Abstract

Several papers have considered the relevance or quality of earnings by examining its relationship to prices, implicitly assuming that the quality of prices (or the market in which prices are set) remains constant. However, the quality of or noise in prices can vary across firms and over time, and trading pressure beyond what can be justified by correlated information about fundamentals can contribute to such variation. So we relax the assumption that the quality of prices is constant and reconsider the relevance of earnings. We construct a firm-specific measure of speculative intensity based on autocorrelation in daily trading volume adjusted for the amount of information available, and find that speculative intensity has a significant positive impact on returns. However, after controlling for speculative intensity, our results confirm a key result of previous research that earnings numbers still matter but departs from other work that suggests that earnings relevance has declined. We find that the explanatory power of earnings surprises has not declined, the influence of speculative intensity has increased, and so the omission of speculative intensity explains the previously documented decline in earnings relevance. This result is robust to excluding loss observations, which is another potential explanation for previous results.

Keywords: noise in prices; measuring speculation; earnings quality; earnings response coefficients.

*We have benefited from comments and suggestions of several people at seminars and discussions at Rutgers and Georgetown, the 14th Conference on Financial Economics and Accounting at the University of Maryland, and the Washington Area Finance Association Conference, including Bikki Jaggi, Prem Jain, Russell Lundholm, Sundaresh Ramnath, and Rohan Williamson. Special thanks are due to our discussants at the Maryland Conference, Sudhakar Balachandran, and the WAFA Conference, Chris Jones, for very detailed comments. All of the data used in this study are available from public sources cited in the text.

Corresponding author

† The Securities and Exchange Commission disclaims responsibility for any private publication or statement by any SEC employee or Commissioner. This presentation expresses the author’s views and does not necessarily reflect those of the Commission, the Commissioners or other members of the staff.
Abstract

Several papers have considered the relevance or quality of earnings by examining its relationship to prices, implicitly assuming that the quality of prices (or the market in which prices are set) remains constant. However, the quality of or noise in prices can vary across firms and over time, and trading pressure beyond what can be justified by correlated information about fundamentals can contribute to such variation. So we relax the assumption that the quality of prices is constant and reconsider the relevance of earnings. We construct a firm-specific measure of speculative intensity based on autocorrelation in daily trading volume adjusted for the amount of information available, and find that speculative intensity has a significant positive impact on returns. However, after controlling for speculative intensity, our results confirm a key result of previous research that earnings numbers still matter but departs from other work that suggests that earnings relevance has declined. We find that the explanatory power of earnings surprises has not declined, the influence of speculative intensity has increased, and so the omission of speculative intensity explains the previously documented decline in earnings relevance. This result is robust to excluding loss observations, which is another potential explanation for previous results.

Keywords: noise in prices; measuring speculation; earnings quality; earnings response coefficients.

Data Availability: All of the data used in this study are available from public sources cited in the text.
Earnings Quality And Price Quality

I. Introduction
There is considerable empirical research that shows that earnings are relevant for setting prices and that earnings quality affects prices (see e.g. Lev (1989)). This research has implicitly assumed that price quality or the quality of the market in which prices are formed remains constant.\(^1\) Given that many of these empirical analyses in prior research use panel data over long periods, extending over three decades or more, it is important to allow for variation in the level of noise in prices. Speculative intensity or mimicking by traders beyond what is justified by information about fundamentals is one source of noise in prices, and can give rise to volatility in financial markets beyond what is caused by volatility in fundamentals or information (De Long et al., 1990).

Speculative intensity can cause prices to deviate from fundamentals. Conventional wisdom has sometimes suggested that speculative intensity cannot persist, because speculators would incur losses and be arbitraged away. However, recent work has shown this deviation of prices from fundamentals can be sustained when rational participants in the market such as institutional traders have short horizons and cannot successfully employ contrarian strategies to outlast the speculators.\(^2\) Hence speculative intensity can affect prices for long periods of time.

The De Long et al., (1990) and Dow and Gorton (1994) models suggests that speculative intensity can be characterized by traders who mimic other traders for reasons other than correlated information. This suggests that the trading behavior in one period is related to trading behavior in the next period and this can be captured by the autocorrelation in daily volume for a quarter for each stock. But autocorrelation can also occur due to information. We purge the autocorrelation of daily trading volume of such informational effects by regressing it on proxies for the amount of information, such as firm size and the number of firms in an industry (Bhushan, (1989a)). The residual from this regression is termed as SPEC and is our measure of

---

\(^1\) Exceptions are Dontoh, Radhakrishnan and Ronen(2001), who assume that the noise in prices is not constant and therefore choose to first measure ‘true earnings’ and then the quality of earnings directly, i.e. from the deviation of reported earnings from ‘true earnings’, and Aboody, Hughes and Liu (2002), who make assumptions that permit them to estimate the error in prices.

\(^2\) (see, e.g. De Long et al 1990, and Dow and Gorton (1994))
speculative intensity. The first objective of our paper is to show that prices respond not only to earnings news but also to speculative intensity.

There is a related theme prominent in recent accounting literature. Lev and Zarowin (1999) and Francis and Schipper (1999) use annual data and suggest that the relevance of earnings is decreasing over time. Landsman and Maydew (2002) use quarterly data, focus on different market statistics (abnormal volume and return volatility, instead of abnormal returns), and offer a dissenting opinion. All of these studies assume that the quality of prices, or of the market in which prices are set, is constant. If this does not hold and speculative intensity affects prices then – as Francis and Schipper (1999) explicitly suggest -- the evidence on the relevance of earnings is biased towards the conclusion that earnings numbers matter less. This leads us to our second objective, to reexamine the relevance of earnings over time after controlling for speculative intensity.

We first show that SPEC has a cross-sectional and time series pattern consistent with stylized facts, e.g., speculative intensity is higher in high tech industries than in stable industries like insurance and utilities. Further, the market-wide aggregate of SPEC is consistent with Shiller’s Bubble Expectations Index. Then we address our first objective: our results show that the level of speculative intensity in a firm-quarter (as measured by SPEC) is positively related to the absolute value of the cumulative abnormal returns around an earnings announcement. This suggests that including a control for speculative intensity is important in an analysis of price effects of earnings. We also document that including SPEC in a regression of absolute abnormal returns on absolute unexpected earnings shows that the explanatory power of earnings does not decrease over time. Lastly, we show that the effect of speculative intensity on prices is increasing over time.

The structure of this paper is as follows. In Section II we summarize previous work that we draw upon, while in Section III we describe the construction of our SPEC measure. Section IV describes the rest of the data and provides descriptive statistics. Section V presents our main results, and Section VI some additional diagnostic tests. Section VII offers concluding remarks.
II. Related Work and Hypothesis Development

A key question in accounting research is simply whether the earnings number belongs to the common information set used by market participants in setting prices. Empirical research has regressed abnormal returns on unexpected earnings and the coefficient on unexpected earnings has been termed the earnings response coefficient (ERC). It is common in accounting research to estimate the above regression with data spanning 30 or so years (annual data studies such as Hayn [1995], use data even from 1962). Such regressions assume that the quality of prices or markets across firms and over time is constant, and so any differences in ERCs or explanatory power are ascribed to variations in earnings quality. We assume that the quality in prices or more accurately, of the market in which prices are set, varies inversely with the level of speculative intensity. Prices are influenced not only by information but also by fads that lead to speculative intensity.

This argument relies essentially on ideas in De Long et al (1990) and Kyle and Wang (1997). De Long et al construct an example in which there is no fundamental uncertainty (so informational issues are moot) yet the presence of irrational noise traders can create risk. Conventional wisdom before De Long et al (1990) held that irrationality could not persist, as buying high and selling low would cut into trading profits. But De Long et al (1990) showed that such irrational noise traders could persist for long periods if rational traders are risk averse and have short horizons. To drive the irrational traders out of the market the rational traders need to adopt contrarian strategies, e.g. buy when the irrational people are selling. Yet if the rational traders have sufficiently short horizons they may have to cash out before their contrarian strategies begin to bear fruit (e.g. if they are buying when the irrational traders are selling, persistent herding by the latter may keep prices low for very long).

