets generally confirm our conclusion that technical trading in U.S. equity markets is not profitable after adjusting for transaction costs and risk (Fama and Blume, 1966; Murphy, 1986; Brock et al., 1992; Savin et al., 2007). Existing studies of technical analysis cannot identify noise trading, however, for two reasons. First, they do not evaluate whether people actually trade on the signals (market participants report that some of the strategies most intensively studied by academics are rarely used in practice). Second, they do not evaluate whether the signals have market impact.

This paper has four additional sections and a conclusion. Section 2 discusses our data, describes our algorithm for identifying head-and-shoulders patterns, and explains our methodology for testing profitability. Section 3 shows that trading on head-and-shoulders patterns does not profitably predict directional moves in U.S. equity markets and discusses how this could reflect illusory correlations. Section 4 shows that trading volume is exceptionally high when head-and-shoulders traders open positions. Section 5 shows that bid-ask spreads narrow when trading associated with head-and-shoulders patterns is heaviest. This section 6 also discusses whether head-and-shoulders trading qualifies as noise trading and how an unprofitable trading strategy could survive for decades. Section 6 concludes.

2. Predictive Power: Methodology

This section evaluates the claim that head-and-shoulders patterns predict directional price movements and produce substantial speculative profits.

2.1. Data

We use two datasets comprising daily dividend-adjusted returns and trading volume from the CRSP equities database. Our first dataset includes all 304 NYSE and AMEX firms with price data spanning July 2, 1962, the database's starting date, to December 31, 2002. This represents 40.5 years, or about 10,200 daily observations. Large firms will presumably be over-represented in this dataset because large firms have tended to gravitate to the NYSE and because our selection criterion induces survivorship bias. We also analyze the 373 NASDAQ firms with at least five years of consecutive data ending December 31, 2002. For each firm we create a dividend-adjusted price series by applying historical returns to the initial price.

2.2. Identifying Head-and-Shoulders Patterns

A head-and-shoulders pattern comprises a series of three peaks (Figure 1), where the middle peak (the "head") is higher than both the left and right peaks (the "shoulders"). When a head-and-shoulders pattern occurs after an up-trend it is called a "head-and-shoulder top," and technical analysts claim it predicts a downtrend. A pattern in which the roles of peaks and troughs are reversed is called a "head-and-shoulder bottom." If such a pattern occurs after a downtrend, technical analysts claim it predicts an up-trend.

To evaluate the validity of these predictions we construct a computer-based algorithm that identifies head-and-shoulders patterns and simulates associated speculative positions. To learn the subtleties we consulted eight technical analysis manuals and had numerous conversations with practicing technical analysts.[2] The sources agree to a striking extent. One should not enter a position unless the pattern is "confirmed," which occurs if and when the price crosses the "neckline" soon after forming the right shoulder. The neckline is a straight line connecting the pattern's two troughs and extending forward in time. A symmetric criterion applies to head-and-shoulders bottoms. Our computer algorithm conforms to these requirements, as well as others consistently mentioned in the manuals. We also constrain the slope of the pattern, asymmetries between left and right shoulders, and the delay between the right shoulder and the neckline crossing. (Details of these constraints are provided in the Appendix.) The exact parameters we choose to implement these constraints are necessarily somewhat arbitrary: in some cases, neither a close reading of the manuals nor conversations with practicing technical analysts provided much guidance. We use robustness tests to show that our results are insensitive to these choices.

To identify confirmed head-and-shoulders patterns we follow Chang and Osler (2000) in first identifying the peaks and troughs in the actual (dividend-adjusted) price series. Lo et al. (2000) and Savin et al. (2007), who also examine this pattern, first smooth the data using kernel regressions and pick out peaks and troughs in the smoothed series. Our approach has the advantage of mimicking the way the eye of someone reading charts will scan for extreme values. All the tests here can be viewed as out-of-sample, since the belief in the predictive power of a well-defined set of chart patterns developed prior to 1930 (Shabacker, 1930).

2.3. PREDICTIVE POWER: METHODOLOGY

We estimate the profits that would have been generated by head-and-shoulders trading on each firm's dividend-adjusted price series. For each confirmed head-and-shoulders pattern, profits are measured as cumulative percentage returns between entry and exit dates, signed to reflect

[2] The eight manuals we consulted are: Arnold and Rahfeldt (1986), Edwards and Magee (1966), Hardy (1978), Kaufman (1978), Murphy (1986), Pring (1985), Shabacker (1930) and Sklarew (1980).

whether the position would have been long or short. Positions are opened at closing prices on the day the price crosses the neckline, or "entry days." For exit strategies we do our best to mimic the likely behavior of technical traders. Positions are closed when any profitable trend has clearly ended and small deviations from the predicted trend are ignored. 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. Further details on the exit strategy are provided in the Appendix.

The profitability of technical trading strategies is typically evaluated using the bootstrap methodology (Efron 1979, Efron 1982), in part because it requires no assumptions about the statistical distribution of returns.[3] Statistical agnosticism seems appropriate here, since the distribution of equity returns is known to differ from the normal and since there is no consensus on an alternative. The null hypothesis is that head-and-shoulders patterns are meaningless noise. To simulate the distribution of a given firm's profits under this null, we generate 10,000 simulated price series by drawing randomly with replacement from the firm's historical daily returns. 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, returns in the simulated data have no intertemporal dependence and cannot be predicted from past returns.

To verify that the artificial data closely resemble the actual data, we calculate the first four central moments of the actual return series and of 1,000 simulated series for eight randomly chosen firms, four each from the NYSE/AMEX and NASDAQ samples. Reassuringly, the *p*-values of the central moments from the actual data are all fairly close to 0.50 (Table I).

[3] See, for example, Brock, Lakonishok, and LeBaron (1992), Levich and Thomas (1993), Allen and Karjalainen (1995), LeBaron (1991), and LeBaron (1996).

To clarify our statistical tests for profitability we begin by considering one 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 the 10,000 simulated series. We then use the distribution of average profits from these simulated series to calculate the *p*-value for observed average profits under the null. We then repeat this calculation for the other 303 NYSE/AMEX firms. In a large group of firms for which head-and-shoulders trading is truly unprofitable, the resulting 304 *p*-values will be distributed uniformly over [0,1] if the *p*-values are independently distributed across firms. By contrast, if the head-and-shoulders pattern is profitable, then the *p*-values will likely be concentrated at low levels. We use the Anderson-Darling test statistic, A^2, to evaluate whether the observed distribution of *p*-values is statistically likely to have been drawn from a uniform [0,1]. The Anderson-Darling statistic, which is a weighted average of the differences between actual and theoretical c.d.f.s, is more powerful than the more familiar Kolmogorov-Smirnov statistic (D'Agostino and Stephens, 1986).

We repeat this procedure for the 373 firms in the NASDAQ sample. Note that there are two rounds of marginal significance levels. The first round of marginal significance levels includes 304 for the NYSE/AMEX sample and 373 for the NASDAQ sample. For clarity we exclusively call these "*p*-values." For each dataset, the second round produces one marginal significance level associated with the Anderson-Darling statistic.

The assumption that the *p*-values are generated independently might be questioned, given the known correlations of daily returns across U.S. firms. Nonetheless, positions signaled by head-and-shoulders patterns are relatively brief and infrequent: we identify about one confirmed head-and-shoulders pattern per firm per year, and holding periods average about two weeks. Thus the *p*-values from head-and-shoulders trading may be effectively independent across firms. To test for independence it is natural to examine the pair-wise correlations of daily head-and-shoulders returns. For each firm we create a vector with zero on any day our trading algorithm had no position and the daily trading return otherwise. There are 46,056 pair-wise correlations among our NYSE/AMEX firms: for 90 percent of these the associated *t*-statistic is below 1.0. Similar results are obtained for the NASDAQ sample. We infer that it is reasonable to view these *p*-values as independent across firms.

