Explaining Momentum Profits with an Epidemic Diffusion Model

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Abstract

We show that information diffusion is a function of its dissemination and assimilation. Whereas dissemniation is proportional to observable factors such as volume and price volatility, assimilation is dependent on unobservable factors such as the usefulness and reliability of information. We find that buying low volume (or low volatility) past losers and shortselling low volume (or low volatility) past winners generates a positive net return across the entire sample period and especially during bear markets. Second, buying high volatility past winners and shortselling high volatility past losers generates a positive net return, especially during bear markets.

Keywords: Information diffusion, momentum profits, trading volume, price volatility

JEL Classifiers: G11, G14

Introduction

Over the past several years, a large volume of empirical work has documented a variety of anomalous return patterns which are difficult to explain from the perspective of the Efficient Market Hypothesis (EMH). In particular, several recent papers have documented that stock returns are positively correlated at lags of three to twelve months and display a negative autocorrelation at horizons of one to five years. Return patterns tend to exhibit momentum in the short run, with past winners continuing to perform well, and past losers continuing to perform poorly. For example, Jegadeesh and Titman (1993) find that a strategy that buys stocks that have performed in the highest decile over the past six months and simultaneously sells short stocks in the lowest decile over the same time period earns a positive momentum net profit over the next six to twelve months. Rouwenhorst (1998) finds a similar pattern of intermediate-term price momentum in twelve other countries, suggesting that the results are not due to a data snooping bias. Few explanations have been offered for this intermediate-term momentum effect. For example, Fama and French (1996) show that a three-factor model of returns fails to explain intermediate-term price momentum. More recently, Conrad and Kaul (1998) suggest that the cross-sectional variation in the mean returns of individual securities might account for the momentum effect. Similarly, Moskowitz and Grinblatt (1999) theorize that a significant component of firm-specific momentum can be explained by industry momentum. However, Grundy and Martin (2001) show that momentum effects are not explained by cross-sectional variations in expected returns or industry effects.

Other research shows that return patterns have a tendency to exhibit short and intermediate term continuation, leading to overreaction and ultimate reversal of some of the overreaction in the long term. For example, DeBondt and Thaler (1985) find that portfolios of prior "losers" are found to outperform prior "winners". Thirty-six months after portfolio formation, the losing stocks have earned about twenty-five percent more than the winners. This is consistent with the predictions of the overreaction hypothesis. Similarly, as pointed out by Chan, Jegadeesh, and Lakonishok (1996), the predictability of future returns from past returns is due to the market's under-reaction to past earnings news. However, price momentum is not directly correlated with earnings momentum. Moreover, following observable public news announcements (as for example, earnings announcements, dividend declaration, stock splits and repurchases), stock returns tend to experience a drift in the same direction of the initial event impact. This is referred to in the literature as post announcement drift (PAD). Ball and Brown (1968) were the first to note that even after earnings were announced, abnormal positive returns accrued for "good news" firms and abnormal negative returns accrued for "bad news" firms. Foster, Olsen, and Shevlin (1984) estimate that over the sixty trading days subsequent to an earnings announcement, a long position in stocks with unexpected positive earnings surprises in the top decile combined with a short position in stocks with unexpected negative earnings surprises in the lowest decile yields an annualized abnormal return of around twenty-five percent, before transactions costs. Bernard and Thomas (1989) conclude that there is a delay in investors' response to earnings reports, and this delay is responsible for the post announcement drift.

The above results suggest that both past returns and public announcements help to predict future returns. Given that the stock market responds only gradually to new information, trading based on momentum strategies and on publicly available information can yield abnormal returns. However, given the difficulty that the traditional asset-pricing models have in explaining momentum profits and other anomalies to the EMH**,** "behavioral" theories have gained popularity in the academic literature. Some of the more recent works in the behavioral literature include Daniel et al (1998) and Barberis et al (1998), who explain momentum profits by constructing quasi-rational models based on conventional psychological theories. A different approach is proposed by Hong and Stein (1999), who emphasize the interaction between heterogeneous agents rather than trying to model the psychology of investors. Since the Hong and Stein (1999) gradual information diffusion model is the starting point for our paper, their most significant conclusions are summarized below:

- Both short-run continuation and long-run reversals should be more pronounced in those stocks for which information diffuses at a slower rate. Since company size and trading volume are used as proxies for the speed of information diffusion, Hong and Stein conclude short-run continuation and long-run reversals should be more pronounced in small, thinly traded stocks, rather than in large, high volume stocks. It follows, therefore, that momentum trading or "trend chasing" strategies should be more profitable for small cap, thinly traded stocks rather than for large cap, high volume securities.
- For similar reasons, there may be more long-run overreaction to information which is initially private (information that is initially expensive to obtain or is not easily retrievable by all investors) than to public news announcements (earnings announcements or analyst upgrades and downgrades). This should lead to lower momentum profits from publicly disclosed news.

Later empirical studies contradict the above conclusions inferred from the Hong and Stein (1999) gradual information diffusion model. For example, Lee and Swaminathan (2000) find that the momentum strategy of buying past winners and selling past losers performs better among low volume winners as compared to high volume winners. However, in the case of losers, short selling high volume losers shows greater momentum profits as compared to short selling low volume losers.

In sum, the empirical evidence that momentum strategies work is convincing. However, the explanation of why they work is essentially incomplete. This paper builds on the Hong and Stein (1999) gradual information diffusion model by drawing a parallel between existing mathematical representations of the transmission of an infectious disease during an epidemic and develops a model which considers both the dissemination and assimilation of information in a financial marketplace as important ingredients of information diffusion and consequential momentum profits. The next section develops the epidemic diffusion model and explains the dynamics of its functioning. We then examine the empirical evidence of the relationship between volume, volatility, and momentum profits during a bull and bear market environment and explain this relationship within the context of our epidemic diffusion model. The last section concludes the paper.