Noise traders who follow a mimicking strategy benefit from the risk that their own participation creates. They make risk averse traders less willing to participate in the market so prices are lower and returns higher, and these higher returns are more likely to be earned by the participating noise traders. Thus there is a positive association between returns and the level of speculative intensity. De Long et al. (1990) also show that if the proportion of irrational noise trading is sufficiently high then even the rational traders will find it optimal to try and predict
how the irrational traders will behave, rather than seeking to be guided in any way by their information about fundamentals.

Dow and Gorton (1994) further show that agents with short horizons decide on whether to participate in the market based on expectations of subsequent traders following them. When a trader purchases a stock because he knows a firm is going to pay out a high dividend, its stock price goes up. With sufficiently long horizons the trader will realize his profits if he either holds the stock till the dividend declaration date, or if some other trader purchases the shares from him. If the trader has a short horizon, and cannot hold the stock till the dividend declaration date, then he would buy the stock in the first place only if he believes that another trader will follow him subsequently. So he realizes some profit – in general regardless of whether he has information about fundamentals -- from the follower who pushes the price up further and helps him complete the roundtrip transaction. If the probability of a trader following the first trader is low, then there is a lower probability that the first trader would trade at all.

Kyle and Wang (1997) show that market structure is not critical to the argument used in this paper. In an imperfectly competitive market in which a market maker sets prices rationally conditional on all public information, they show that even in equilibrium there can be groups of irrational traders who take larger positions than is justified by their information. Their argument does require the existence of some ‘pure’ noise traders who trade for exogenous reasons regardless of costs.

Allen et al (2002) make the point that noise in prices from a mimicking strategy by traders is consistent also with a model of fully rational behavior. The key technical ingredient in their work is the result that the law of iterated expectations does not apply to average beliefs. So in a setting reminiscent of a beauty contest in which agents seek to predict average beliefs as it is average beliefs that determine prices, they tend to weight public information – whether about fundamentals or about anything else – more than they should. This can create the same herding by traders that occurs in De Long et al (1990) even without the assumption of irrationality.

From our perspective the crux of these papers can be summarized as saying that they regard abnormal returns as a function of both unexpected earnings and the degree of mimicking
by irrational investors. We call the parameter governing the relation between returns and SPEC the SPEC Response Coefficient. This leads us to our first hypothesis in the alternate form:

\( H_{A1} \): Speculative intensity affects the absolute value of price changes positively; hence the SPEC Response Coefficient is positive.

The effect of speculative intensity on returns has immediate implications for research related to the relevance of earnings over time. Lev and Zarowin (1999) and Francis and Schipper (1999) have documented that there is a secular decline since the 60s not only in the Earnings Response Coefficient (ERC), but also in the explanatory power of unexpected earnings. Landsman and Maydew (1994) find however in the context of quarterly earnings announcements that the information content of earnings is not decreasing and if at all it is increasing over time. Their metrics of information content are abnormal trading volume and return volatility, which reflect posterior variance and not a change in posterior mean. They find that abnormal trading volume and return volatility have been increasing over time. Information as well as speculative intensity also affect abnormal volume and return volatility. Hence, it is important to separate the effect of information from non-information based trading, regardless of whether information content is defined in terms of mean or variance of posterior returns.

Dontoh et al (2001) make the interesting point that relevance of earnings is decreasing only if the quality of prices is assumed constant across time. If the quality of prices is falling over time, then not accounting for the decrease in the quality of prices, could bias the conclusion about the decline of earnings relevance. Dontoh et al. (2001) then adopt the strategy of developing an estimate of the error in each period’s earnings. Aboody et al (2002) also have a similar starting point that results pertaining to earnings relevance need to be adjusted for possible mispricing by the market, and make assumptions that allow them to estimate the pricing error in each period.

Our strategy in this paper is complementary to that of Dontoh et. al. (2001) and Aboody et al (2002). Instead of estimating the realized error in either earnings or prices, we estimate a parameter governing noise in prices that arises from mimicking by market participants beyond
what is justified by correlated information. It is consistent with a remark in Francis and Schipper (1999), that there may be other reasons (besides a decline in value relevance) why ERCs have declined over time. Specifically Francis and Schipper (1999, page 321) state that

“… Depending on the source of returns volatility, failing to control for it could affect the interpretation of our results. For example, if the absolute amount of value-relevant information in financial statements is (truly) constant through time, but the volatility of market returns is increasing for reasons that cannot be traced to information sources, the explained variation tests will be biased toward the result that relevance is decreasing over time.”

From the above discussion of Francis and Schipper (1999), it is clear that controlling for SPEC (one parameter governing noise in prices) may affect our conclusions about whether the relevance of earnings has declined over time. This leads us to our second hypothesis in the alternate form:

\[ H_{A2} : \text{Value relevance of earnings has not changed over time after controlling for SPEC.} \]

In the next section we focus on the measurement of SPEC (other variables used to test the above hypotheses are defined in Section 4).

**III. Measuring speculative intensity**

Speculative intensity in general can take many forms, for example, it could consist of strictly random behavior (like picking stocks by throwing darts). This strategy will not generate any time series correlation in trading behavior, or any systematic pressure on prices. We ignore this source of speculation a priori, as we believe that the measurement error that this introduces is small and does not vary systematically across stocks or over time. At worst in our tests this would create a bias in favor of the null of no relationship between returns and SPEC. Herding or following fads on the other hand creates serial correlation in trading volume, gives rise to order imbalances and consequently requires price setting market makers to adjust prices in response to such trading pressure. This is the reason we focus on autocorrelation in daily trading volume as a
candidate measure of trading pressure arising from speculative intensity or herding behavior. Prior work on fads has used the change in volume as a measure of herding (Bikhchandani and Sharma, 2000). Other research on trading volume has measured dispersion of beliefs of investors (Bamber (1987), Jain (1988)), and has focused on a different statistic based on trading volume: market-adjusted abnormal volume.

Autocorrelation in daily trading volume could also result from strictly contrarian strategies: buying a lot when most traders appear to be selling, and vice versa. This strategy would however create less pressure on prices, whereas speculative intensity via mimicking creates more pressure on prices. Further, contrarian strategies would preclude a positive association between autocorrelation in daily trading volume and the absolute value of cumulative abnormal returns, so again in a test of Hypothesis 1 it would create a bias only in favor of the null, making our results more conservative. The financial press has suggested that following fads or herding is often a key factor in trading.

The popular literature on day trading has highlighted how easy it has become for the average person to now participate in chat rooms, access market information, and to place a trade. A mantra for day traders has been to follow the behavior of previous traders, in the hope that there are in turn enough traders who will follow them, so that they may quickly complete a roundtrip transaction before the market changes direction. Unlike institutional traders, such day traders by and large only have limited resources to invest in private information acquisition or in gaining access to corporate management. So their primary concern is with minimizing order execution risk within a very short horizon, which also explains why volume begets more volume.

However, the bulk of the market has always been institutional trading, even in the 90s. Why would mimicking or following a fad also be plausible as an equilibrium strategy for institutional investors? Bikhchandani and Sharma (2000) suggest three reasons for institutional herding. First, other investors may have information about the return on the investment and their actions may reveal this information. Second, the incentives provided, to money managers in particular who invest on behalf of other investors, by the compensation schemes and terms of employment may be such that imitation is rewarded. Third, investors may have an intrinsic preference for conformity (Bikchandani and Sharma, 2000, page 3).
Our goal in this paper is to test if noise in markets caused by speculative intensity is important enough to affect conclusions about earnings quality. So we focus on why even institutional traders may herd for reasons other than information. Consider a description of mutual fund managers’ behavior in Hickey (1999):

“… No matter how off-the-wall their valuations or how low (or nonexistent) their profits, all things dotcom have caught fire over the past year. This makes managing a technology sector fund especially tricky, because the managers have to sift through white-hot stocks--some with little or no earnings--to find companies that will grow fast, but won’t blow up in their faces.”