3. Predictive Power: Results and Discussion

These 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 -0.44 percent on positions held for an average of ten business days. These profits are not, however, significantly below the -0.19 percent average for simulated profits. Figure 2A shows the c.d.f. for the 304 *p*-values, which is quite close to the c.d.f. associated with the null, i.e., the 45-degree line. Under the alternative hypothesis that the pattern successfully predicts directional movements, the observed c.d.f. would generally lie above the 45-degree line, since the *p*-values would be concentrated at low values. The Anderson-Darling statistic, at 2.27, is below the 2.5 critical value associated with 5 percent significance, confirming that the observed distribution of *p*-values is not statistically significantly different from the uniform [0,1]. We conclude that head-and-shoulders patterns do not profitably predict directional price moves for NYSE/AMEX firms.

The NASDAQ sample tells the same story. The difference between trading profits in the original series and their mean in the simulated series is again negative, at -3.0 percent, and this time the difference is statistically significant. Consistent with the alternative hypothesis that profits are negative, the *p*-values are concentrated at high values (Figure 2B). This raises the possibility of profitably trading the head-and-shoulders pattern in reverse, buying when technical analysts recommend selling and vice versa. However, transactions costs would wipe out any potential profits: Keim and Madhavan (1997) find that technical traders on NASDAQ pay between 1.39 percent and 1.68 percent per trade, for total round-trip costs around 3.0 percent. Since one must also consider risk, the reverse strategy would seem inadvisable.

3.1. Predictive Power: Robustness

We examine the robustness of this result with nine sensitivity analyses (Table II). (Details of the tests are provided in the Appendix.) The first four investigate the importance of the precise criteria used to identify head-and-shoulders patterns. Three change the restrictions on allowable asymmetries in the pattern; the fourth adds a trading volume criterion. These modifications bring no noticeable changes in the results.

We next split the sample according to a firm's average trading volume (large or small), since research has found numerous differences in trading behavior across firms of different sizes (e.g., Wermers, 1999). The pattern appears to be unprofitable for firms of all sizes. We also split the sample in July of 1982, which is about half-way through the sample period. The pattern appears to have been unprofitable in both halves of our sample period.

To examine whether the results are affected by autocorrelation in volatility, we incorporate AR(1) and GARCH(1,1) dependencies in the simulated return process (Bollerslev, 1987). Finally, we experiment with a relatively aggressive exit strategy, which closes positions more quickly if losses begin to accrue. Like the previous robustness tests, these tests do not affect our qualitative conclusion.

3.2 Predictive Power: Relation to 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 technical trading is not profitable in U.S. equity markets (Fama and Blume, 1966; Murphy, 1986; Brock et al., 1992). Lo et al. (2000), arrive at a conclusion more supportive of technical analysis. For a variety of patterns including the head-and-shoulders they find that the conditional distribution of one-day returns differs statistically from the unconditional distribution of returns. Further, the head-and-shoulders patterns they identify produce positive (direction-adjusted) absolute one-day returns and volatility is lower on those days than otherwise. This combination raises natural questions about the risk-return relation.

Beyond the focus in Lo et al. (2000) on fixed-horizon returns rather than profits, that paper's methodology differs in many ways from the present study. Lo et al.'s approach to smoothing the data using kernel regressions constrains them (for technical reasons) to take positions beginning three days after a pattern is identified. In addition, Lo et al. impose fewer constraints on peaks and troughs and they do not require patterns to be "confirmed" by a neckline crossing. Third, Lo et al. scan through the data only once looking for patterns of a given size and thus presumably exclude patterns of other sizes.

To provide directly comparable results we calculate returns for fixed-length positions against quantiles of the unconditional returns. Like Lo et al., (2000) we find that the conditional distribution of returns following head-and-shoulders patterns differs from the unconditional distribution. Figures 3A through 3D show the numbers of conditional returns within each of twenty unconditional-return quantiles for four fixed holding periods: 1 day, 3 days, 5 days, and 10 days. The differences between the conditional and unconditional distributions are readily visible. At the 1-day horizon there is an over-representation of returns near the mean; at the longer horizons there is an over-representation of extreme adverse returns. Anderson-Darling statistics confirm that these differences are significant.[4]

With respect to the risk-return relation, our results are less puzzling than those of Lo et al. (2000). As shown in Table III, the average conditional return is statistically the same as, or lower than, its unconditional counterpart for all return horizons. The conditional average standard deviation, by contrast, is consistently higher than its unconditional counterpart.

Savin et al. (2007) adopt Lo et al.'s basic approach to identifying head-and-shoulders patterns but impose more constraints on the peaks and troughs and scan through the data multiple times to ensure they find patterns in varying sizes. Rather than testing directional predictive power, as claimed by technical analysts, Savin et al (2007) evaluate excess returns relative to a stock market index. They find no excess returns, a finding we confirm by calculating our estimated head-and-shoulders returns with returns to a concurrent parallel position 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. The corresponding excess return for NASDAQ firms, -0.89 percent, is also negative and highly significant.

Empirical studies of currency markets typically find that technical strategies *are* profitable after adjustments for transaction costs and risk (Dooley and Shafer, 1984; Levich and Thomas, 1993; LeBaron, 1999). Using the same methodology applied in the current paper, Chang and Osler (2000) shows that the head-and-shoulders pattern was profitable in two major currency pairs over the period 1973–1994, though unprofitable in four other currency pairs. Chang and Osler also show that the profitability of the chart pattern can be traced to the profitability of

[4] For the 1-, 3-, 5-, and 10-day horizons the Anderson-Darling statistics are 37.7, 39.1, 39.3, and 39.2 respectively.

simpler trend-following trading signals. This suggests that the lack of predictive power for technical analysis in equities reflects the greater difficulty of predicting trends in those markets.

3.3 Illusory Correlations

Our conclusion that head-and-shoulders patterns do not profitably predict equity trends is contrary to the standard predictions of technical analysts. The description of head-and-shoulders patterns in Investopedia, an online encyclopedia of practical finance, is representative:

> 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. " (Investopedia : http://www.investopedia.com/university/charts/charts2.asp).

The contrast between this prediction and our results suggests that technical analysts have identified an "illusory connection" between head-and-shoulders patterns and directional movements in U.S. equities.[5] As articulated in a prominent psychology text: "People have a tendency to find connections among groups of events that do not exist" (Yates, 1990). 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). Indeed, we can see this tendency throughout human history. Hercules, now considered a historical curiosity, was believed for centuries to have great powers. Likewise, blood-letting was a recommended medical treatment for centuries in the west, though it is now known to compromise health.

In this light, a tendency for people to discover illusory correlations in financial markets may not be very surprising, and similar results have indeed emerged within finance. Kroll et al.

[5] It is possible that the strategy was actually profitable when it was first identified. During that initial period, prior to 1930, insider trading and market manipulation were reportedly rampant (Sobel 1965). However remote the possibility may seem a priori, such practices could conceivably have generated nonlinear price patterns with predictive power. Legislation in the 1930s made such practices illegal and, as the practices became relatively rare, the behavior of prices may have changed, eliminating the predictive power of the patterns.

(1988) conduct an experiment in which subjects are asked to choose between two assets whose returns are sampled randomly and independently from normal distributions. The authors find that "even in the extreme case of our experiment, 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." De Bondt (1993) reaches the same conclusion based on a series of experiments about forecasting stock prices and exchange rates, including a "technical analysis game." Results indicate that "people are prone to discover 'trends' in past prices and to expect their continuation," even when "stock prices changes are highly unpredictable" as is the case over short horizons.