The Epidemic Diffusion Model

Our model presumes the existence of a financial marketplace populated by heterogeneous, boundedly rational investors. It assumes a constant population of *N* active investors, subdivided into two trading groups, namely arbitrageurs and momentum traders, of size *Z* and *N-Z*, respectively. At any time *t,* each individual investor forms expectations for the price of the security at time *t+1*. Each trading group forms its expectations of the fair value of the asset, A_t, either on the basis of (a) the historical performance of the asset, or (b) the available fundamental information concerning the asset. We assume that investors are boundedly rational, and that information acquisition and processing imposes significant cognitive costs, related to the efforts of information identification, gathering and understanding. The assumption of bounded rationality implies that uninformed agents use simple univariate forecasting methods to form their price expectations. Momentum traders rely solely on historical returns and believe that asset returns are distributed as follows:

$$(\Delta A_t / A_{t-1},..., A_0) \sim N(\Delta A_{t-1}, \sigma_{t-1}^2) \qquad (1)$$

where $\Delta A_t = A_t - A_{t-1}\ \forall t$ denotes the risky asset price change in between time *t* and *t-1.* Arbitrageurs, on the other hand, use the available knowledge to detect and exploit arbitrage opportunities arising at time *t*. We assume that informed arbitrageurs believe that the fundamental asset price is normally distributed:

$$(\Phi_t / I_{t-1}) \sim N(\phi_t, \omega_t^2) \tag{2}$$

Using our assumption of bounded rationality, we postulate that uninformed arbitrageurs only use current market prices to make inferences about the fundamental asset value, that is:

$$(\Phi_t \mid \widetilde{I}_{t-1}) \sim N(A_{t-1}, \omega_t^2) \tag{3}$$

Information Diffusion

After defining the characteristics of the traders' classes, we model the information diffusion process. Here we seek the help of non-financial literature. For example, D. Ganesan et al (2002) and Khelil et al (2002) have drawn a parallel between the dissemination of information in a network and the transmission of an infectious disease during an epidemic. We suggest that it is possible to adapt existing mathematical representations describing epidemic processes to model information dissemination in the financial markets. In an epidemic setting, the speed of the contagion depends on two parameters: *X*, the number of contacts per individual per unit of time and β $(0 < \beta < 1)$, the probability of contagion, which depends on the virulence of the disease. In our model, we posit that information diffusion is dependent on two factors: (a) the dissemination of information, measured by an objective factor, *X*, which is directly proportional to such observable factors as trading volume and volatility, and (b) the assimilation of information, measured by a subjective, unobservable parameter, β $(0 < \beta < 1)$, which is a proxy for information assimilation and measures the perceived reliability of the information and its economic usefulness. The parameter β is a subjective estimate since it is impossible to measure precisely the likelihood that traders will actually incorporate any news surrounding a stock in their expectations. Unlike the information assimilation factor, β, the information dissemination factor, *X,* is observable and is directly proportional to a stock's trading volume and price volatility. However, we posit that the information assimilation factor, β, is more important than the information dissemination factor, *X*, in determining the speed of information diffusion and consequential momentum profits.

Let $I(t)$ and $S(t) = Z - I(t)$ denote respectively the number of arbitrage-seeking investors that do and do not possess information *I* at time *t*. Assume that $a = \dfrac{\beta X}{Z}$ denotes the information transmission rate and $P(t) = a\ I(t)$ be the probability that an individual receives the information at any time *t*. Since we are concentrating on the behavior of large scale populations, we will use a deterministic compartmental epidemic model. To develop the solution, we write the mass balance equations for each state as follows:

$$\begin{cases} \dfrac{dS(t)}{dt} = -P(t)S(t) \\ \dfrac{dI(t)}{dt} = P(t)S(t) \end{cases} \tag{4}$$

This balance suggests that every increase of informed investors is matched by an identical decrease of uninformed investors. Replacing $S(t) = Z - I(t)$ and $P(t) = a\ I(t)$ in (4) we obtain a first order differential equation:

$$\frac{dI(t)}{dt} = aI(t)Z - aI(t)^2 \tag{5}$$

with the solution:

$$I(t) = \frac{Z}{1 + (\dfrac{Z - I(0)}{I(0)})\exp(-aZt)} \tag{6}$$

where $I(0)$ is the initial number of informed investors. Obviously, $I(0)$ depends on the initial availability of the information. Public disclosures, like earnings announcements, stock splits etc. are immediately available to the entire market, hence $I(0) = N$. In conclusion, while we construct a discrete market model, we assume that information diffuses continuously in time. This does not cause any inconsistency if we postulate that the number of informed investors is sampled discretely in time, so that *t* takes value in the set of positive natural numbers.

Demand Functions and Equilibrium Price

At this point, we need to analyze how asymmetric information diffusion combined with heterogeneous expectations drives the demand/supply process of the risky asset, and thus determines its price. Momentum traders choose their demand level, D_t^m, to maximize the exponential utility function $U_t^m = E[-\exp(-\gamma_m (D_t^m \Delta A_t)]$, while arbitrageurs pick a trading strategy which maximizes $U_t^a = E[-\exp(-\gamma_a (D_t^a (A_t - \Phi_t)]$, where $D_t^m \Delta A_t$ are momentum profits, $D_t^a (A_t - \Phi_t)$ are arbitrage profits gained by betting on reversal to the fundamental price, and γ_m, γ_a measure risk aversion of momentum traders and arbitrageurs, respectively. The resulting optimal trading strategies are:

$$D_t^m = \frac{\Delta A_{t-1}}{\sigma^2 \gamma_m}$$
$$(D_t^a \mid I) = \frac{A_t - \phi_t}{\omega^2 \gamma_a} \qquad (7)$$
$$(D_t^a \mid \widetilde{I}) = \frac{A_t - A_{t-1}}{\omega^2 \gamma_a}$$

for momentum traders, informed and uninformed arbitrageurs respectively.

The aggregate demand-supply function is simply the weighted sum of the individual demands of momentum traders, and informed and uninformed arbitrageurs.

$$AD_t = \frac{(N-Z)}{N} D_t^m + \frac{(Z - I(t))}{N} (D_t^a \mid \widetilde{I}) + \frac{I(t)}{N} (D_t^a \mid I) \qquad (8)$$

We assume that there exists a market-maker who mediates trading in the market. The market-maker helps to meet the excess demand/supply by adjusting the market price until equilibrium is reached. Combining equations (6), (7) and (8), we find that the time *t* equilibrium price satisfies the following condition.

$$A_t - A_{t-1} = \frac{I(0)(\phi_t - A_{t-1})}{I(0) + (Z - I(0))\exp(-aZt)} + \frac{2\Delta A_{t-1}\gamma_a \omega^2 (N-Z)}{\gamma_m \sigma^2 Z} \qquad (9)$$

Illustrating the Dynamics of the Epidemic Diffusion Model

To illustrate the price dynamics of our model, we plot a realization of the difference equation (9) when a piece of "bad news" is disclosed privately to a small group of people during an upward swing of the security price. We term this a case of "low volume" dissemination. The results are plotted in Figure 1. Next, we plot the realization of the difference equation (9) assuming there is a public announcement of "bad news". We term this a case of "high volume" dissemination. The results are plotted in Figure 2.