The key idea is that even fund managers at fairly well established fund families feel some pressure to invest in stocks about which they know relatively little. A typical mutual fund manager is faced with a tradeoff between two different risks. The strategy of following the crowd and investing heavily in glamour or fad stocks, even when her information about fundamentals does not always offer much support for these stocks’ prospects, carries the risk that the price rise is a speculative bubble that will burst. However, not following the crowd also means incurring a risk: the risk of being correct but not having one’s competence recognized in time because the bubble does not burst within the investor’s horizon. Given the importance of relative performance evaluation in the mutual fund industry most mutual fund managers and investors have short horizons. This assumption of short horizons plays a key role in De Long et al (1990), Dow and Gorton (1994), and many similar papers in the asset pricing bubbles literature, in generating an incentive for agents to participate in the market only if they expect others to follow on the same side of the market. It also makes more plausible that in some periods the optimal choice of agents such as mutual fund managers is to follow the crowd. So the mimicking strategy is important not only for day traders but also for institutional traders. This is the key in justifying our measure of speculative intensity, which is derived from the autocorrelation in daily trading volume.

While this particular type of speculative intensity gives rise to autocorrelation in volume, it is clear that such autocorrelation can arise also for informational reasons. Beaver (1968) and Bamber (1986, 1987) have shown that there is a significant volume response to earnings announcements, while Jain (1988) shows there is a volume response to a variety of other public
announcements as well. Suppose correlated information about a firm leaks in small doses over a quarter, that by itself could also cause similar autocorrelation. Hence it is important to make a statistical correction for the possible contribution of informational reasons on the autocorrelation in daily trading volume before using it as a measure of speculative intensity.

The information releases need not all be public or available from sources such as the Dow Jones News Retrieval Service. But previous work (e.g. Bhushan (1989a,b)) has suggested proxies for the amount of information available in general about a firm. These include measures of firm size such as market capitalization or total assets, the number of firms in an industry, the number of analysts, or sales or asset growth. Because analyst data is scarce for earlier periods, we limit ourselves to using other proxies. So we define SPEC, our measure of mimicking in the following two-step procedure.

First, for each firm \(i\) and quarter \(q\) we calculate the autocorrelation coefficient \(a_{1,ijq}\) or \(ACC_{ijq}\) from daily trading volume data.\(^3\) Previous work (see, e.g. Ajinkya and Jain (1989)\(^4\)) has suggested that dominance of the first-order autocorrelation in daily trading volume is a salient feature of this time series\(^5\). Each firm should exist in the CRSP database during 1972-2000 and have fiscal quarters that correspond to the calendar quarters. In each quarter there are about 60 trading days, and, we filtered out firm-quarters with less than 25 days to ensure we had enough observations for each autocorrelation parameter estimate. After calculating the autocorrelation coefficient for each firm-quarter, to limit the influence of outliers we further trimmed the data by eliminating the extreme one percent from each tail, resulting in 142,841 firm-quarter autocorrelation coefficients. Using Fisher’s z-transform we examined the significance of each firm quarter autocorrelation coefficient. This entailed dividing each of the autocorrelation coefficients by the standard deviation of the distribution of autocorrelations. The resulting z-scores (over the CRSP universe) range from 0.26 to 23.8, with a mean and median of 6.74 and 6.18 respectively. The first and 99\(^{th}\) percentiles of the z-scores were 0.91 and 17.21 respectively.

\(^3\) We also used the autoregression coefficients from an AR(1) model of daily trading volume with and without an intercept, and replicated all of the tests that follow. Our qualitative conclusions continue to hold.

\(^4\) The primary goal in Ajinkya and Jain (1989) is not to identify the time series properties of individual firms’ daily trading volumes but to refine the market model for volume used in studies of volume reaction to earnings announcements.

\(^5\) We also investigated the autocorrelation properties of daily trading volume in the firm-quarters that had at least 25 observations. In an overwhelming preponderance of cases the first lag was the most important.
So the overwhelming preponderance of z-scores is significantly positive, suggesting a priori a strong possibility that mimicking behavior is important.

We then regress these autocorrelation coefficients on proxies for the amount of information available about each firm, \( \ln(TA_{iq}) \), where \( TA \) is the total assets at the end of each quarter, and \( SIC_{iq} \), the number of firms in an industry. We define the corresponding residual from the regression as \( SPEC_{iq} \), the measure of speculative intensity or non-information based trading, in each given firm-quarter. So we have, in the second step:

\[
ACC_{iq} = \beta \times \ln(TA_{iq}) + \gamma \times SIC_{iq} + SPEC_{iq} \tag{1}
\]

The adjusted \( R^2 \) for the above specification was 86%. We also estimate this equation by including (a) an intercept, (b) sales instead of assets, (c) both sales and assets (d) including a term for sales growth, (e) firm fixed effects, and (f) firm fixed effects along with a correction for autocorrelation in error terms. The correlations between the \( SPEC \) variable calculated from equation 1 and the \( SPEC \) variable calculated from the variations of equation 1, were all significantly positive and ranged from 0.41 to 0.98. Our qualitative results are robust to using \( SPEC \) from the variations of equation (1).

**Properties of SPEC**

Since \( SPEC \) is simply the residual term in the regression model of equation (1) above, the grand mean (for all firm-quarters in the above regression) is close to zero by construction. So a \( SPEC \) value equal to the mean does not mean zero speculation via mimicking. Rather it is the *long run market average level of speculative intensity* (across all firm-quarters over the entire 29-year period from 1972 to 2000). An individual firm-quarter’s \( SPEC \) is a *market-adjusted number* measuring the abnormal degree of speculative intensity in a particular stock beyond what is justified by information about that stock.

---

\(^6\) We also considered using the number of news stories in the Dow Jones News Retrieval Service (used by Rajgopal et al), but decided not to do so because, it caused a sharp reduction in sample size.

\(^7\) It is exactly zero when we use an intercept.
There are clearly several alternative econometric approaches to calculating SPEC, even given the model in (1), which could be more relevant to other applications. Instead of assuming fixed coefficients we could allow coefficients to vary by quarter. In this case the mean value of SPEC across all firms would be zero in each quarter. We could also use out of sample residuals for SPEC. But since a goal of this paper is to make a comparison over three decades of data, we use the strategy defined above.

To gain some confidence that SPEC does indeed capture this abnormal degree of mimicking by traders in a firm’s stock beyond what is justified by the amount of information available about a firm, we first examined the average SPEC over each year and across various SIC codes. This is shown in Table 1, in which 30 industries with the highest and lowest SPEC values are presented. The fifteen industries on the left side of the table include many stable and regulated industries, which are believed to be a less speculative group e.g., utilities. The fifteen industries on the right side of the table are those that had the highest SPEC values and are generally perceived as being more speculative, e.g., hi-tech industries. We also calculated mean SPEC for the 3-digit SIC codes of the high and low technology industries that were identified by Francis and Schipper (1999). We find that the high tech industry SPEC is significantly higher than the mean low-tech industry SPEC and with a p-value of less than 0.001.

The closest measure of speculative intensity found in previous research is the Bubble Expectations Index in Shiller (1999). He surveyed the attitudes of institutional investors twice a year, and then constructed an index by aggregating responses to questions dealing with whether an institutional investor felt stock prices were unstable, and would increase only in the short run. This Bubble Expectations Index can be interpreted either as the degree to which the survey respondents feel investors should be cautious following the date of the survey or as the degree to which they feel there has been an unjustifiable price rise in the immediately preceding period. This index is computed twice a year.

To the extent that the Bubble Expectations Index is trying to measure behavior not justified by information its goal is to capture roughly what we try to do with SPEC. However Shiller (1999)’s index is an aggregate measure for the entire market while we calculate SPEC for each firm quarter. To compare the mean SPEC for all firms for each half-year with the Bubble
Expectations Index we first standardize and center both series. The transformed series are depicted in Figure 1, which clearly reveals a strong positive correlation. The correlation coefficient is 0.59 and has a two-tailed p-value of less than 0.01. This gives further validation to our use of SPEC as a measure of speculative intensity.