Why might people build illusory correlations upon price patterns? Recent evidence from brain science highlights a neurological predilection to find patterns. In Huettel et al. (2002), subjects were shown a sequence of observations they knew to be random. Nonetheless, they reacted more quickly to entries that continued an existing pattern than to entries that violated the pattern. The authors trace the pattern-seeking activity to the prefrontal cortex using functional magnetic resonance imaging. They conclude: "The recognition of patterns is an obligatory dynamic process that includes the extraction of local structure from even random series."

Given a natural tendency to focus on patterns, an illusory connection from price patterns to future returns could be fostered by three other well-documented psychological tendencies. First, wishful thinking: "People tend to think that positively valued events have a greater chance of occurring than negatively valued events" (Yates, 1990). Second, overconfidence: "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). Evidence shows that this tendency towards overconfidence does exist in financial markets (e.g., Glaser and

Weber, 2007). Third, memory bias: people have a greater tendency to remember pleasant and successful experiences than unpleasant ones (Yates, 1990).

4. Trading Volume

To identify the head-and-shoulders pattern as a potentially illusory correlation is not sufficient to identify head-and-shoulders trading as noise trading, since it is possible that no one bothers to trade on this pattern. The section first discusses the prevalence of technical analysis in general and then provides evidence that head-and-shoulders patterns in particular are associated with substantial trading activity.

4.1. Technical Trading Activity in General

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 largely devoted to the subject, Stocks and Commodities Magazine, 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 a circulation of around 65,000. There are, by now, myriad online sources of information, software, and data for technical traders. 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.[6]

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)

[6] Subscriptions and enrollment figures from personal communications with the institutions mentioned.

finds that 96 percent of London currency dealers rely on some form of technical analysis for short-horizon speculation. Lui and Mole (1998) finds 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.

4.2. HEAD-AND-SHOULDERS AND TRADING VOLUME: METHODOLOGY

We examine whether trading volume is unusually high on days when traders are likely to enter positions, defined as the day the closing price crosses the neckline. The null hypothesis is that trading volume is not unusual on such days. We consider entry days but not exit days because, as mentioned earlier, technical analysis manuals are relatively ambiguous about exit criteria.[7]

Unusual trading volume ("excess trading") is measured as the residuals from a regression of (log) daily volume on a constant, fifty own lags, ten lags of volatility measured as the daily percentage spread between high and low prices (Rogers and Satchell, 1991), a linear trend, and the log of the closing price:

$$\ln(Volume_t) = \alpha + \beta_i \sum_{i=1}^{50} \ln(Volume_{t-i}) + \gamma_i \sum_{i=0}^{9} [\ln(high_{t-j} / low_{t-j})] + t + \ln(p_{t+10}) + \varepsilon_t . \quad \textbf{(1)}$$

The volatility term controls for the familiar positive relationship between volume and volatility (e.g. Karpoff, 1987). The trend and log price terms allow for the strong trends evident in volume for many firms.[8] The log of the closing price is advanced ten periods to avoid biasing the residuals on the days before and including the entry day. This has only trivial effects on the regression results, while ensuring that residuals on or before entry days for head-and-shoulders

[7] We exclude 13 NYSE/AMEX firms and 24 NASDAQ firms with incomplete volume data.
[8] Regressions for randomly sampled firms indicate that either the trend or the log price is statistically or economically important, but not both.

tops (bottoms) are not artificially inflated (deflated) by the known concurrent price decline (rise). This formulation eliminates virtually all residual correlation for randomly selected test firms.[9]

For each firm we calculate average excess trading on entry days. This average has mean zero under the null that entry-day trading volume is not unusual, since the mean of all residuals is identically zero. The central limit theorem tells us further that the average has a normal distribution. Given the symmetry of the normal distribution, we can view each firm as a single Bernoulli trial of the outcome that average entry-day residuals are positive, with $p = 0.5$. With independent observations across firms, the number of firms with positive average entry-day excess trading has a binomial distribution with parameters $p = 0.5$, $n = 291$.

Once again, it is relevant to examine the independence assumption. Daily trading volume itself is correlated across firms (Lo et al., 2000), but our focus is excess trading. Even more narrowly, our focus is excess trading on entry days. We construct a time series for each firm comprising excess trading volume on entry dates and zeroes otherwise, and then calculate correlations for each of the 42,195 bilateral firm pairs in the NYSE/AMEX dataset. The vast majority of these 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.

4.3. HEAD-AND-SHOULDERS AND TRADING VOLUME: RESULTS

Our results indicate that equity trading is unusually active on head-and-shoulders entry days. Average excess trading volume on entry days is 40.4 percent for NYSE/AMEX firms and 41.4 percent for NASDAQ firms. Average entry-day excess trading exceeds zero for all but ten of the 291 NYSE/AMEX firms and for 318 of the 349 NASDAQ firms, highly significant results.

[9] For four randomly selected firms, marginal significance of the *Q*-statistic for residual autocorrelation was 1.00.

Head-and-shoulders trading could also occur before or after our formal entry day. Confident traders might enter before a "decisive" neckline crossing, despite warnings in the manuals. Traders who cannot monitor prices intraday or who require particularly decisive confirmation of a trading signal might enter later. Some traders might calculate different entry days, if instead of daily closing prices they use high-low-close prices, weekly data, point-and-figure charts, or candlestick charts.

Considering now a seven-day interval centered on our formal entry day, we find that unusual trading activity in NYSE/AMEX firms begins effectively at zero, rises modestly for two days before the formal entry day, surges to a sharp peak on the entry day itself, falls rapidly the next day, and falls modestly for one more day before returning to zero (Table IVA). In aggregate such excess trading exceeds 64 percent of a day's volume.[10] For the NASDAQ sample, the interval of significant excess trading is one day shorter but aggregate excess trading is larger, at 76 percent of a day's volume (Table IVB; Figure 3).

These results suggest substantial trading is associated with head-and-shoulders patterns. It is important to note, however, that this trading could well include more than technical trading. It could, for example, include informed trading attracted by the possibility of enhanced "camouflage" from uninformed traders. It could also include any type of trading attracted by the narrow spreads we document later. Indeed, it seems unlikely that technical traders initiate all this excess trading because, if so, we might have found self-fulfilling profits over the next few days.

4.4. HEAD-AND-SHOULDERS AND TRADING VOLUME: ROBUSTNESS

We apply six of the nine sensitivity analyses used earlier (the remaining tests are not relevant here). These tests consistently support our initial finding: excess trading takes place on four or

[10] Some readers, like the authors, find these results surprisingly strong. We have checked the methodology numerous ways and would willingly share our data and programs with other researchers.

more days around neckline-crossing days, totals 60 percent or more of a day's volume, and is highly statistically significant (Tables IVA and IVB). The pattern of slow rise, quick burst, and then slow decline is consistent across time and across firms with high and low trading volume.

To provide further evidence that some of the excess trading just identified is related to head-and-shoulders patterns, we examine excess trading on an arbitrary set of days. Specifically, we consider a five-day window centered on the date sixty trading days after the "head" of each pattern. In this interval, the average excess trading is uniformly small – below 0.6 of a percent of a day's trading volume in absolute value – and insignificant.[11]

Linnainmaa (2010) shows that many striking properties of retail trading, such as the disposition effect, can be partly traced to picking-off risk associated with stale retail limit orders. Since retail traders are considered more likely than institutional traders to rely on technical analysis in equity markets , it is natural to wonder whether excess trading on entry days merely reflects the tendency of existing retail limit orders to be executed when the market moves dramatically. We examine this possibility by comparing excess trading on entry dates to the bootstrapped distribution of excess trading on dates with comparable returns. This distribution should represent the excess volume one could associate with picking-off risk.