[Figure 1 about here]

Observe from Figure 1 that the asset price continues to exhibit its short term upward momentum, as the "bad news" is still not publicly known. The gradual nature of information dissemination explains the initial tendency of the stock price to maintain its upward trend or momentum in the short term. As the information diffuses further, informed traders begin to sell the stock, creating a switch in the trend and inviting uninformed momentum traders to ride the down trend. This lends further support to the price decline. At some point, the cumulative selling causes the price to drop below the level warranted by the original information. When this happens, informed arbitrageurs consider the stock to be under-priced, and therefore begin to buy the stock, trading against the down trend. This action eventually moves the security price back to its fair or equilibrium level.

[Figure 2 about here]

Next, in Figure 2 we illustrate the effect of a public announcement of some "bad news" at the current time, assuming that the entire market is immediately aware of the information. The stock price immediately reacts negatively to the bad news, with fundamental traders initiating the selling action and the down trend. Momentum traders join in the selling, and this causes the price of the stock to fall below its fair value. Eventually, this overreaction invites an opposing reaction from arbitrageurs, who move the price back to its fair level. However, this conclusion is based on the assumption of a balanced market composition. The rationale of our model suggests that in a marketplace dominated by technical or momentum traders, we would expect return patterns similar to those encountered in a gradually diffusing information scenario, with long drifts that result in marked overshooting and reversals. As fundamentalists have a limited weight in the price dynamics, their contrarian reaction would acquire sufficient strength to reverse the trend only after the price deviates appreciably from its fair fundamental value. This reasoning leads to the conclusion that the price dynamics of securities that exhibit long-lasting post announcement drifts are principally driven by technical or momentum trading. Conversely, securities that exhibit very short-term post announcement drifts are driven primarily by fundamental traders.

The model dynamics discussed so far focus primarily on the effect on stock prices of dissemination of information to a small or large group of people. In the following section, we will examine the empirical evidence for the existence of momentum profits across a wide range of publicly traded companies classified according to two important factors influencing information dissemination.

Empirical Results

In this section, we will examine historic data between August 1982 and December 2004 to study the effect on momentum profits of trading volume and price volatility. The sample period selected is divided into two sub-periods: (a) August 1982 to March 2000, marking one of the most significant bull markets in the United States, and (b) April 2000 to December 2004, a major bear market in United States stocks. The objective is to check for consistency in the pattern of momentum profits during bull and bear markets. Next, we explain the observed momentum profits within the context of our two-factor epidemic diffusion model.

Data and Sample Specifications

Our initial sample comprises all firms in the CRSP database which are listed on the NYSE and AMEX stock exchanges during the period August 1982 to December 2004. All NASDAQ firms are excluded from the initial sample. Also excluded are any firms that represent a closed-end fund, an ADR, a Real Estate Investment Trust (REIT), and primes and scores (i.e. we exclude any stock with a CRSP share type code which is not 10 or 11). Finally, we exclude all securities with incomplete or missing data for any part of the sample period. At the beginning of each month, all securities in the sample are categorized in one of three groups on the basis of one distinguishing attribute, namely, the daily trading volume or volatility of daily stock prices over the past one month, also called the portfolio formation period. Group 1 includes 30% of stocks with the smallest value for a given attribute, namely, price volatility or trading volume. Group 3 includes 30% of the stocks with the highest value for the same attribute. Group 2 consists of all the remaining stocks. At the beginning of each month, all securities in each of the three groups are ranked in descending order of returns in one of ten groups over the formation period: 10% of the stocks with the lowest returns are classified as past losers (portfolio *P10*), whereas 10% of the stocks with the highest returns are classified as past winners (portfolio *P1).* The momentum trading strategy is to buy all past winners (portfolio *P1*) in a given group, and short-sell all past losers (portfolio *P10*) in the same group at the beginning of each month. The momentum strategy is based on the assumption that prices under-react to news and that past winners will continue with their winning ways whereas past losers will continue to lose in the future. The contrarian strategy is to buy all past losers (portfolio *P10*) in a given group, and short-sell all past winners (portfolio *P1*) in the same group at the beginning of each month. The contrarian strategy is based on the fact that prices over-react to news and that past losers will turn around and fare better in the future, whereas past winners will not be as lucky in the future.

For both the momentum and contrarian strategies, the portfolios are held for a period of six, nine, or twelve months after their creation, generally called the holding period. Upon closing out the positions at the end of the holding period, we compute the buy-and-hold return on each of the decile portfolios, *P1* through *P10,* over the duration of the holding period, as also the buy-and-hold return earned on an equally weighted portfolio of all stocks (*EWI*) in a given group over the same holding period. The difference in returns, *P1 – P10*, represents the profit for the momentum strategy of buying past winners and short-selling past losers over a specific holding period. Conversely, the difference in returns, *P10 – P1*, represents the profit for the contrarian strategy of buying past losers and short-selling past winners. The contrarian strategy is the mirror-image of the momentum strategy. Both strategies are evaluated for each of the three groups (low, medium, or high) for the attributes of trading volume and price volatility. Transaction costs are ignored for the purposes of this exercise. We first examine the empirical evidence regarding abnormal profits resulting from differences in trading volume and price volatility. Next, using our epidemic diffusion model, we explain the observed relationship between each of these attributes and the observed profits.

Tables 1 and 2 begin by reporting the average monthly holding period returns across all stocks for the ten decile portfolios ranked on the basis of returns over the previous month (referred to as the formation period) between August 1982 and December 2004, and also across two sub-periods, August 1982 to March 2000 (representing a bull market in U.S. stocks) and April 2000 to December 2004 (representing a bear market in U.S. stocks). Tables 1 and 2 show that over the entire sample period (August 1982 to December 2004), the contrarian strategy of buying past losers and short-selling past winners was profitable, whereas the momentum strategy of buying past winners and short-selling past losers was consistently unprofitable. This is true across each of three holding periods. Moreover, the contrarian strategy fared better in the post-March 2000 bear market as compared to the earlier bull market. For example, whereas the contrarian strategy earned a statistically significant positive monthly return of 0.22% for the six month holding period during the bull market of August 1982 to March 2000, it earned a much higher return of 0.47% per month during the bear market from April 2000 to December 2004. Similarly, the contrarian strategy lost 0.09% per month for the twelve month holding period during the 1982/2000 bull market, whereas it earned a statistically significant positive return of 0.32% per month during the bear market which followed since April 2000.