IV. Sample, Constructed Variables and Descriptive Statistics

Sample

The sample for our empirical investigation is drawn from the COMPUSTAT quarterly tapes and the CRSP daily tapes for the period of 1972-2000. To remain in the sample firms had to have SPEC quarterly values, which required volume data for at least 25 trading days in a firm quarter, earnings and earnings announcement information for current and previous quarters, price per share at the end of the previous quarter, from two days following the preceding quarterly announcement and till one day following the current announcement. After trimming 1% extreme values from each tail, our final sample resulted in 142,841 observations.

Collins et. al. (1997) suggests that the increasing proportion of losses over time would in itself be a candidate explanation for the declining relevance of earnings, because losses do not have any information content. Hence, in the primary results we report in this paper we drop all loss observations and estimate all our regressions only on observations with positive earnings. This resulted in a sample of 118,666 observations.  

Dependent Variable

The cumulative abnormal returns for firm \(i\) in quarter \(q\) (denoted as \(\text{CAR}_{iq}\)) is the sum of the daily abnormal returns for the period beginning two days after the previous quarterly earnings announcement and ending one day after the current announcement. The abnormal return is defined as the firm return less an equally weighted market return from the corresponding size decile calculated over all firms in the CRSP tapes. \(\text{ABSCAR}_{iq}\) denotes the absolute value of the cumulative abnormal returns (\(\text{CAR}_{iq}\)). This measure is similar to the one employed by Freeman and Tse (1992).

Independent Variables

\[\text{8 The results are qualitatively robust to including the loss observations.}\]
Similar to Freeman and Tse (1992) we calculated unexpected earnings (UE) as follows:

$$UE_{i,q} = \frac{(E_{i,q} - E_{i,q-4})}{P_{iq}}$$

Where $E_{i,q}$ is the actual quarterly earnings per share before extraordinary items for firm $i$ quarter $q$, and $P_{iq}$ is the price per share of firm $i$’s common stock on the last day of quarter $q$. $ABSUE_{i,q}$ is the absolute value of unexpected earnings for firm $i$ and quarter $q$. SPEC as defined in the previous section is the residual term from equation (1).

Descriptive statistics

Tables 2 and 3 contain descriptive statistics and correlations of our primary variables. All correlations in the table have p-values less than 0.001. Examination of SPEC reveals that SPEC values range between -0.53 and 0.52 with a mean of 0.05. They are also significantly positively correlated with the autocorrelation in daily volume (ACC$_{i,q}$) before we control for the amount of information (using firm size and number of firms in a 3 digit SIC). We find that sales and assets are highly correlated and this suggests why using either or both these variables as proxies for information yields similar values of SPEC. SPEC values are positively and significantly correlated with both the signed and the absolute values of CAR, and UE.

To the extent that mimicking causes volatility in prices and returns, we should expect SPEC to be positively correlated with such measures of volatility. Since prices are not stationary and we have data over a very long period we examine the variance of three different return volatility measures: VARRET (variance of raw daily returns for each quarter), VARADJRET1 (variance of daily returns for each quarter adjusted for value-weighted market returns), and VARADJRET2 (variance of daily returns for each quarter adjusted for equally-weighted market returns). What is most noteworthy in the correlation table is that despite ACC (raw autocorrelation in daily trading volume) and SPEC being significantly positively correlated, our correction for the amount of information has some bite. The correlation between the three measures of return volatility and ACC are negatively correlated, but they are all positively correlated with SPEC. If we think of any autocorrelation in daily volume as a measure of trading pressure, ACC which includes the effect of information besides non-informational trading, has the effect of reducing return volatility (consistent with a step or spike in returns after news) while
SPEC which isolates the non-informational trading pressure results in increased volatility. Previous work has not tried to disentangle the two effects.

The descriptive statistics of Cumulative Abnormal Returns and Unexpected Earnings are broadly consistent with what other papers using quarterly data have found (see, e.g. Freeman and Tse (1992), whose variable definitions are the closest to ours), despite our using a much longer sample period. Signed and absolute cumulative returns are positively related to signed and absolute unexpected earnings at magnitudes that are comparable with prior research.

V. Empirical Design and Results
To test the effect of SPEC on prices we estimate the following regression equation

\[
ABSCAR_{iq} = \beta_0 + \beta_1 \times ABSUE_{iq} + \beta_2 \times SPEC_{iq} + \epsilon_i
\]  

(2)

We need to use absolute values for Cumulative Abnormal Returns and Unexpected Earnings because while SPEC captures speculative intensity beyond what is justified by information, it does not distinguish between buying pressure and selling pressure generated by speculative intensity. For the case of buying pressure the price movement is positively related to trading pressure; for selling pressure, negatively related. Hence we partition by the sign of CAR, and test if for positive (negative) CAR, CAR is positively (negatively) related to SPEC. This is an attempt to separate the buying and selling pressure on increasing and decreasing returns, respectively. If buying pressure is related to increasing returns then SPEC will be positively related to CAR for positive CAR. Further, if selling pressure is related to negative returns, then SPEC will be negatively related to CAR for negative CAR. Since SPEC is unrelated to information we do not partition by the sign of the unexpected earnings. In the above regression we control for the effect of information on returns by way of absolute unexpected earnings. Hypothesis 1 suggests that SPEC is positively related to ABSCAR_{iq} and the SPEC Response Coefficient \( \beta_2 \) should be positive.

Table 4 summarizes our regression results related to Hypotheses 1. Column A shows that the regression results of absolute CAR on absolute UE, and confirms that the earnings numbers
matter as has been shown in previous papers (Francis and Schipper, 1999). We also performed
the same regression on signed CAR and signed UE and the level of earnings and obtained similar
results. In contrast to long window studies of annual data the adjusted $R^2$ is smaller using
quarterly data.

Column B is one test of Hypothesis 1, and shows that speculative intensity (SPEC) is
significantly positively associated with returns (absolute CAR). The ERC drops from 0.67 in
Column A to 0.62 in Column B. SPEC itself has a coefficient of 0.08 which is very significant (p
value < 0.0001). Adjusted $R^2$ increases to 4% compared with 2% in column A. Taken together
this tells us that speculative intensity is an important explanatory variable for returns, and that it
is important to control for it before drawing conclusions about ERCs. Column C and D show
the results for estimating equation 2 using signed CAR and signed unexpected earnings, whereas
SPEC remains unsigned. We find that SPEC is positively related to CAR when CAR is positive
and negatively related to CAR when CAR is negative. This further supports hypothesis 1 and
shows that speculative intensity affects prices. We also test whether the effect of speculative
intensity on returns is symmetric between price increases and price decreases, and find that the
effect on positive returns is significantly larger in absolute value than the effect on negative
returns (F value = 369.55, p value < 0.0001).

To test whether earnings relevance is decreasing over time (hypothesis 2), we first
partition our sample by year, and estimate two equations for each year. First we estimate a
regression of absolute UE on absolute CAR to replicate Francis and Schipper (1999), except that
we use absolute values instead of signed values. Next we estimate equation (2), which is a
regression of absolute UE and SPEC on absolute CAR by year. The results are shown in Table 5.
The simple absolute CAR on absolute UE results show a decline of the adjusted $R^2$, and a
relatively flat trend of the ERC coefficient across the years. The adjusted $R^2$ of estimating
equation (2) on the other hand is relatively flat over time.
To test whether the adjusted $R^2$ is declining over time we regress time (year less 1971) on the adjusted $R^2$. This is similar to the tests employed by Francis and Schipper (1999). The following equation is estimated.

$$\text{Adjusted } R^2_{y} = \beta_0 + \beta_1 \times y + \varepsilon_i$$ (3)

where $y$ is the calendar year (less 1971) corresponding to the year of the underlying estimated equation. Hypothesis 2 suggests that when SPEC is included in the model $\beta_1$ should not be different from zero. We find similar to Francis and Schipper (1999) that adjusted $R^2$ is declining over time if SPEC is not included in the returns regression (coefficient = -0.0006, p value = 0.08). However, when SPEC is included in the returns regression there is no relation between adjusted $R^2$ and time (coefficient = 0.0002, p value = 0.50). This suggests that earnings relevance is not declining over time. However there are two variables in equation (2), absolute UE and SPEC, and the lack of decline in adjusted $R^2$ over time could occur due to either of the two variables. Hence we calculate the partial adjusted $R^2$ for each variable from equation (2) and regress the partial adjusted $R^2$ on time. We find that the partial $R^2$ due to unexpected earnings is now not significant (coefficient = -0.0005, p value = 0.12) contrary to the findings of Francis and Schipper (1999) and the partial $R^2$ due to SPEC is significantly increasing over time (coefficient = 0.0008, p value = 0.03). This result supports hypothesis 2 that earnings relevance is not declining over time after controlling for speculative intensity which contributes to noise in prices.