We standardize each firm's returns by dividing by their standard deviation and then partition these standardized returns, rs_t, into seven buckets: $rs_t < 1$, $rs_t \in [1, 2)$, etc., and $rs_t \geq 6$. We then create simulated samples of standardized returns that match the size distribution of the original entry-day returns. For example, if a given firm has four entry-day returns in bucket one, then each simulated sample for that firm includes four bucket-one returns sampled at random. Finally, we calculate average excess volume for each simulated sample. Mean excess trading is 10.5

[11] Detailed results available from the authors.

(18.1) percent in the return-matched NYSE/AMEX (NASDAQ) samples, well below the average of 40.4 percent (41.4) for the original entry-day samples. For each firm we calculate the *p*-value for observed excess entry-day trading relative to the distribution of excess trading in that firm's simulated samples. These *p*-values averaged over 90 percent for both samples. Anderson-Darling statistics are calculated by comparing the distribution of these *p*-values against the null of a uniform distribution. This effectively tests the null hypothesis that excess entry-day trading is no different than would be expected given stale limit orders. The Anderson-Darling statistics are 756.0 for the NYSE/AMEX sample and 114.4 for the NASDAQ sample, well above the 3.9 critical value for 1-percent significance. We infer that the existence of stale limit orders does not explain excess trading around entry days.

5. Bid-Ask Spreads

If head-and-shoulders trading is indeed imperfectly rational noise trading as our evidence suggests so far, then the microstructure literature provides additional implications for the behavior of bid-ask spreads. Specifically, a long tradition of work on models with asymmetric information indicates that spreads should narrow when uninformed trading is more active (Copeland and Galai, 1983; Glosten and Milgrom, 1985; Easley and O'Hara, 1987). Evidence indicates that U.S. equity markets conform to this theory. Lee et al. (1993), for example, show that market makers increase spreads around earnings announcements, when the share of informed trading is likely to be high. Lei and Wu (2003) show that bid-ask spreads on the NYSE can be partially predicted by the estimated probability of informed trading. The theory can also explain the positive relation between spreads and trade size on the NYSE (Harris and Hasbrouck, 1996). This section tests our inference that head-and-shoulders trading is uninformed noise trading by examining whether bid-ask spreads narrow when such trading is active.

5.1. HEAD-AND-SHOULDERS AND SPREADS: METHODOLOGY

We focus on the same two sets of firms examined earlier. CRSP has no bid and ask quotes for NYSE/AMEX firms so for these firms we rely on Trade and Quote (TAQ) data, which begin only in 1994. Our baseline measure of spreads for these firms is the average of all spreads during the final quarter hour of trading on a given day. CRSP provides closing bid and ask quotes for NASDAQ firms so we rely on those. We measure spreads as the difference between bid and ask quotes relative to the mid-quote.

Our methodology closely parallels the methodology used earlier to examine trading volume. The null hypothesis is that spreads on head-and-shoulders entry days have the same distribution as spreads on other days. For each firm we estimate a model of spreads and then examine excess spreads on head-and-shoulders entry days.

Microstructure theory highlights three key dimensions of equity spreads: operating costs, inventory risk, and adverse selection. In empirical research, operating costs are typically captured by the constant term. Because we have a relatively long sample and there has been a secular decline in such costs, we include not only a constant but also a trend term. Inventory costs are typically captured with volatility, which we measure once again as the proportionate gap between daily high and low prices. Adverse-selection risk depends on the probability of informed trading which is known to vary systematically across firms. For example, the probability of informed trading is lower for more actively traded stocks (Easley et al., 1996). The constant terms can also capture this form of cross-sectional variation. During most of our sample period spreads were constrained by the mandated minimum tick sizes of one-eighth (and later one-sixteenth), which tended to raise average spreads for firms with low prices (Easley et al., 1996). We therefore include the (log) closing price though, to eliminate any simultaneity, we use the price ten days in the future rather than the contemporaneous price. To capture any remaining influences we include lagged spreads.

$$Spread_t = \alpha + \sum_{j=1}^{50} \beta_i Spread_{t-j} + \sum_{j=0}^{10} \gamma_i [\ln(high_{t\text{-}j} / low)_{t\text{-}j}] + \theta_t + \mu \log(p_{t+10}) + \eta_t \quad \textbf{(2)}$$

5.2. HEAD-AND-SHOULDERS AND SPREADS: RESULTS

Consistent with the hypothesis that head-and-shoulders traders serve as noise traders, we find that spreads are unusually low on head-and-shoulders entry days. Excess entry-day spreads average -0.32 percent for the NYSE/AMEX firms and -0.24 percent for the NASDAQ firms (Tables VA and VB). This implies that 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. The average entry-day spread residual is negative for a highly significant 215 of our 304 NYSE and AMEX firms and for a similarly significant 234 of our 373 NASDAQ firms.

Further support for our hypothesis that imperfectly rational head-and-shoulders trading is associated with relatively narrow spreads comes from the pattern of spreads around entry days, which crudely mirrors the up-down pattern of excess trading (Tables VA and VB; Figure 4). Though the overall pattern is more uneven for excess spreads than for excess trading, a similar picture emerges for both samples: the average of excess spreads falls rapidly and becomes significantly negative on the entry day and then recovers quickly.

To verify the robustness of these results we run a series of additional tests (Tables VA and VB). For the NYSE/AMEX firms we first show that results are not sensitive to the time period over which we calculate bid-ask spreads by taking the average over the last hour of the day rather than the last quarter hour. For both sets of firms we verify that the results are not sensitive to our parameterization of a head-and-shoulders pattern. We also examine whether the results are sensitive to firm size by splitting the sample between firms with high and low trading volume. The split-sample test confirms the overall narrowing of spreads on head-and-shoulders entry days but they also suggest that spreads narrow most for firms with low trading volume.

Theory indicates that only the adverse selection component of spreads should decline when uninformed trading intensifies. Prominent estimates indicate that this component represents 43 percent of equity spreads (Stoll, 1989), 20.3 percent (Glosten and Harris, 1988), and 9.6 percent (Huang and Stoll, 1997). With these figures, we calculate crude estimates of the extent to which the adverse selection component shrinks in association with head-and-shoulders patterns. For the NYSE/AMEX sample these estimates are 21 percent, 44 percent, and 93 percent, respectively, indicating that the decline is economically substantial. For the NASDAQ sample these estimates are similarly impressive at 11 percent, 24 percent, and 50 percent.

One might reasonably wonder how spreads could narrow with active head-and-shoulders trading, if technical traders tend to use market rather than limit orders as found in Keim and Madhavan (1997). Shouldn't spreads widen when there are more market orders? Not necessarily. In fact, Kalay and Wohl (2005) provide evidence from the Tel Aviv Stock Exchange consistent with the hypothesis that "liquidity traders submit market orders and strategic traders submit limit orders" , which could imply the opposite. To reconcile these two perspectives on spreads it is important to remember that the original theoretical connection between noise traders and spreads depends on the overall balance between informed and uninformed traders, and does not involve an explicit analysis of liquidity per se. In the model of Glosten and Milgrom (1985), for example, there is no distinction between limit and market orders. Even if technical traders do use market orders, however, their activity need not be associated with reduce liquidity (or wider spreads) because net liquidity provision is endogenous (Goettler et al., 2005). When the number of market buy orders rises, for example, rational traders place more limit sell orders. In the specific context of head-and-shoulders trading, if some traders believe that head-and-shoulders trading is uninformed (and some market participants do explicitly espouse this view), they could rationally provide sufficient liquidity to generate narrower spreads.