Volume and Momentum Profits

Although the role of trading volume in generating momentum profits has been widely researched and well documented, there are conflicting views on the nature of the relationship. Datar, Naik, Radcliffe (1998) show that low (high) volume firms earn higher (lower) future returns. According to Datar et al (1998), volume serves as a liquidity proxy, and firms with low liquidity tend to earn a "liquidity premium" in the form of a higher future return. Hong and Stein (1999) use different logic to reach the same conclusion. They maintain that trading volume is a proxy for information diffusion. Low trading volume leads to insufficient diffusion of information and consequently higher momentum profits. On the other hand, De Long et al (1990) maintain that trading volume is a proxy for positive feedback trading, and hence high volume fuels higher momentum profits. This view is also supported by Daniel et al (1998), who theorize that when a stock is popular, the trading volume for that stock increases. Conversely, when a stock is unpopular, its trading volume shrinks. Hence volume is a proxy for investor preference for a stock at a given point in time, and this preference results in more people buying the stock, resulting in higher stock prices and greater momentum profits. Lee and Swaminathan (2000) conclude that both the commonly held views about volume's effect on momentum profits, i.e. the "information diffusion" hypothesis and the "fueling" hypothesis, are only partially correct in explaining reality. They find that whereas volume "fuels" momentum profits in the case of high volume losers, it fails to do so for high volume winners. They also find that the "information diffusion" hypothesis works in case of winners, with low volume winners showing greater momentum profits as compared to high volume winners. Our goal is to study the role of trading volume in generating momentum profits across two very different market phases, namely a bull market and a bear market, and to explain our findings in terms of our epidemic diffusion model.

For the purposes of our research, trading volume is defined as the daily turnover ratio, which is the ratio of the number of shares traded each day to the total number of shares outstanding at the end of the day. All stocks in the sample are categorized into one of three groups based on their average daily turnover ratios over the formation period. The stocks with the highest 30% of daily turnover ratios are categorized as "high" volume, the next 40% are categorized as "medium" volume, and the lowest 30% are categorized as "low" volume. The momentum and contrarian trading strategies are implemented for a six, nine, or twelve month holding period for each of the three groups. The results are presented in Panel A, B and C of Table 1, for the six, nine, and twelve month holding periods respectively.

[Table 1 about here]

Table 1 analyzes abnormal returns generated by low, medium and high volume stocks across the entire sample period as well as during the 1982/2000 bull market and the ensuing bear market since April 2000. We observe that the contrarian strategy of buying past losers and short-selling past winners convincingly outperformed the momentum strategy of buying past winners and short-selling past losers for low and medium volume stocks across all three holding periods. Moreover, the contrarian strategy generated the highest positive net return for low volume stocks. This is consistently true for the six, nine, and twelve month holding periods. For example, we observe from Panel A that the contrarian strategy applied to low volume stocks across a six month holding period earned a statistically significant net monthly return of 0.31% over the entire sample period, as opposed to 0.16% for medium volume stocks and a statistically insignificant 0.06% for high volume stocks. Similar results are observed in Panels B and C for the nine and twelve month holding periods. On the other hand, the momentum strategy generated losses for low and medium volume stocks, and generated a small positive net return for high volume stocks across the nine and twelve month holding periods. Across the entire sample period, the momentum strategy for high volume stocks earned a statistically significant net monthly return of 0.13% for the nine month holding period as per Panel B, whereas the same strategy earned a statistically significant net monthly return of 0.09% for the twelve month holding period as per Panel C. For the record, Panel A shows that the momentum strategy suffered a statistically insignificant net loss of 0.06% per month for the six month holding period.

Second, we find that while the contrarian strategy worked well across the entire sample period for low volume stocks, it worked especially well during bear markets, clearly outperforming its performance during bull markets. For example, in Panel A we observe that the contrarian strategy for low volume stocks across a six month holding period generated a net monthly return of 0.71% during the bear market from April 2000, as opposed to a net monthly return of 0.20% during the 1982/2000 bull market. Both returns are statistically significant at 1% level of significance. Similar results are observed in Panels B and C for the nine and twelve month holding periods. Conversely, the momentum strategy for high volume stocks worked better during bull markets and not so well during bear markets. For example, from Panels B and C for the nine and twelve month holding periods, we observe that the momentum strategy for high volume stocks yielded a net monthly return of 0.15% during the 1982/2000 bull market. In contrast, the momentum strategy earned a net monthly return of only 0.05% during the bear market from April 2000 for the nine month holding period, and a net loss of 0.05% per month during the same period for the twelve month holding period.

Volatility and Momentum Profits

Unlike volume, the role of volatility in generating momentum profits has not been as thoroughly researched. Kim et al (2004) find strong evidence of a volatility feedback effect which gives rise to a positive relationship between market volatility and the equity premium. The existence of an equity premium for highly volatile stocks pumps up prices of these stocks contemporaneously. Our goal in this section is to examine the existence or otherwise of momentum profits over the next six, nine, or twelve month holding period as a result of unusually high or low price volatility in the portfolio formation period. Next, we seek to explain our results using our two-factor epidemic diffusion model.

For the purposes of our research, the volatility of a stock is defined in terms of the standard deviation of excess returns of that stock over the S&P 500 index over a 30 day period prior to the stock holding period. The stocks with the highest 30% volatility are categorized as "high" volatility, the next 40% are categorized as "medium" volatility, and the lowest 30% are categorized as "low" volatility. The momentum and contrarian strategies are implemented for each of the three volume/volatility groups across a six, nine, or twelve month holding period. The results are presented in Panels A, B, and C of Table 2 alongside the result for the buy-and-hold strategy for an equally weighted portfolio of all stocks in the sample.

[Table 2 about here]

Panels A, B, and C of Table 2 break down returns generated by low, medium, and high volatility stocks across six, nine, and twelve month holding periods respectively. Across all three holding periods, the contrarian strategy of buying past losers and short-selling past winners outperformed the momentum strategy of buying past winners and short-selling past losers for low and medium volatility stocks. For example, Panel A of Table 2 shows that the contrarian strategy applied to low volatility stocks across a six month holding period earned a statistically significant net monthly return of 0.46% over the entire sample period, as opposed to 0.32% per month for medium volatility stocks and a loss of 0.15% per month for high volatility stocks. Similar results are seen in Panels B and C for the nine and twelve month holding periods. Conversely, the momentum strategy of buying past winners and short-selling past losers generated a statistically significant positive net return for high volatility stocks across all three holding periods. The momentum strategy earned a net monthly return of 0.15% for the six month holding period, a net monthly return of 0.17% for the nine month holding period, and a net monthly return of 0.10% for the twelve month holding period. All three returns are significant at the 5% level of significance.