VI. Further Analysis and Sensitivity Checks

Related to specification

We list below the various additional checks we implemented to examine sensitivity of our results to changes in specification and experimental design.

(a) We use White’s (1980) consistent standard errors to control for heteroskedasticity in the error terms of equations 1, 2 and 3. Our results are qualitatively similar to those reported. For example, in Table 4 column B, t statistics for OLS (reported) results for SPEC are t

---

9 We regress adjusted $R^2$ on time and also calculate partial adjusted $R^2$. In the limit using $R^2$ (Francis and Schipper, 1999) is the same as using adjusted $R^2$. 

16
value=52.25, p value < 0.0001. For the same column, White’s (1980) consistent t statistics for SPEC are, t value =30.99, and p-value < 0.0001.

(b) To test for a more general monotone relation between absolute CAR, absolute UE and SPEC we rank the three variables and estimate a rank regression. Rank of SPEC is significantly positively related to Rank of CAR (Coefficient = 0.135, t statistic = 47.0 and p value < 0.001) suggesting that irrespective of functional form, speculative intensity affects returns.

(c) In addition to using a continuous value of SPEC, we also create a dummy variable defined as SPECDUMMY. SPEC for all firm quarters is ranked based on their values and divided into three equal fractiles. The SPEC groups were coded as 0 for low SPEC and 1 for high SPEC, and we drop the middle group. Our results shown in Table 4 are robust to using the dummy variable instead of a continuous variable for SPEC. The coefficient for SPECDUMMY is significant and positively related with absolute returns (coefficient = 0.0396, t statistic = 47.87 and p value < 0.0001).

(d) We introduce an interaction term in equation (2) as a specification check. We find that the interaction term between SPEC and absolute unexpected earnings is not significant (coefficient = 0.0747, t statistic = 1.06, p value = 0.288). The coefficient on SPEC is however significant and positive (coefficient = 0.0826, t statistic = 52.29, and p value < 0.001). We also ran the same regression replacing SPEC with ACC (the raw autocorrelation in daily trading volume) and an interaction term between it and UE, and that interaction term was significantly positive. Note that we transform ACC by adjusting for proxies for the amount of information to create SPEC. These results with different interaction terms are consistent with our interpretation of SPEC, as the effect of mimicking beyond what is justified by correlated information.

(e) We split the sample into big and small firms to test whether SPEC is related to returns for both sets of firms. Smaller firms have on average less information available about them, and – if the underlying fundamental uncertainty is the same – this can increase speculative opportunities. This should lead to a higher coefficient on SPEC for smaller firms. We define big firms as those firms with total assets greater than the sample median, and small firms as
those firms with total assets less than the sample median.\(^{10}\) We find that SPEC is positively related to returns for both big (coefficient = 0.053, t statistic = 24.39, p value <0.0001) and small firms (coefficient = 0.071, t statistic = 25.30, p value < 0.0001). We also find that the SPEC coefficient is significantly higher for small firms than for big firms.

(f) Francis and Schipper (1999) investigate whether earnings relevance is the same for high tech versus low tech firms. We split the sample based on the definition of high tech and low tech utilized by Francis and Schipper (1999) and estimate equation 2 to test whether SPEC is related to absolute returns for both high and low tech firms. We find that SPEC is positively related to high tech (coefficient = 0.085, t statistic = 16.95, p value < 0.0001) and to low tech (coefficient = 0.069, t statistic = 12.52, p value < 0.0001) firms returns. Further, the relation between SPEC and absolute returns is significantly higher for high tech firms than for low tech firms (F value = 2.07 and p value = 0.038).

(g) In our main tests the event window used to calculate CAR stretches from the previous earnings announcement to the current earnings announcement. Prior research has also used a narrow announcement window of 3 days around the earnings announcement (Landsman and Maydew (2002)). We estimated the regressions in Table 4 using this narrow announcement window. Our results are very similar to those reported in Table 4, however the adjusted R\(^2\) is much smaller.

(h) The event window has been calculated as the number of days from two days after the earnings announcement of quarter (t-1) to one day after the earnings announcement of the current quarter. This means the period over which CAR is calculated is different for different firm quarters because firms do not announce earnings at the same number of days after the end of the quarter, each quarter. Many firms miss their earnings announcements due to unusual circumstances and obtain extensions from the SEC. This yields a distribution of number of days in the event window, with a mean number of days as 90.33. The minimum number of days is 3, and the maximum number of days is 528, and the mode is 90 days. To reduce the effect of outliers in the event window we truncate the data used in the tests to the 5\(^{th}\) and 95\(^{th}\) percentile of the number of days distribution. This deletes 11,549 observations.

\(^{10}\) We also define big firms as those in the top third of total asset value and small firms as those in the bottom third
Our results in Table 4 are robust to this alternate sample and SPEC is positively and significantly related to Absolute CAR (coefficient 0.0844, t statistic = 51.01 and p value < 0.0001).

**Sensitivity checks**

(a) We estimate equation (1) with an intercept to test whether inclusion of an intercept affects our results. All our results are robust to calculating SPEC using an intercept. The SPEC variable is highly correlated (0.81, p value < 0.0001) with the variable used in Table 4.

(b) We substitute sales instead of assets as a measure of firm size to proxy for the amount of information existing about a firm. We also add sales as an additional variable to assets as two proxies for firm size. Our results from estimating equation 3 remain robust to calculating SPEC in these alternate ways. The two SPEC measures are correlated (0.90 and 0.98, p values < 0.0001) with the SPEC measure used in Table 4.

(c) Lakonishok, Shleifer and Vishny (1994) suggest that investors follow growth stocks more than other stocks. This could be the result of greater amount of information available for such growth stocks. Hence we include a sales growth variable to proxy for amount of information when estimating equation 2 and calculating SPEC. Our results are robust to this alternate calculation of SPEC. The SPEC variable is highly correlated (0.98, p value < 0.0001) with the variable used in Table 4.

(d) Since equation (1) is estimated using a panel of cross section and time series observations, it is necessary to control for firm specific fixed effects. We include a dummy variable for each firm as a firm-specific fixed effect and calculate SPEC after controlling for such fixed effects. Equation (1) has as a regressor firm size which is correlated over time leading to time dependence in the error term. To control for such time dependence we also include an AR (1) term correction for the residuals in addition to the firm-specific fixed effects when calculating SPEC. Our results in equation 3 (Table 4 column B) are robust to both these alternate calculations of SPEC. SPEC is positive and significant (coefficients 0.07, 0.03 and
t statistics 37.24, 14.42 and p value < 0.001 respectively) for the two alternate definitions of SPEC.

(e) For the 90s where we also have substantial data on number of analysts, we added a variable (number of analysts, as reported on I/B/E/S) as a proxy for information to equation (1) and recalculated SPEC. This definition of SPEC is highly correlated with the variable that is used in our main tests (correlation coefficient = 0.95, p-value <<0.0001). Our results for estimating equation (2) are robust to using this alternate definition of SPEC.

(f) For the 90s we also calculate SPEC for firms belonging to indices representing highly speculative sectors such as biotech and information technology firms, and contrasted these with the SPEC measures for firms in a low-speculation sector, the Dow Jones Utility Index. The SPEC measures for the former were significantly higher than for the latter, confirming that SPEC does capture what we want it to capture.