5.3. Head-and-Shoulders and Noise Trading

This paper has provided evidence that, together, suggest that head-and-shoulders trading qualifies as imperfectly rational noise trading, consistent with the description of noise traders 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". The lack of profits distinguishes head-and-shoulders trading from the imperfectly rational speculation of DeLong et al. (1990, 1991) and Kyle and Wang (1997), which earns positive profits.

Our results suggest a certain amount of predictability for head-and-shoulders trading around entry days. This would not affect our characterization of such trading as imperfectly rational noise trading. Even with our results it is presumably difficult to forecast head-and-shoulders trading before and even after the price crosses the neckline.[12] Such forecasts would face all the challenges associated with forecasting aggregate trading volume, plus challenges idiosyncratic to technical trading: uncertainty about neckline crossings, uncertainty about how different traders actually view prices, etc. Even if its magnitude could be anticipated, head-and-shoulders trading could qualify as noise trading. As shown in the literature, noise trading can be common knowledge as it occurs (DeLong et al., 1989; Campbell et al., 1993) or even before it occurs (DeLong et al., 1990; Campbell et al., 1993; Admati and Pfleiderer, 1991).

[12] 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.

Our results raise the possibility that technical trading in aggregate contributes sizeable amounts of noise trading. The head-and-shoulders pattern is just one among a few dozen chart patterns in common use, and chart patterns represent just one of myriad approaches to generating technical trading signals. The number of existing technical trading signals easily exceeds one thousand. Even if only a fraction of these strategies represent "illusory correlations," technical trading could provide a qualitatively important source of noise trading.

The consequences of imperfectly rational trading are generally considered to be adverse. Theory suggests, for example, that it brings excess trading and higher volatility (Odean, 1998) and that it can undermine pricing efficiency (Daniel et al., 1998; Daniel et al., 2001). Theory also suggests, however, certain ways in which such trading could be beneficial. It could provide camouflage for informed traders; it could help exchanges achieve economies of scale, thus lowering costs for all traders; and it could help markets avoid no-trade equilibria.

Our finding that the trading associated with head-and-shoulders patterns has remained elevated over time is contrary to a famous argument by Friedman (1953). He predicts a decline in such trading, arguing that irrational traders buy high and sell low and will ultimately be driven out of the market by losses. We finish this section by reviewing how an unprofitable trading strategy could remain in use for decades.

Psychologists have shown that beliefs and behaviors, once established, are difficult to "extinguish" if they are randomly reinforced (Carlson and Buskist, 1997). The randomness of profits from technical trading, combined with wishful thinking, overconfidence, and selective memory, could therefore support a belief in the profitability of head-and-shoulders trading that is not easily dispelled by evidence to the contrary.

Oberlechner and Osler (2011) provide evidence that overconfident traders survive in currency markets even as they gather decades of experience. They suggest that this could reflect self selection, since currency trading requires a high tolerance for risk and overconfidence tends to foster such tolerance. 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; Gruen and Gyzicki, 1993). Imperfectly rational traders with on-average unprofitable strategies could even come to dominate the market (DeLong et al., 1991).

New traders could be encouraged to adopt the unprofitable strategy by the success of surviving agents. 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. Hirshleifer (2010) shows that the social transmission mechanism will favor the transmission of active strategies – like technical analysis – relative to passive strategies. Psychologists have shown that such social forces are especially powerful when there is little objective information to confirm an individual’s own opinion (Sherif, 1937, cited in Shiller, 1989). There may indeed be a lack of objective information in equity markets, since finance professionals often disagree about fundamentally correct prices and the evidence on technical analysis is mixed. In this situation investors may be more susceptible to buying into the belief that meaningless price patterns have predictive power – especially given the intense conviction displayed by practicing technical analysts.

6. Summary

This paper provides evidence for a specific form of imperfectly rational noise trading that originates in a cognitive bias known as “illusory correlations.” We focus on the head-and-shoulders pattern, one of the most familiar and trusted technical trading signals. We first provide evidence that trading on this signal is not profitable, using daily return data for 304 NYSE/AMEX firms and 373 NASDAQ firms. This implies that the correlation between the signal and future U.S. equity price movements asserted by technical analysts does not exist. Cognitive psychologists have long recognized in human beings a tendency to discover correlations among phenomena where such correlations don't really exist (Chapman and Chapman, 1967). Brain science confirms a biological proclivity toward pattern discovery (Huettel et al., 2002).

To support the hypothesis that this illusory correlation generates noise trading, we first provide evidence that the pattern is associated with substantial trading. Trading volume is over 60 percent higher than normal when traders would normally enter positions based on head-and-shoulders patterns. We next show that spreads narrow contemporaneously with this excess trading. The narrowing amounts to nine percent of average spreads, which could represent over half of the adverse-selection component of spreads.

The connection 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 on other aspects of finance, most notably "the aggregate stock market, the cross-section of average returns, individual trading behavior, and corporate finance." In future research it would be appropriate to investigate more closely the possible influence of imperfect rationality on market microstructure.

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

A.1. 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.[13] 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.

A.2. 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

[13] 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.

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: 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. We 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.

Though not advocated by technical analysts, it would be possible to exit according after a fixed time interval, such as five days. Chang and Osler (2000) compare exogenous exit rules of this nature were compared with the endogenous exit strategy outline above. They find that the endogenous exit strategy is profitable, but the exogenous strategies are not. Thus, by focusing on the endogenous exit strategy we attempt to give the head-and-shoulders pattern its best chance for profitability.

A.3. ROBUSTNESS CHECKS

Many of the choices made in establishing a base case were somewhat arbitrary, even though we 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.

(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.[14] (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) *Split Sample Across Time*: The sample is split at the end of 1982, roughly the midpoint of the entire sample period, and each segment is examined separately.

(vi) *Split Sample by Trading Volume*: The sample is partitioned into sets of firms, according to average trading volume over the entire sample period (large and small).

(vii) *Stop-loss Reduced*: The stop-loss 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 10,000 simulated series.

(x) *A GARCH(1,1) Process for Returns*: For each firm, estimated GARCH(1,1) coefficients are is used to create the 10,000 simulated series.

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[14] Blume, Easley, and O'Hara (1994) present a theoretical model in which volume information is informative.

Table I. *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 for the NYSE/AMEX sample consist of daily closing prices from July 2, 1962 to December 31, 2002 for 304 NYSE or AMEX firms from the CRSP database. The NASDAQ data consist of daily closing prices for 373 NASDAQ firms with at least five consecutive years of data in the CRSP database.

I.A: NYSE/AMEX Sample

% Change in Daily Close	**Mean**	**Std. Deviation**	**Skewness**	**Kurtosis**
Firm I	0.512	0.531	0.47	0.558
Firm II	0.483	0.532	0.452	0.55
Firm III	0.486	0.536	0.471	0.536
Firm IV	0.494	0.539	0.485	0.511

I.B: NASDAQ Sample

% Change in Daily Close	**Mean**	**Std. Deviation**	**Skewness**	**Kurtosis**
Firm I	0.484	0.525	0.489	0.516
Firm II	0.493	0.505	0.55	0.569
Firm III	0.506	0.512	0.476	0.511
Firm IV	0.513	0.556	0.579	0.588

Table II: Head-and-Shoulders Patterns Do Not Profitably Predict Trend Reversals
Using an objective pattern identification algorithm, we compute average percent profits from head-and-shoulders based speculation using actual returns and 10,000 simulated return series created by drawing randomly with replacement from observed daily returns. Profits for each firm are compared with the distribution of simulated profits for that firm. Under the null hypothesis that head-and-shoulders trading is not profitable, the associated *p*-values should be distributed uniformly over [0,1].