Moreover, we find that whereas the contrarian strategy worked best across the entire sample period for low volatility stocks and the momentum strategy worked best across the entire sample period for high volatility stocks, both strategies worked better in bear markets as compared to bull markets.

For example, from Panel A of Table 2 we see that the contrarian strategy for low volatility stocks earned a net monthly return of 0.96% during the post April 2000 bear market, as opposed to a net monthly return of 0.32% during the 1982/2000 bull market and a net monthly return of 0.46% for the entire sample period. All three returns are significant at the 5% level of significance. Similarly, from Panel A of Table 2 we see that the momentum strategy for high volatility stocks earned a statistically significant net monthly return of 0.61% during the post April 2000 bear market, as opposed to a statistically insignificant net monthly return of 0.03% during the 1982/2000 bull market, and a statistically significant net monthly return of 0.15% for the entire sample period. The same pattern is observed in Panels B and C for nine and twelve month holding periods.

Explaining Momentum Profits with the Epidemic Diffusion Model

Based on our epidemic diffusion model, we offer a possible explanation as to profitability of the contrarian strategy of buying low volume/volatility past losers and short-selling low volume/volatility past winners, especially during a bear market. We posit that although volume or volatility can certainly serve as a proxy for information diffusion, it is an incomplete measure, inasmuch as it fails to take into account the willingness to absorb and use the information. Although the observed value of X is small for low volume/volatility past losers and winners given the slow speed of information dissemination, it is conceivable that traders react differently to news relating to past winners and losers, and this translates in differing speeds of information assimilation, reflected in differing β values for winners and losers. Investors are inhibited by the belief that past losers are likely to continue losing in the future, and do not hold any promise for a quick turnaround. This is especially true during a bear market when most stocks are depressed to begin with. This perception leads to a low rate of assimilation or low β for information concerning low volume past losers. The low assimilation factor or β value complements the already slow rate of information dissemination or X value, leading to a lower than average speed of information diffusion and above average momentum profits for low volume/volatility past losers. Conversely, the performance of low volume/volatility past winners stands out, especially during a bear market when winners are outnumbered by losers. Whereas investors are upbeat about the abnormal economic value of information contained in low volume past winners, they have reason to be upbeat about the continued profitability of these low volatility past winners. The perceived usefulness of information concerning low volume/volatility past winners leads to a high β value, signifying quick assimilation of any economic information concerning these stocks. The high β value offsets the low X

value reflecting the slow rate of information dissemination, leading to an average speed of information diffusion and average momentum profits for low volume/volatility past winners. Therefore, the return from buying low volume past losers is likely to exceed that from buying low volume past winners. Consequently, the contrarian strategy of buying low volume/volatility past losers and selling low volume/volatility past winners results in a positive net profit, especially during bear markets.

Next, we offer an explanation for the momentum profits resulting from buying high volume/volatility past winners and short-selling high volume/volatility past losers. We posit that although volume or volatility can certainly serve as a proxy for information diffusion, it is an incomplete measure, inasmuch as it fails to take into account the willingness to absorb and use the information. Although the observed value of X is large for high volume/volatility stocks, it is conceivable and very likely that traders are inhibited by the belief that the abnormal economic advantage yielded by the information is limited. In the case of high volume stocks, the widespread dissemination of information adversely impacts its assimilation. This leads to a low β value for assimilating information concerning high volume stocks, both winners and losers. Therefore, although information disseminates quickly for high volume stocks, it is assimilated more gradually in investor expectations. The low β value offsets the high X value, neutralizing the quick dissemination of information, slowing the speed of information diffusion and leading to above average momentum profits for high volume past winners and losers. However, since the return from buying high volume past winners is about equal to that from buying high volume past losers, the net return from the momentum strategy of buying high volume past winners and short-selling high volume past losers is likely to be marginal.

In the case of high volatility stocks, we are of the opinion that the information assimilation profiles for past winners are likely to be different from those for past losers. Let us begin with a discussion of high volatility past winners. Given the unpredictability associated with high volatility and the likelihood that past profits may not be sustainable in the future, traders are likely to assimilate very slowly any information pertaining to high volatility past winners. The slow assimilation of information results in a low β value which offsets the high X value, neutralizing the quick dissemination of information, slowing the speed of information diffusion and leading to above average momentum profits for high volatility past winners. Conversely, in the case of high volatility past losers, information is likely to be assimilated more quickly, as the unpredictability associated with high volatility suggests that there is a good chance that we could see a reversal from past losses in the near future. The quick assimilation of information results in a high β value which complements the high X value, increasing the speed of diffusion and resulting in below average momentum profits. Therefore, the return from buying low volatility past winners is likely to exceed the return from buying low volatility past losers. The net return from buying low volatility past winners and short-selling low volatility past losers is likely to be positive.

Conclusions

This paper seeks to explain the phenomena of momentum profits using a two factor information diffusion model: (a) the potential for information dissemination per unit of time, which is dependent on the trading volume and size of the company, and (b) the receptivity of investors to assimilate or use the information received. We believe that our approach provides a valid modeling base for two reasons. First, it provides a unified theory to explain the existence of momentum profits without any additional limiting assumptions. Second, our model does not sacrifice a realistic representation of the market for the sake of simplicity.

We examine the performance of momentum and contrarian trading strategies based on trading volume and price volatility, and find that the highest momentum profits arise from buying high volatility past winners and short-selling high volatility past losers. To a lesser degree, we observe positive momentum profits from buying high volume past winners and short-selling high volume past losers. We argue that whereas high trading volume and price volatility are observable factors responsible for a high speed of information dissemination, the low perceived reliability and usefulness of the news is an even more important, albeit unobservable, factor which is responsible for the low receptivity of investors to assimilate this information. Both factors considered jointly result in a low overall rate of information diffusion for high volume and high volatility stocks, leading to higher momentum profits.

Second, we find that the contrarian strategy of buying low volume (or low volatility) past losers and short-selling low volume (or low volatility) past winners generates a positive net return, especially during a bear market. Finally, we find that buying low volume (or low volatility) past losers generates high momentum profits during bear markets. We posit that the low rate of information dissemination for low volume (or low volatility) stocks reinforces a low rate of information assimilation for information contained in past losers, leading to a low rate of information diffusion and higher than average momentum profits. Conversely, the high rate of information assimilation for information contained in low volume (or low volatility) past winners offsets the low rate of information dissemination for such stocks, leading to normal information diffusion and average momentum profits. The strategy of buying low volume (or low volatility) past losers and short-selling low volume (or low volatility) past winners therefore results in positive net profits.