VII. Concluding remarks

The primary purpose of this paper is to show that it is important to control for speculative intensity and its effect on returns before drawing conclusions with respect to the effect of earnings on returns. Our argument is in two parts. First, we document that our measure of speculative intensity, SPEC, does affect returns. Second we show that adding SPEC can affect our conclusions about earnings relevance: our results show that relevance of accounting has not decreased over time. Price quality has declined over time.

So speculative intensity or herding beyond what is justified by information offers a partial explanation of the results in previous work suggesting that earnings numbers may have lost their relevance. Our methodological contribution in this paper has been to show how speculative intensity can be measured. We believe this is of independent interest to capital market researchers.
REFERENCES


### TABLE 1
Mean SPEC values grouped by four-digit SIC codes

<table>
<thead>
<tr>
<th>SIC</th>
<th>SIC Description</th>
<th>Low Speculation</th>
<th>SIC</th>
<th>SIC Description</th>
<th>High Speculation</th>
</tr>
</thead>
<tbody>
<tr>
<td>6021</td>
<td>NATIONAL COMMERCIAL BANKS</td>
<td>4009 (0.26)</td>
<td>1040</td>
<td>GOLD AND SILVER ORES</td>
<td>688 0.18</td>
</tr>
<tr>
<td>6111</td>
<td>FEDERAL CREDIT AGENCIES</td>
<td>160 (0.25)</td>
<td>3825</td>
<td>ELEC MEAS &amp; TEST INSTRUMENTS</td>
<td>948 0.19</td>
</tr>
<tr>
<td>6022</td>
<td>STATE COMMERCIAL BANKS</td>
<td>3102 (0.23)</td>
<td>2250</td>
<td>KNITTING MILLS</td>
<td>209 0.19</td>
</tr>
<tr>
<td>6035</td>
<td>SAVINGS INSTN, FED CHARTERED</td>
<td>1548 (0.21)</td>
<td>3559</td>
<td>SPECIAL INDUSTRY MACHY, NEC</td>
<td>1036 0.19</td>
</tr>
<tr>
<td>6036</td>
<td>SAVINGS INSTN, NOT FED</td>
<td>780 (0.17)</td>
<td>2451</td>
<td>MOBILE HOMES</td>
<td>253 0.20</td>
</tr>
<tr>
<td>6331</td>
<td>FIRE, MARINE, CASUALTY INS</td>
<td>2139 (0.16)</td>
<td>2835</td>
<td>IN VITRO, IN VIVO DIAGNOSTICS</td>
<td>647 0.20</td>
</tr>
<tr>
<td>6321</td>
<td>ACCIDENT &amp; HEALTH INSURANCE</td>
<td>203 (0.14)</td>
<td>8071</td>
<td>MEDICAL LABORATORIES</td>
<td>300 0.20</td>
</tr>
<tr>
<td>4412</td>
<td>DEEP SEA FRN TRANS-FREIGHT</td>
<td>162 (0.14)</td>
<td>3845</td>
<td>ELECTROMEDICAL APPARATUS</td>
<td>1327 0.21</td>
</tr>
<tr>
<td>4911</td>
<td>ELECTRIC SERVICES</td>
<td>1414 (0.10)</td>
<td>3844</td>
<td>X-RAY &amp; RELATED APPARATUS</td>
<td>282 0.21</td>
</tr>
<tr>
<td>6421</td>
<td>SURETY INSURANCE</td>
<td>362 (0.08)</td>
<td>3576</td>
<td>NON-OPERATING</td>
<td>995 0.21</td>
</tr>
<tr>
<td>4931</td>
<td>ELECTRIC &amp; OTHER SERV COMB</td>
<td>997 (0.07)</td>
<td>9995</td>
<td>ESTABLISHMENTS</td>
<td>174 0.21</td>
</tr>
<tr>
<td>5051</td>
<td>METALS SERVICE CENTERS-WHSL</td>
<td>272 (0.07)</td>
<td>3843</td>
<td>DENTAL EQUIPMENT &amp; SUPPLIES</td>
<td>171 0.22</td>
</tr>
<tr>
<td>6141</td>
<td>PERSONAL CREDIT INSTITUTIONS</td>
<td>421 (0.05)</td>
<td>8731</td>
<td>COML PHYSICAL, BIOLOGCL RESH</td>
<td>352 0.24</td>
</tr>
<tr>
<td>4922</td>
<td>NATURAL GAS TRANSMISSION</td>
<td>324 (0.05)</td>
<td>3575</td>
<td>COMPUTER TERMINALS</td>
<td>273 0.24</td>
</tr>
</tbody>
</table>

This table presents the mean of SPEC grouped by four-digit SIC codes and the following variables: (1) selected SIC CODES (SIC codes were selected after calculating the mean of SPEC of each SIC code and eliminating industries with less than 200 firm-quarter observation. The 15 industries with the highest and lowest SPEC values are presented in this table).

(2) SPEC values where SPEC\(_{iq}\) is the residual term calculated from the following regression:

\[
\text{ACC}_{iq} = \beta \times \ln(\text{TA}_{iq}) + \gamma \times SIC_{iq} + SIC\_{3iq} + SPEC_{iq}
\]

where: ACC\(_{iq}\) is the autocorrelation coefficient from daily trading volume data, TA is the total assets, SIC\(_{3iq}\) is the number of firms in an industry, and the corresponding residual, is the measure of speculative intensity or non-information based trading, in each given firm i-quarter q.
TABLE 2
Descriptive Statistics 1972-2000

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACC</td>
<td>118,666</td>
<td>0.60</td>
<td>0.19</td>
<td>0.63</td>
<td>0.08</td>
</tr>
<tr>
<td>SPEC</td>
<td>118,666</td>
<td>0.04</td>
<td>0.21</td>
<td>0.06</td>
<td>-0.53</td>
</tr>
<tr>
<td>CAR</td>
<td>118,666</td>
<td>0.03</td>
<td>0.17</td>
<td>0.02</td>
<td>-0.57</td>
</tr>
<tr>
<td>ABSCAR</td>
<td>118,666</td>
<td>0.13</td>
<td>0.12</td>
<td>0.10</td>
<td>0.00</td>
</tr>
<tr>
<td>EPS</td>
<td>118,666</td>
<td>0.32</td>
<td>1.32</td>
<td>0.22</td>
<td>0.00</td>
</tr>
<tr>
<td>UE</td>
<td>118,666</td>
<td>0.01</td>
<td>0.02</td>
<td>0.00</td>
<td>-0.31</td>
</tr>
<tr>
<td>ABSUE</td>
<td>118,666</td>
<td>0.01</td>
<td>0.02</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>SALES</td>
<td>118,666</td>
<td>315.26</td>
<td>1,016.00</td>
<td>57.61</td>
<td>0.01</td>
</tr>
<tr>
<td>TA</td>
<td>118,666</td>
<td>2,368.00</td>
<td>11,505.00</td>
<td>252.50</td>
<td>1.44</td>
</tr>
</tbody>
</table>

This table presents the descriptive statistics for our final sample. The sample includes companies with positive earnings, valid SPEC values and other data constraints as described in section 5 of the paper.

CAR<sub>iq</sub> is the sum of the daily abnormal returns for firm i quarter q for the period beginning two days after the previous quarterly earnings announcement and ending one day after the current announcement.

UE<sub>iq</sub> is calculated as

\[
UE_{iq} = (E_{iq} - E_{i,q-4}) / P_{i,q-1}
\]

Where \(E_{iq}\) is the actual quarterly earnings per share for firm i quarter q, and \(P_{i,q-1}\) is the price per share of firm i’s common stock on the last day of quarter q-1.

SPEC<sub>iq</sub> is the residual term calculated from the following regression:

\[
ACC_{iq} = \beta \ln(TA_{iq}) + \gamma SIC_{iq} + SPEC_{iq}
\]

where ACC<sub>iq</sub> is the autocorrelation coefficient from daily trading volume data,

TA is the total assets, and

SIC<sub>iq</sub> is the number of firms in an industry, and the corresponding residual

SPEC<sub>iq</sub> is the measure of speculative intensity or non-information based trading, in each given firm i quarter q.