The first column of each pair reports the difference between observed profits and average simulated profits. The second column reports the Anderson-Darling test statistics (A^2) for the uniform distribution. Values over 2.5 (3.9) are significant at the five (one) percent level. The NYSE/AMEX data comprise daily returns and trading volumes for all 304 firms for which data exist for July 2, 1962 to December 31, 2002. The NASDAQ data comprise daily prices and trading volumes for all 373 firms for which such data exist in CRSP for five consecutive years. Statistically significant figures highlighted in bold. Details of the robustness tests (1 through 9) are in the Appendix.

	NYSE/AMEX		**NASDAQ**	
	Effect on Average Profits	**A^2**	**Effect on Average Profits**	**A^2**
Base Case	-0.25	2.27	**-3.02**	**154.7**
Modified Identification Algorithm:				
1. Horiz. Sym. Stronger	**-0.18**	**2.67**	**-2.97**	**125.2**
2. Horiz. Sym. Relaxed	**-0.27**	**2.73**	**-3.05**	**166.0**
3. Vert. Sym. Relaxed	**-0.26**	**7.13**	**-2.94**	**246.0**
4. Volume Criterion Added	-0.26	1.93	**-2.89**	**77.8**
Split Sample:				
5a. High Trading Vol.	0.034	0.51	**-2.12**	**31.7**
5b. Low Trading Vol.	**-0.54**	**6.4**	**-3.92**	**152.2**
6a. 1962-1982	-0.06	0.92	*NA*	*NA*
6b. 1982-2002	**-0.42**	**2.63**	*NA*	*NA*
Modified Assumed Returns Process:				
7. AR(1)	-0.25	1.69	**-3.04**	**53.2**
8. GARCH(1,1)	-0.25	1.83	**-3.02**	**403.3**
Modified Exit Strategy:				
9. Stop-Loss Reduced	-0.17	1.37	**-2.98**	**170.6**

Table III: Conditional vs. Unconditional Returns

Using an objective pattern identification algorithm, we compute average percent returns after head-and-shoulders patterns and average unconditional returns over 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 entries for conditional and unconditional should not differ.

III.A: NYSE/AMEX	**1-day**	**3-days**	**5-days**	**10-days**
Mean (%)				
Conditional	0.13	0.15	0.22	0.23
Unconditional	0.11	0.18	0.3	0.59*
Standard Deviation (%)				
Conditional	0.59	0.92	1.16	1.57
Unconditional	0.03	0.05	0.08	0.16
Skewness				
Conditional	0.57	-0.42	-0.30	-0.25
Unconditional	6.17	1.53	0.63	0.18
Kurtosis				
Conditional	8.52	8.08	7.02	7.79
Unconditional	57.58	4.55	4.55	3.42

III.B: NASDAQ	**1-day**	**3-days**	**5-days**	**10-days**
Mean (%)				
Conditional	-1.53	-1.36	-1.53	-1.63
Unconditional	0.11*	0.22*	0.34*	0.63*
Standard Deviation (%)				
Conditional	2.86	3.59	3.96	4.88
Unconditional	0.10	0.23	0.36	0.72
Skewness				
Conditional	-0.59	1.12	-0.96	-0.20
Unconditional	4.10	3.61	3.17	3.55
Kurtosis				
Conditional	18.45	12.36	7.75	6.85
Unconditional	35.50	26.76	19.98	23.03

Table IV: Trading Volume is Unusually High Around Head-and-Shoulders Entry Days
Table shows average residual trading volume around head-and-shoulders entry days, measured as percent of a day's volume. To calculate excess trading volume we run the following regression for each firm *i*:

$$\ln(Volume_t) = \alpha + \beta_i \sum_{i=1}^{50} \ln(Volume_{t-i}) + \gamma_i \sum_{i=0}^{9} [\ln(high_{t-i} / low_{t-i})] + t + \ln(p_{t+10}) + \varepsilon_t$$

where closing prices are labeled *p*. Using an objective pattern identification algorithm on all firms, we identify days when head-and-shoulders pattern crosses the neckline and compute the average residuals from those days, $\overline{\varepsilon_i}$. Bootstrapped marginal significance levels are reported as the lower entry in the Base Case. Though not reported, similarly bootstrapped marginal significance levels underlie the significance ratings for the robustness tests. Table IVA provides results for NYSE/AMEX firms, using daily prices and trading volumes for the 291 firms for which these data exist for the entire CRSP database (July 2, 1962 to December 31, 2002). Table IVB provides results for NASDAQ firms, using daily prices and trading volumes for the 349 firms that have at least five consecutive years of these data in CRSP. Statistically significant figures are highlighted in bold.

IV.A: NYSE/AMEX	**Entry – 3**	**Entry - 2**	**Entry - 1**	**Entry**	**Entry + 1**	**Entry + 2**	**Entry + 3**	**Total Sig.**
Base Case	0.51	**3.72**	**8.53**	**40.35**	**11.74**	**0.87**	0.32	**66.90**
Marg. Sig.	0.70	**0.00**	**0.00**	**0.00**	**0.00**	**0.11**	0.98	
Modified Identification of H&S:								
1. Horiz. Sym. Stronger	0.06	**5.14**	**6.77**	**40.28**	**13.33**	1.23	1.63	**68.43**
2. Horiz. Sym. Relaxed	0.16	**3.43**	**8.83**	**40.06**	**11.21**	1.17	0.13	**64.99**
3. Vert. Symmetry Relaxed	0.54	**2.24**	**7.70**	**39.50**	**11.22**	1.25	0.33	**62.78**
4. Volume Criterion Added	1.03	**4.62**	**8.40**	**40.19**	**11.26**	0.62	-1.27	**64.86**
Split Sample:								
5a. High Trad. Vol.	2.10	**1.99**	**9.18**	**34.44**	**10.43**	**1.52**	-2.30	**57.35**
5b. Low Trad. Vol.	-1.22	**5.70**	**7.74**	**46.70**	**12.89**	0.24	3.37	**75.42**
6a. 1962-1982	-0.21	**4.19**	**8.35**	**37.89**	**10.46**	1.24	0.12	**62.05**
6b. 1982-2002	1.15	**4.77**	**9.26**	**42.09**	**11.45**	-2.21	0.73	**67.57**

IV.B: NASDAQ	Entry - 3	Entry - 2	Entry - 1	Entry	Entry + 1	Entry + 2	Entry + 3	Total
Base Case	-0.13	**7.48**	**12.04**	**41.44**	**12.41**	1.21	-1.97	**76.08**
Marg. Sig.	0.60	**0.01**	**0.00**	**0.00**	**0.00**	0.12	0.48	**Sig.**
Modified Identification of H&S:								
1. Horiz. Sym. Stronger	-4.44	7.59	**16.17**	**44.74**	**10.64**	1.70	-0.23	**76.17**
2. Horiz. Sym. Relaxed	-0.06	**7.36**	**13.71**	**48.85**	**11.03**	-0.81	-1.92	**78.17**
3. Vert. Symmetry Relaxed	-0.20	**7.23**	**13.59**	**48.98**	**10.88**	-0.88	-1.98	**77.62**
4. Volume Criterion Added	3.32	11.93	**9.66**	**46.16**	**10.69**	-3.25	1.40	**79.91**
Split Sample:								
5a. High Trad. Vol.	-4.28	**5.80**	**13.35**	**48.44**	**16.37**	0.94	1.95	**82.57**
5b. Low Trad. Vol.	5.12	12.44	**12.94**	**42.66**	**13.32**	4.39	0.11	**90.97**