References

Ball, R. and P. Brown. 1968. "An Empirical Evaluation of Accounting Income Numbers." *Journal of Accounting Research* number 6: 159-178.

Barberis, N., A. Shliefer, and R. Vishny. 1998. "A Model of Investor Sentiment." *Journal of Financial Economics* 49: 307-343.

Bernard, V., and J. Thomas. 1989. "Post-earnings Announcement Drift: Delayed Price Response or Risk Premium?" *Journal of Accounting Research* 27: 1-48.

Chan, L., N. Jegadeesh, and J. Lakonishok.1996. "Momentum Strategies." *Journal of Finance* 51: 1681-1713.

Conrad, J. S., and G. Kaul. 1998. "An Anatomy of Trading Strategies." *Review of Financial Studies* 11: 489-519

Daniel, K., D. Hirshliefer, and A. Subrahmanyam. 1998. "Investor Psychology and Security Market Overreactions." *Journal of Finance* 58: 1839-1885.

DeBondt, W., and R. Thaler. 1985. "Does the Stock Market Overreact?" *Journal of Finance* 40: 793-808

De Long, J. Bradford, A. Shleifer, L. H. Summers, and R. J. Waldmann. 1990. "Positive Feedback Investment Strategies and Destabilizing Rational Speculation." *Journal of Finance* 1990, 45: 379-395

Fama, E. and K. R. French. 1996. "Multifactor Explanations of Asset Pricing Anomalies." *Journal of Finance* 51: 55-84.

Foster, G., C. Olsen, and T. Shevlin. 1984. "Earnings Releases, Anomalies, and the Behavior of Security Returns." *The Accounting Review* 59: 574-603.

Ganesan, D., B. Krishnamachari, A. Woo, D. Culler, D. Estrin, and S. Wicker. 2002. "An Empirical Study of Epidemic Algorithms in Large Scale Multihop Wireless Networks." In *Intel Research Proceedings*. Berkely: University of California at Berkely.

Grundy, B. D., and J. S. Martin. 2001. "Understanding the Nature of Risks and the Sources of the Rewards to Momentum Investing." *The Review of Financial Studies* 14: 29-78.

Hong, H., and J. Stein. 1999. "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets." *Journal of Finance* 54: 2143-2184.

Jegadeesh, N., and S. Titman. 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance* 48: 65-91.

Khelil, A., C. Becker, J. Tian, and K. Rothermel. 2002. "Analysis of Ad Hoc Networks: An Epidemic Model for Information Diffusion in MANETS." In *Proceedings of the 5th ACM International Workshop on Modeling Analysis and Simulation of Wireless and Mobile Systems*. New York: ACM Press.

Kim, C., J. Morley, and C. Nelson. 2004. "Is there a Positive Relationship between Stock Market Volatility and the Equity Premium?" *Journal of Money, Credit, and Banking* 36: 339-360.

Lee, C., and B. Swaminathan. 2000. "Price Momentum and Trading Volume." *Journal of Finance* 55: 2017-2069.

Moskowitz, T. J., and M. Grinblatt. 1999. "Do Industries Explain Momentum?" *Journal of Finance* 54:1249-1290.

Rouwenhorst, G..K.. 1998. "International Momentum Strategies." *Journal of Finance* 53:267-284

TABLE 1. VOLUME AND MOMENTUM PORTFOLIO RETURNS

Panel A: Volume and Momentum Portfolio Monthly Returns for a 6-month Holding Period

	All Stocks			Low Volume			Medium Volume			High Volume		
	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004
P1(Past winners)	0.90	0.91	0.83	0.75	0.77	0.64	0.88	0.89	0.89	1.08	1.13	0.83
P2	0.83	0.87	0.68	0.65	0.69	0.49	0.75	0.82	0.52	0.70	0.74	0.47
P3	0.81	0.87	0.59	0.66	0.71	0.47	0.78	0.84	0.15	0.55	0.66	0.55
P4	0.85	0.90	0.68	0.73	0.86	0.28	0.85	0.98	0.65	0.96	1.04	0.36
P5	0.91	0.99	0.60	0.69	0.81	0.27	0.97	1.09	0.25	0.77	0.91	0.50
P6	0.90	0.95	0.69	0.88	0.93	0.67	0.78	0.83	0.48	0.83	0.92	0.59
P7	0.96	1.06	0.63	0.79	0.86	0.53	0.91	1.03	0.39	0.91	1.05	0.49
P8	1.01	1.07	0.77	0.85	0.93	0.55	0.97	0.99	0.84	1.01	1.06	0.88
P9	1.04	1.02	1.09	0.99	1.04	0.81	1.04	1.10	-0.08	0.77	1.00	0.79
P10 (Past losers)	1.17	1.14	1.30	1.05	0.97	1.35	1.04	1.08	1.28	1.14	1.10	0.88
P1-P10	-0.27	-0.22	-0.47	-0.31	-0.20	-0.71	-0.16	-0.19	-0.39	-0.06	0.03	-0.05
P10-P1	0.27	0.22	0.47	0.31	0.20	0.71	0.16	0.19	0.39	0.06	-0.03	0.05
P value	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.12	0.49	0.68	0.07
EWI	0.94	0.98	0.78	0.80	0.86	0.61	0.90	0.97	0.54	0.87	0.96	0.63

Panel B: Volume and Momentum Portfolio Monthly Returns for a 9-month Holding Period