<table>
<thead>
<tr>
<th></th>
<th>ACC</th>
<th>SPEC</th>
<th>CAR</th>
<th>ABSCAR</th>
<th>EPS</th>
<th>UE</th>
<th>ABSUE</th>
<th>SALES</th>
<th>TA</th>
<th>VARRET</th>
<th>VARADJRET1</th>
<th>VARADJRET2</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACC</td>
<td>1</td>
<td>0.568</td>
<td>0.016</td>
<td>0.020</td>
<td>0.031</td>
<td>-0.003</td>
<td>-0.054</td>
<td>0.275</td>
<td>0.187</td>
<td>-0.077</td>
<td>-0.091</td>
<td>-0.099</td>
</tr>
<tr>
<td>SPEC</td>
<td>0.518</td>
<td>1</td>
<td>0.084</td>
<td>0.158</td>
<td>-0.065</td>
<td>0.059</td>
<td>0.078</td>
<td>-0.163</td>
<td>-0.202</td>
<td>0.191</td>
<td>0.182</td>
<td>0.180</td>
</tr>
<tr>
<td>CAR</td>
<td>0.012</td>
<td>0.073</td>
<td>1</td>
<td>0.292</td>
<td>-0.005</td>
<td>0.160</td>
<td>0.068</td>
<td>-0.028</td>
<td>-0.015</td>
<td>0.130</td>
<td>0.129</td>
<td>0.128</td>
</tr>
<tr>
<td>ABSCAR</td>
<td>0.008</td>
<td>0.146</td>
<td>0.202</td>
<td>1</td>
<td>-0.030</td>
<td>0.083</td>
<td>0.130</td>
<td>-0.077</td>
<td>-0.051</td>
<td>0.263</td>
<td>0.259</td>
<td>0.258</td>
</tr>
<tr>
<td>EPS</td>
<td>0.137</td>
<td>-0.261</td>
<td>-0.019</td>
<td>-0.128</td>
<td>1</td>
<td>0.039</td>
<td>0.016</td>
<td>0.049</td>
<td>0.049</td>
<td>-0.052</td>
<td>-0.052</td>
<td>-0.052</td>
</tr>
<tr>
<td>UE</td>
<td>0.007</td>
<td>0.080</td>
<td>0.225</td>
<td>0.049</td>
<td>0.156</td>
<td>1</td>
<td>0.589</td>
<td>-0.016</td>
<td>-0.013</td>
<td>0.105</td>
<td>0.104</td>
<td>0.105</td>
</tr>
<tr>
<td>ABSUE</td>
<td>-0.088</td>
<td>0.103</td>
<td>0.059</td>
<td>0.124</td>
<td>-0.066</td>
<td>0.359</td>
<td>1</td>
<td>-0.040</td>
<td>-0.033</td>
<td>0.202</td>
<td>0.203</td>
<td>0.205</td>
</tr>
<tr>
<td>SALES</td>
<td>0.407</td>
<td>-0.372</td>
<td>-0.070</td>
<td>-0.151</td>
<td>0.422</td>
<td>-0.046</td>
<td>-0.140</td>
<td>1</td>
<td>0.566</td>
<td>-0.100</td>
<td>-0.102</td>
<td>-0.107</td>
</tr>
<tr>
<td>TA</td>
<td>0.388</td>
<td>-0.522</td>
<td>-0.081</td>
<td>-0.173</td>
<td>0.454</td>
<td>-0.082</td>
<td>-0.192</td>
<td>0.865</td>
<td>1</td>
<td>-0.069</td>
<td>-0.070</td>
<td>-0.074</td>
</tr>
<tr>
<td>VARRET</td>
<td>-0.069</td>
<td>0.356</td>
<td>0.127</td>
<td>0.330</td>
<td>-0.383</td>
<td>0.080</td>
<td>0.235</td>
<td>-0.457</td>
<td>-0.519</td>
<td>1</td>
<td>0.997</td>
<td>0.995</td>
</tr>
<tr>
<td>VARADJRET1</td>
<td>-0.097</td>
<td>0.347</td>
<td>0.127</td>
<td>0.334</td>
<td>-0.388</td>
<td>0.075</td>
<td>0.236</td>
<td>-0.486</td>
<td>-0.539</td>
<td>0.991</td>
<td>1</td>
<td>0.999</td>
</tr>
<tr>
<td>VARADJRET2</td>
<td>-0.130</td>
<td>0.340</td>
<td>0.124</td>
<td>0.335</td>
<td>-0.386</td>
<td>0.073</td>
<td>0.239</td>
<td>-0.514</td>
<td>-0.559</td>
<td>0.981</td>
<td>0.994</td>
<td>1</td>
</tr>
</tbody>
</table>

This table presents the correlation between select variable for our final sample. All correlations are significant, and have p-values less than 0.0001. The sample includes companies with positive earnings, valid SPEC values and other data constraints as described in section 5 of the paper.

**CAR**<sub>iq</sub> is the sum of the daily abnormal returns for firm i quarter q for the period beginning two days after the previous quarterly earnings announcement and ending one day after the current announcement.

**UE**<sub>iq</sub> is calculated as  
\[ UE_{iq} = \left( E_{iq} - E_{i,q-4} \right) / \left( P_{i,q-1} \right) \]

Where \( E_{iq} \) is the actual quarterly earnings per share for firm i quarter q, and \( P_{i,q-1} \) is the price per share of firm i’s common stock on the last day of quarter q-1.

**SPEC**<sub>iq</sub> is the residual term calculated from the following regression:

\[ ACC_{iq} = \beta \times \ln(TA_{iq}) + \gamma \times SIC3_{iq} + SPEC_{iq} \]

Where **ACC**<sub>iq</sub> is the autocorrelation coefficient from daily trading volume data,

**TA** is the total assets, and

**SIC3<sub>iq</sub>** is the number of firms in an industry, and
$SPEC_{iq}$, is the corresponding residual and is a measure of speculative intensity or non-information based trading, in each given firm i quarter q.

VARRET = Variance of raw daily returns for each quarter;

VARADJRET1 = Variance of daily returns for each quarter adjusted for value-weighted market returns

VARADJRET2 = Variance of daily returns for each quarter adjusted for equally-weighted market returns
TABLE 4
Regression of signed and absolute cumulative abnormal returns on signed and absolute unexpected earnings and SPEC.

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>Absolute CAR</th>
<th>Positive CAR</th>
<th>Negative CAR</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Independent Variables</strong></td>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>Absolute value of Unexpected Earnings</td>
<td>0.67</td>
<td>0.62</td>
<td>45.11***</td>
</tr>
<tr>
<td>Unexpected Earnings</td>
<td>0.66</td>
<td>0.25</td>
<td>35.48***</td>
</tr>
<tr>
<td>Speculative Intensity</td>
<td>0.08</td>
<td>0.11</td>
<td>-0.05</td>
</tr>
<tr>
<td>Adjusted R-Square</td>
<td>0.02</td>
<td>0.04</td>
<td>0.05</td>
</tr>
</tbody>
</table>

We report the coefficient estimates for the following regressions, run for the period of 1972-2000.

\[
CAR_{iq} = \beta_0 + \beta_1 UE_{iq} + \beta_2 SPEC_{iq} + \beta_3 (UE_{iq} \times SPEC_{iq}) + \varepsilon_{iq}
\]

Where \( CAR_{iq} \) is the sum of the daily abnormal returns for firm i quarter q for the period beginning two days after the previous quarterly earnings announcement and ending one day after the current announcement. \( UE_{iq} \) is calculated as

\[
UE_{iq} = (E_{iq} - E_{i,q-4}) / P_{i,q-1}
\]

Where \( E_{iq} \) is the actual quarterly earnings per share for firm i quarter q, and \( P_{i,q-1} \) is the price per share of firm i’s common stock on the last day of quarter q-1.; \( SPEC_{iq} \) is the residual term calculated from the following regression:

\[
ACC_{iq} = \beta \times \ln(TA_{iq}) + \gamma \times SIC_{three} + SPEC_{iq};
\]

where \( ACC_{iq} \) is the autocorrelation coefficient from daily trading volume data, \( TA \) is the total assets, and \( SIC_{three} \) is the number of firms in an industry, and the corresponding residual \( SPEC_{iq} \), is the measure of speculative intensity or non-information based trading, in each given firm i-quarter q. All the regressions use mean-corrected variables, hence intercepts are zero.
TABLE 5
Regression results by year (1972 – 2000)