Table V: Spreads Are Unusually Low on Head-and-Shoulders Entry Days
Table shows average residual spreads around head-and-shoulders entry days. To calculate spread residuals we run the following regression for each firm i:

$$Spread_t = \alpha + \sum_{j=1}^{50} \beta_i Spread_{t-j} + \sum_{j=0}^{10} \gamma_i [\ln(high_{t-j} / low_{t-j})] + \theta_t + \mu \log(p_{t+10}) + \eta_t$$

where spreads are measured as (ask-bid)/mid and p represents the closing mid-price. Using an objective pattern identification algorithm on 373 firms, we identify days when head-and-shoulders patterns cross the neckline and compute the average residuals from those days, $\overline{\eta_{\bar{t}}}$. Bootstrapped marginal significance levels are reported as the lower entry in the Base Case. Though not reported, similarly bootstrapped marginal significance levels underlie the significance ratings for the robustness tests. The data for Table VA include TAQ end-of-day bid-ask spreads for the NYSE and AMEX firms examined in Sections I and II. The data for Table VB include all NASDAQ firms with five or more consecutive years of returns in the CRSP database.

V.A: NYSE/AMEX	**Entry - 3**	**Entry - 2**	**Entry - 1**	**Entry**	**Entry + 1**	**Entry + 2**	**Entry + 3**
Base: Excess spread	**-0.43**	**-0.09**	**0.34**	**-0.32**	**-0.41**	-0.10	**-0.05**
Marg. Sig.	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.96	**0.00**
Spread over last hour	**-0.12**	**0.01**	**0.02**	**-0.14**	**-0.10**	-0.03	**-0.01**
Modified Identification of H&S:							
1. Horiz. Sym. Stronger	-0.31	**-0.15**	**0.01**	**-0.18**	**0.05**	**-0.06**	-0.01
2. Horiz. Sym. Relaxed	-0.25	-0.04	**-0.04**	**-0.28**	**-0.32**	-0.15	**-0.08**
3. Vert. Symmetry Relaxed	-0.15	**-0.01**	**0.15**	**-0.35**	**-0.23**	**-0.05**	0.02
4. Volume Criterion Added	0.04	**-0.04**	**0.02**	**-0.09**	**0.02**	-0.01	-0.02
Split Sample:							
5a. High Trad. Vol.	-0.38	0.06	0.50	**-0.25**	**-0.22**	-0.01	-0.03
5b. Low Trad. Vol.	**-0.46**	**-0.12**	**0.15**	**-0.37**	**-0.46**	-0.14	**-0.08**

V.B: NASDAQ	Entry - 3	Entry - 2	Entry - 1	Entry	Entry + 1	Entry + 2	Entry + 3
Base: Excess spread	0.16	0.03	0.04	**-0.24**	0.03	-0.01	0.01
Marg. Sig.	0.81	0.08	0.28	**0.00**	0.52	1.00	0.52
Modified Identification of H&S:							
1. Horiz. Sym. Stronger	0.08	-0.02	-0.05	**-0.23**	0.09	0.00	**-0.09**
2. Horiz. Sym. Relaxed	0.12	0.00	0.00	**-0.22**	0.05	-0.02	0.03
3. Vert. Symmetry Relaxed	0.05	-0.01	0.04	**-0.14**	0.03	0.05	0.00
4. Volume Criterion Added	0.06	0.01	0.00	**-0.16**	0.10	-0.07	0.02
Split Sample:							
5a. High Trad. Vol.	0.11	0.02	-0.02	**-0.07**	0.11	-0.11	0.02
5b. Low Trad. Vol.	0.19	0.02	0.07	**-0.44**	-0.14	0.08	-0.01

Figure 1: Hypothetical Head-and-Shoulders Pattern

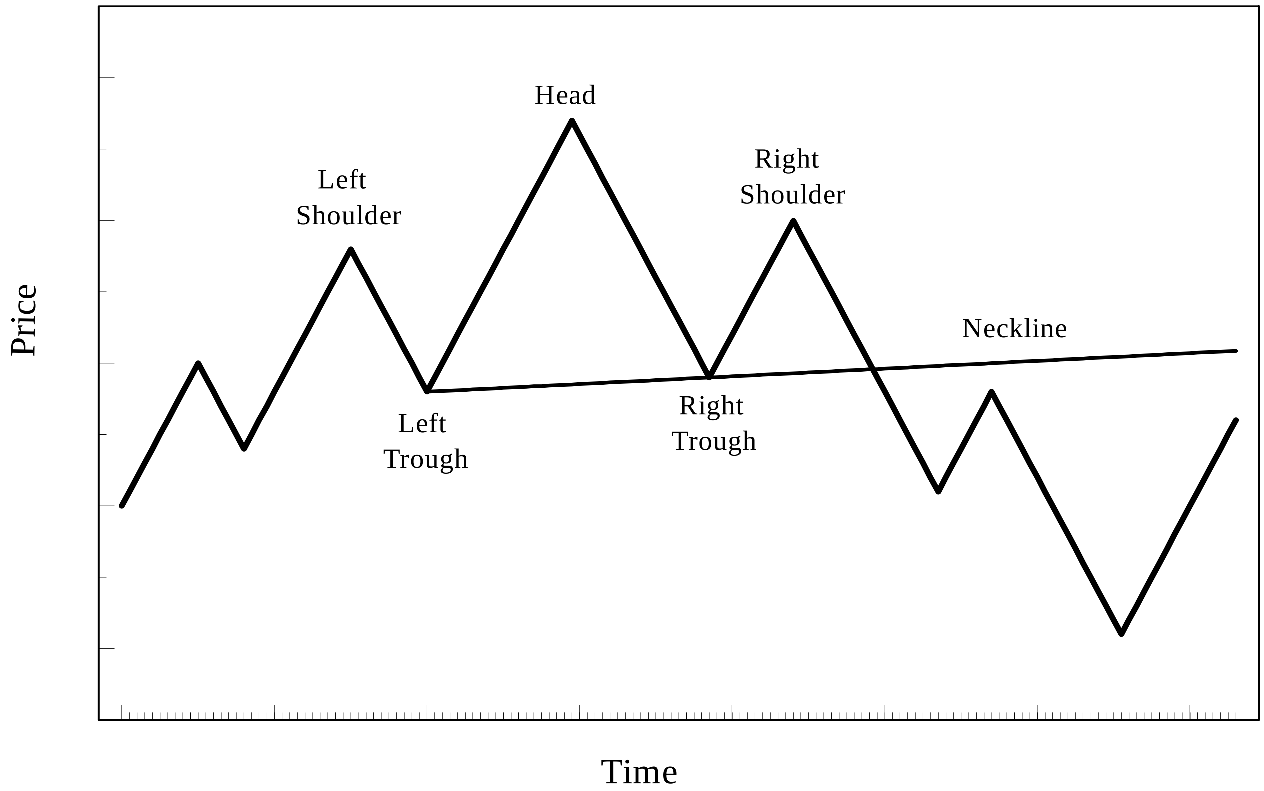
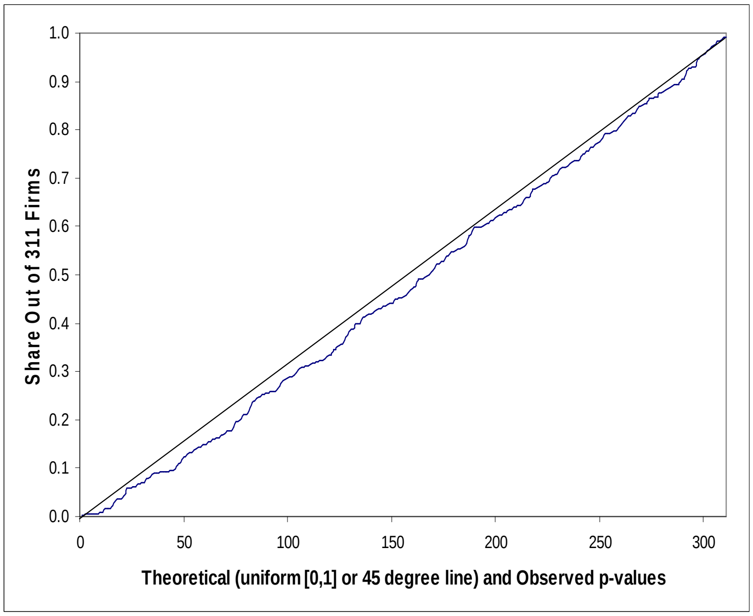