	All Stocks			Low Volume			Medium Volume			High Volume		
	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004
P1 (Past winners)	0.97	1.00	0.83	0.89	0.94	0.72	0.90	0.96	0.69	1.10	1.15	0.92
P2	0.88	0.96	0.59	0.85	0.93	0.49	0.74	0.81	0.56	0.81	0.88	0.53
P3	0.86	0.92	0.62	0.83	0.91	0.37	0.68	0.76	0.52	0.63	0.78	0.05
P4	0.82	0.89	0.57	0.84	0.98	0.29	0.69	0.80	0.36	0.92	1.05	0.41
P5	0.88	0.95	0.62	0.92	1.03	0.40	0.72	0.81	0.50	0.73	0.84	0.30
P6	0.86	0.93	0.62	0.79	0.83	0.62	0.81	0.86	0.65	0.71	0.86	0.13
P7	0.90	0.98	0.61	0.87	0.97	0.47	0.75	0.82	0.52	0.76	0.90	0.27
P8	0.93	0.97	0.77	0.86	0.91	0.37	0.73	0.83	0.68	0.91	0.96	0.74
P9	0.96	0.96	0.95	0.96	1.01	0.88	0.93	0.94	0.75	0.75	0.91	0.19
P10 (Past losers)	1.06	1.05	1.09	0.97	1.06	1.04	0.95	0.93	0.64	0.97	1.00	0.87
P1-P10	-0.10	-0.05	-0.26	-0.08	-0.12	-0.32	-0.05	0.03	0.05	0.13	0.15	0.05
P10-P1	0.10	0.05	0.26	0.08	0.12	0.32	0.05	-0.03	-0.05	-0.13	-0.15	-0.05
p value	0.00	0.13	0.01	0.03	0.00	0.02	0.35	0.57	0.60	0.03	0.01	0.08
EWI	0.91	0.96	0.73	0.88	0.96	0.57	0.79	0.85	0.59	0.83	0.93	0.44

Panel C: Volume and Momentum Portfolio Monthly Returns for a 12-month Holding Period

	All Stocks			Low Volume			Medium Volume			High Volume		
	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004
P1 (Past winners)	1.01	1.05	0.86	0.88	0.91	0.73	0.93	0.99	0.80	1.00	1.08	0.73
P2	0.91	0.98	0.65	0.79	0.83	0.37	0.82	0.90	0.64	0.87	1.00	0.51
P3	0.85	0.94	0.55	0.66	0.72	0.11	0.90	0.99	0.42	0.65	0.80	0.59
P4	0.83	0.92	0.52	0.71	0.81	0.32	0.86	0.98	0.34	0.93	1.10	0.40
P5	0.90	0.95	0.71	0.75	0.82	0.28	0.92	1.01	0.47	0.74	0.86	0.59
P6	0.87	0.92	0.67	0.83	0.88	0.07	0.81	0.86	0.66	0.70	0.87	0.62
P7	0.90	0.98	0.62	0.78	0.85	0.31	0.88	0.96	0.52	0.74	0.86	0.59
P8	0.90	0.94	0.73	0.77	0.87	0.82	0.82	0.89	0.40	0.89	0.91	0.58
P9	0.94	0.95	0.91	0.88	0.90	0.25	0.93	0.96	0.79	0.74	0.87	0.80
P10 (Past losers)	1.00	0.96	1.18	0.92	0.92	0.88	0.90	0.94	0.91	0.92	0.93	0.78
P1-P10	0.00	0.09	-0.32	-0.04	-0.02	-0.15	0.03	0.05	-0.11	0.09	0.15	-0.05
P10-P1	0.00	-0.09	0.32	0.04	0.02	0.15	-0.03	-0.05	0.11	-0.09	-0.15	0.05
P value	0.96	0.00	0.00	0.30	0.65	0.28	0.28	0.07	0.28	0.06	0.00	0.05
EWI	0.91	0.96	0.74	0.80	0.85	0.41	0.88	0.95	0.60	0.82	0.93	0.62

Notes: This table reports the monthly returns for momentum portfolios formed based on past month returns and held for six, nine, 12 months. P1 is the equal-weighted portfolio of 10 percent of the stocks with the highest returns over the previous month, P2 is the equal-weighted portfolio of 10 percent of the stocks with the next highest returns, and so on. The "All Stocks" sample includes all stocks traded on the NYSE and AMEX excluding closed-end funds, ADRs, Real Estate Investment Trusts (REIT), and primes and scores. Volume is defined as the daily turnover ratio, which is the ratio of the number of shares traded each day to the total number of shares outstanding at the end of the day. The "High Volume" subsample comprises 30 percent of the stocks in the "All Stocks" sample with the highest volume. The "Medium Volume" subsample comprises 40 percent of the stocks in the "All Stocks" sample with the next highest volume. The "Low Volume" subsample comprises 30 percent of the stocks in the "All Stocks" sample with the lowest volume. "EWI" is the returns on the equal-weighted index of stocks in each sample.

TABLE 2. VOLATILITY AND MOMENTUM PORTFOLIO RETURNS

Panel A: Volatility and Momentum Portfolio Monthly Returns for a 6-month Holding Period

	All Stocks			Low Volatility			Medium Volatility			High Volatility		
	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004
P1 (Past winners)	0.90	0.91	0.83	0.77	0.81	0.61	0.68	0.74	0.48	1.07	0.99	1.35
P2	0.83	0.87	0.68	0.93	1.03	0.56	0.70	0.82	0.26	0.94	0.90	1.05
P3	0.81	0.87	0.59	0.99	1.11	0.53	0.77	0.90	0.30	0.65	0.79	0.13
P4	0.85	0.90	0.68	0.87	0.92	0.72	0.87	0.93	0.64	0.62	0.73	0.19
P5	0.91	0.99	0.60	0.93	0.96	0.82	0.96	1.04	0.65	0.77	0.85	0.44
P6	0.90	0.95	0.69	1.05	1.05	1.04	0.77	0.91	0.26	0.72	0.78	0.49
P7	0.96	1.06	0.63	0.92	1.05	0.42	0.84	0.92	0.52	0.69	0.75	0.46
P8	1.01	1.07	0.77	0.89	1.03	0.39	0.92	0.99	0.66	0.73	0.81	0.43
P9	1.04	1.02	1.09	1.02	1.07	0.82	0.87	0.96	0.54	0.76	0.80	0.59
P10 (Past losers)	1.17	1.14	1.30	1.23	1.14	1.57	1.01	1.11	0.61	0.92	0.96	0.74
P1-P10	-0.27	-0.22	-0.47	-0.46	-0.32	-0.96	-0.32	-0.38	-0.13	0.15	0.03	0.61
P10-P1	0.27	0.22	0.47	0.46	0.32	0.96	0.32	0.38	0.13	-0.15	-0.03	-0.61
p value	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.14	0.02	0.72	0.00
EWI	0.94	0.98	0.78	0.96	1.02	0.75	0.84	0.93	0.49	0.78	0.84	0.59

Panel B: Volatility and Momentum Portfolio Monthly Returns for a 9-month Holding Period