<table>
<thead>
<tr>
<th>YEAR</th>
<th>N</th>
<th>ABSUE</th>
<th>Adj. R2</th>
<th>ABSUE</th>
<th>SPEC</th>
<th>Adj. R2</th>
<th>Partial (ABSUE)</th>
<th>Partial (SPEC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1972</td>
<td>430</td>
<td>1.25</td>
<td>0.08</td>
<td>1.23</td>
<td>0.02</td>
<td>0.08</td>
<td>0.08</td>
<td>0.00</td>
</tr>
<tr>
<td>1973</td>
<td>612</td>
<td>0.43</td>
<td>0.01</td>
<td>0.41</td>
<td>0.02</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>1974</td>
<td>706</td>
<td>0.48</td>
<td>0.02</td>
<td>0.43</td>
<td>0.05</td>
<td>0.03</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>1975</td>
<td>1750</td>
<td>0.95</td>
<td>0.05</td>
<td>0.90</td>
<td>0.07</td>
<td>0.07</td>
<td>0.04</td>
<td>0.01</td>
</tr>
<tr>
<td>1976</td>
<td>2794</td>
<td>0.45</td>
<td>0.02</td>
<td>0.41</td>
<td>0.05</td>
<td>0.03</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>1977</td>
<td>2918</td>
<td>0.75</td>
<td>0.04</td>
<td>0.66</td>
<td>0.08</td>
<td>0.07</td>
<td>0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>1978</td>
<td>3035</td>
<td>0.57</td>
<td>0.02</td>
<td>0.48</td>
<td>0.08</td>
<td>0.04</td>
<td>0.01</td>
<td>0.03</td>
</tr>
<tr>
<td>1979</td>
<td>2967</td>
<td>0.66</td>
<td>0.01</td>
<td>0.57</td>
<td>0.10</td>
<td>0.06</td>
<td>0.01</td>
<td>0.05</td>
</tr>
<tr>
<td>1980</td>
<td>2811</td>
<td>0.50</td>
<td>0.01</td>
<td>0.41</td>
<td>0.09</td>
<td>0.05</td>
<td>0.01</td>
<td>0.04</td>
</tr>
<tr>
<td>1981</td>
<td>2499</td>
<td>0.24</td>
<td>0.00</td>
<td>0.19</td>
<td>0.06</td>
<td>0.02</td>
<td>0.00</td>
<td>0.02</td>
</tr>
<tr>
<td>1982</td>
<td>2313</td>
<td>0.48</td>
<td>0.01</td>
<td>0.46</td>
<td>0.08</td>
<td>0.04</td>
<td>0.01</td>
<td>0.04</td>
</tr>
<tr>
<td>1983</td>
<td>3195</td>
<td>0.58</td>
<td>0.01</td>
<td>0.52</td>
<td>0.08</td>
<td>0.05</td>
<td>0.01</td>
<td>0.03</td>
</tr>
<tr>
<td>1984</td>
<td>3881</td>
<td>0.61</td>
<td>0.02</td>
<td>0.57</td>
<td>0.06</td>
<td>0.04</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>1985</td>
<td>4144</td>
<td>0.60</td>
<td>0.02</td>
<td>0.56</td>
<td>0.09</td>
<td>0.05</td>
<td>0.02</td>
<td>0.04</td>
</tr>
<tr>
<td>1986</td>
<td>4089</td>
<td>0.85</td>
<td>0.02</td>
<td>0.80</td>
<td>0.08</td>
<td>0.05</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td>1987</td>
<td>4119</td>
<td>0.55</td>
<td>0.01</td>
<td>0.51</td>
<td>0.09</td>
<td>0.04</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td>1988</td>
<td>4350</td>
<td>0.75</td>
<td>0.03</td>
<td>0.71</td>
<td>0.10</td>
<td>0.07</td>
<td>0.02</td>
<td>0.04</td>
</tr>
<tr>
<td>1989</td>
<td>4460</td>
<td>0.88</td>
<td>0.03</td>
<td>0.79</td>
<td>0.11</td>
<td>0.07</td>
<td>0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>1990</td>
<td>4272</td>
<td>0.69</td>
<td>0.02</td>
<td>0.68</td>
<td>0.09</td>
<td>0.04</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>1991</td>
<td>4334</td>
<td>0.71</td>
<td>0.02</td>
<td>0.67</td>
<td>0.12</td>
<td>0.06</td>
<td>0.02</td>
<td>0.04</td>
</tr>
<tr>
<td>1992</td>
<td>4700</td>
<td>0.84</td>
<td>0.03</td>
<td>0.83</td>
<td>0.11</td>
<td>0.06</td>
<td>0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>1993</td>
<td>5148</td>
<td>0.96</td>
<td>0.03</td>
<td>0.91</td>
<td>0.13</td>
<td>0.08</td>
<td>0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>1994</td>
<td>5860</td>
<td>0.68</td>
<td>0.02</td>
<td>0.64</td>
<td>0.12</td>
<td>0.07</td>
<td>0.02</td>
<td>0.06</td>
</tr>
<tr>
<td>1995</td>
<td>6912</td>
<td>0.67</td>
<td>0.01</td>
<td>0.54</td>
<td>0.13</td>
<td>0.08</td>
<td>0.01</td>
<td>0.06</td>
</tr>
<tr>
<td>1996</td>
<td>7176</td>
<td>0.72</td>
<td>0.01</td>
<td>0.62</td>
<td>0.12</td>
<td>0.07</td>
<td>0.01</td>
<td>0.05</td>
</tr>
<tr>
<td>1997</td>
<td>7591</td>
<td>0.88</td>
<td>0.02</td>
<td>0.79</td>
<td>0.08</td>
<td>0.04</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>1998</td>
<td>7423</td>
<td>0.81</td>
<td>0.02</td>
<td>0.73</td>
<td>0.09</td>
<td>0.04</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>1999</td>
<td>7118</td>
<td>0.62</td>
<td>0.01</td>
<td>0.60</td>
<td>0.05</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>2000</td>
<td>6965</td>
<td>0.51</td>
<td>0.01</td>
<td>0.44</td>
<td>0.11</td>
<td>0.04</td>
<td>0.01</td>
<td>0.03</td>
</tr>
</tbody>
</table>

**MEAN**  
0.68 0.02 0.62 0.09 0.05 0.02 0.02

We report the coefficient estimates for the following regressions, run separately for each year:

\[
\text{ABSCAR}_{it} = \beta_0 + \beta_1 \text{ABSUE}_{it} + \epsilon_{it}
\]

\[
\text{ABSCAR}_{it} = \beta_0 + \beta_1 \text{ABSUE}_{it} + \beta_2 \text{SPEC}_{it} + \epsilon_{it}
\]

The last 2 columns report the contribution to the adjusted R-square of the variable indicated, ABSUE or SPEC, holding the other constant.

As a function of time, both ERCs are flat, but the SRC is rising significantly. For the Adj.$R^2$ as a function of time, we find: (a) for UE alone, decreasing (p-value = 0.080) (b) for the full model with both UE and SPEC (p-value =0.5) (c) for the partial $R^2$ of ABSCAR on UE given SPEC, negative (p-value = 0.12) (d) partial $R^2$ of ABSCAR on SPEC given ABSUE, significantly positive (p-value = 0.03).
1. Shiller's Bubble Expectations Index series is available on semi-annual basis from 1989 to 1998. We computed it by dividing the numbers in Shiller (1999)'s Table1 by the corresponding standard deviations given in Table 4, and then centering the resulting numbers.

2. SPEC was calculated for corresponding half-years from 1989 to 1999, and standardized and centered in a similar way.

3. The correlation between the two series is 0.59 and has a two-tailed p-value is less than 0.001.