Figure 2: Cumulative Distribution Functions for Average Percent Profits
The figure shows the theoretical and observed c.d.f.'s for average profitability for the NYSE/AMEX data (2A) and the NASDAQ data (2B). Returns are bootstrapped for 304 NYSE or AMEX firms or 373 NASDAQ firms, to create 10,000 simulated series per firm. For each series, average profits from the head-and-shoulders trading algorithm are calculated, and the marginal significance of observed profits calculated. The distribution of the resulting 311 (373) *p*-values should be uniform under the null hypothesis of no profitability, or should lie above the theoretical c.d.f. under the alternative hypothesis that the pattern profitably predicts trend reversals.

2A: NYSE/AMEX firms



2B: NASDAQ firms

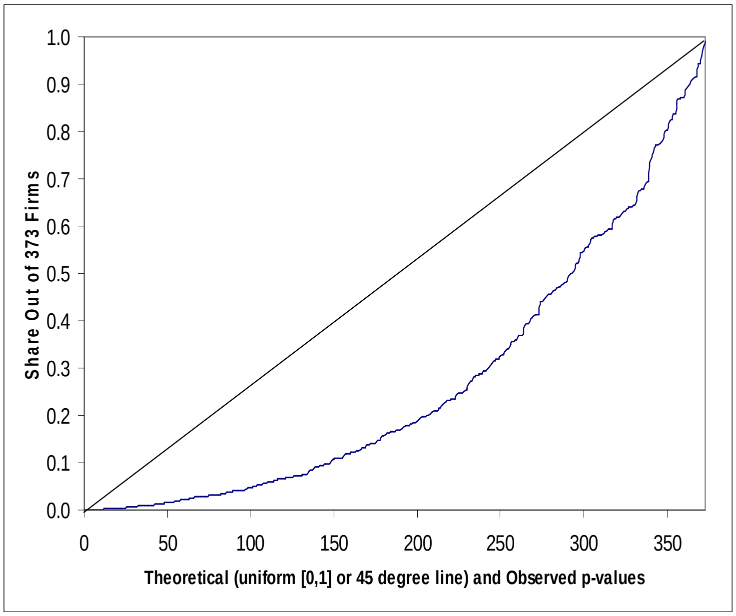
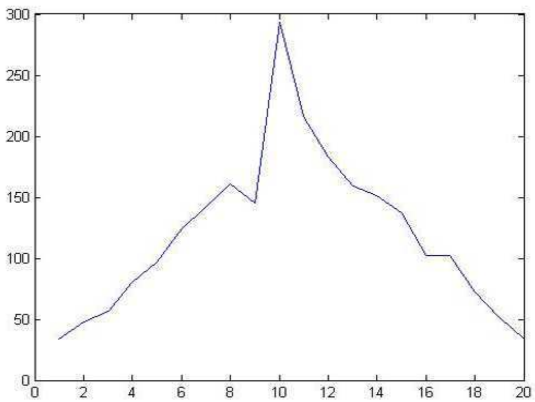
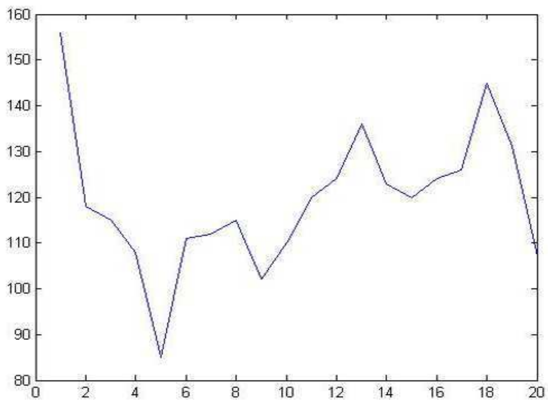


Figure 3: Distribution of Conditional and Unconditional Returns
The figure shows the number of conditional returns following head-and-shoulders trading signals in each of twenty quantiles of the unconditional distribution of returns. Underlying data comprise daily dividend-adjusted returns for all 304 NYSE or AMEX firms for which prices exist for the entire CRSP database through 2002. Anderson-Darling statistics, reported in the text, confirm that the distributions differ statistically.

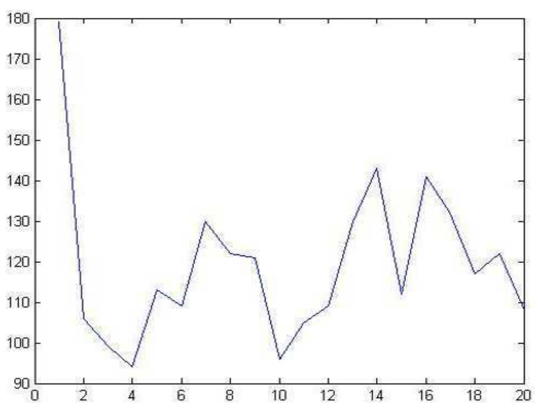
3A. 1-Day Returns



3B. 3-Day Returns



3C. 5-Day Returns



3D. 10-Day Returns

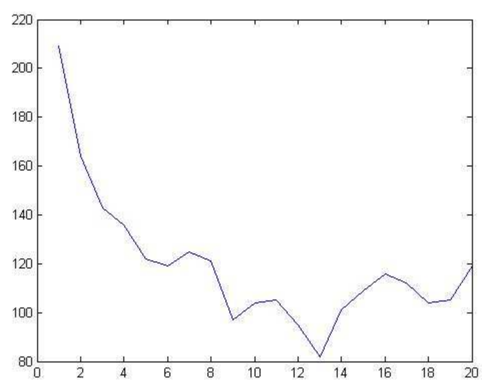


Figure 4: Inverse Relationship Between Excess Trading and Spreads Around Head-and-Shoulders Entry Days: NASDAQ sample

For each firm *i*, we run two regressions:

$$Log(Volume_t) = \alpha + \sum_{j=1}^{50} \beta_i Log(Volume_{t-1}) + \sum_{j=0}^{10} \gamma_i [\ln(high_{t-j} / low_{t-j})] + \theta_t + \mu \log(p_{t+10}) + \varepsilon_t$$

$$Spread_t = \alpha + \sum_{j=1}^{50} \beta_i Spread_{t-i} + \sum_{j=0}^{10} \gamma_i [\ln(high_{t-j} / low)_{t-j}] + \theta_t + \mu \log(p_{t+10}) + \eta_t$$

where closing prices are labeled *p*, and high and low refer to daily high and low prices. Spreads are measured as (ask-bid)/mid, *p* represents the closing mid-price. The data include 373 NASDAQ firms with five or more consecutive years of returns in CRSP. Using an objective pattern identification algorithm, for each firm we identify days when head-and-shoulders patterns cross the neckline and compute the average residuals from those days.