	All Stocks			Low Volatility			Medium Volatility			High Volatility		
	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004
P1 (Past winners)	0.97	1.00	0.83	0.71	0.75	0.57	0.67	0.77	0.28	1.07	1.03	1.22
P2	0.88	0.96	0.59	0.85	0.91	0.60	0.71	0.85	0.20	0.97	1.04	0.71
P3	0.86	0.92	0.62	0.87	0.97	0.52	0.72	0.85	0.24	0.80	0.90	0.44
P4	0.82	0.89	0.57	0.83	0.86	0.70	0.85	0.92	0.56	0.78	0.92	0.25
P5	0.88	0.95	0.62	0.87	0.92	0.68	0.90	0.95	0.71	0.80	0.91	0.39
P6	0.86	0.93	0.62	1.02	1.06	0.86	0.78	0.89	0.38	0.79	0.91	0.34
P7	0.90	0.98	0.61	0.80	0.95	0.25	0.80	0.90	0.42	0.76	0.84	0.44
P8	0.93	0.97	0.77	0.81	0.93	0.35	0.82	0.88	0.60	0.80	0.87	0.53
P9	0.96	0.96	0.95	0.93	0.98	0.75	0.81	0.89	0.49	0.79	0.85	0.57
P10 (Past losers)	1.06	1.05	1.09	1.06	1.03	1.14	0.90	1.01	0.48	0.90	0.97	0.65
P1-P10	-0.10	-0.05	-0.26	-0.34	-0.28	-0.56	-0.23	-0.24	-0.19	0.17	0.06	0.58
P10-P1	0.10	0.05	0.26	0.34	0.28	0.56	0.23	0.24	0.19	-0.17	-0.06	-0.58
p value	0.00	0.13	0.01	0.00	0.00	0.03	0.00	0.00	0.00	0.01	0.34	0.00
EWI	0.91	0.96	0.73	0.87	0.94	0.64	0.80	0.89	0.44	0.85	0.92	0.55

Panel C: Volatility and Momentum Portfolio Monthly Returns for a 12-month Holding Period

	All Stocks			Low Volatility			Medium Volatility			High Volatility		
	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004	Aug1982 -Dec2004	Aug1982 -Mar2000	Apr2000 -Dec2004
P1 (Past winners)	1.01	1.05	0.86	0.70	0.74	0.53	0.68	0.78	0.31	1.02	1.04	0.97
P2	0.91	0.98	0.65	0.84	0.92	0.53	0.74	0.86	0.29	0.95	1.04	0.62
P3	0.85	0.94	0.55	0.88	0.93	0.69	0.71	0.85	0.20	0.82	0.92	0.44
P4	0.83	0.92	0.52	0.84	0.87	0.74	0.86	0.93	0.58	0.84	0.95	0.46
P5	0.90	0.95	0.71	0.81	0.86	0.63	0.90	0.94	0.79	0.79	0.90	0.36
P6	0.87	0.92	0.67	0.97	1.01	0.83	0.78	0.87	0.45	0.86	0.95	0.50
P7	0.90	0.98	0.62	0.79	0.92	0.27	0.82	0.92	0.43	0.77	0.88	0.36
P8	0.90	0.94	0.73	0.80	0.88	0.51	0.82	0.89	0.57	0.83	0.90	0.58
P9	0.94	0.95	0.91	0.83	0.86	0.72	0.83	0.92	0.51	0.80	0.87	0.56
P10 (Past losers)	1.00	0.96	1.18	0.99	0.95	1.16	0.88	0.97	0.54	0.92	1.01	0.59
P1-P10	0.00	0.09	-0.32	-0.30	-0.21	-0.64	-0.20	-0.19	-0.23	0.10	0.03	0.38
P10-P1	0.00	-0.09	0.32	0.30	0.21	0.64	0.20	0.19	0.23	-0.10	-0.03	-0.38
p value	0.96	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.48	0.01
EWI	0.91	0.96	0.74	0.84	0.89	0.66	0.80	0.89	0.47	0.86	0.95	0.54

Notes: This table reports the monthly returns for momentum portfolios formed based on past month returns and held for six, nine, 12 months. P1 is the equal-weighted portfolio of 10 percent of the stocks with the highest returns over the previous month, P2 is the equal-weighted portfolio of 10 percent of the stocks with the next highest returns, and so on. The "All Stocks" sample includes all stocks traded on the NYSE and AMEX excluding closed-end funds, ADRs, Real Estate Investment Trusts (REIT), and primes and scores. The volatility of a stock is defined in terms of the standard deviation of excess returns of that stock over the S&P 500 index over a 30 day period prior to the stock formation period. The "High Volatility" subsample comprises 30 percent of the stocks in the "All Stocks" sample with the highest volatility. The "Medium Volatility" subsample comprises 40 percent of the stocks in the "All Stocks" sample with the next highest volatility. The "Low Volatility" subsample comprises 30 percent of the stocks in the "All Stocks" sample with the lowest volatility. "EWI" is the returns on the equal-weighted index of stocks in each sample.

FIGURE 1.

MOMENTUM AND REVERSAL FOLLOWING "LOW VOLUME" DISSEMINATION OF BAD NEWS

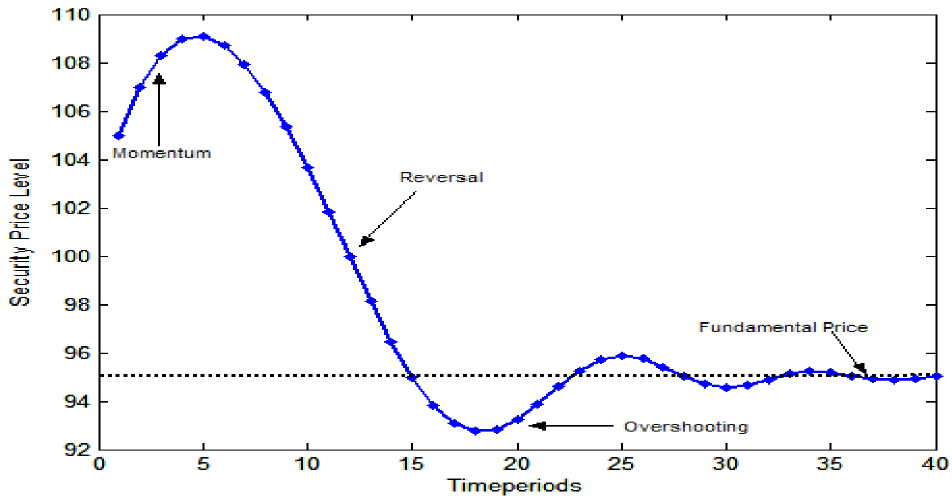

FIGURE 2.

PUBLIC ANNOUNCEMENT OR "HIGH VOLUME" DISSEMINATION OF BAD NEWS