Booms, Busts, and Sentiment[†]

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Abstract:

We study how boom and bust periods affect the speed with which prices reflect information. Based on psychological phenomena, we find that deviations from a steady level of economy-wide sentiment are associated with more timely price discovery. We also find that price discovery is more timely for firms with higher sentiment. However, during bust periods, we find that information is incorporated into prices in a faster manner for low-sentiment stocks. This is consistent with increasing conservatism and representativeness during periods of downturns. Finally, consistent with prior research, price discovery for good news is more timely than for bad news. During boom periods, however, we question this relation. Our research provides evidence on the price formation process during periods of both normal and unusual market activity.

Keywords: Timeliness, Price Discovery, Sentiment

JEL Classification: G01, G02, M41

Over the past three decades the U.S. stock market has been subject to a series of extraordinary movements. These include the Black Monday crash of October 1987, the dot.com bubble burst around the millennium, and the recent financial crisis starting in 2007.[1] All these events mark periods of extreme market exuberance (boom) followed by a related downturn (bust). Boom and bust periods imply changes in sentiment. These periods have been explained by prior literature that uses psychological evidence with respect to cognitive biases, such as overconfidence. We address the question of whether these biases impact how is interpreted by investors and as such impact the speed that information is incorporated into stock prices. The speed that stock prices incorporate information can be measured using a metric that captures the timeliness of price discovery. Prior research shows that firm disclosures, corporate governance, size, and accounting quality affect the timeliness of price discovery (e.g. Beekes and Brown 2006, Jackson 2011). We complement this research and test whether sentiment also affects timeliness.

Recent studies in economics and finance have started to incorporate psychological (behavioral) phenomena into their research designs in an attempt to explain considerable and sudden events on the stock market, and in the economy more generally. For example, a feeling such as overconfidence or trust allows people to 'go beyond the rationale' (Akerlof and Shiller 2009). During periods of extreme economy-wide sentiment, some investors are said to make their decisions not based on traditional sources, but are exposed to cognitive biases, such as general waves of investor optimism or pessimism (Baker and Wurgler 2006).[2] Such behavior is likely to influence the speed with which information is impounded in stock

[1] See Table 2 in Kaplan et al. (2009), which displays the largest declines in U.S. stock market history from January 1871-June 2009. Based on real total returns, only the crash of 1929 was larger than the dot-com bubble burst in 2000.

[2] A critique of Akerlof and Shiller (2009) can be found in Posner (2009). He argues that not emotions but rather other factors caused the recent financial crisis, such as deregulated or laxly enforced financial services and certain incentive structures in contracts. We acknowledge that not people's feelings alone can be related to boom and bust periods but we believe that they contribute strongly to the events. Since the focus of this study is not to predict the start or end of these periods but to analyze the impact on the price formation process, we assume sentiment is a cognitive bias that impacts investors' decision making processes.

prices. Hence, our main research questions are: (1) *Do periods of extreme economy-wide sentiment (booms and busts) influence the timeliness of price discovery?* and (2) *Does extreme firm-specific sentiment influence the timeliness of price discovery?* The precise mechanism by which sentiment affects stock prices is currently unresolved in the literature (Hribar and McInnis 2012; Seybert and Yang 2012). We use investor psychology to provide insight into the link between sentiment and the price formation process to help address these research questions.

We investigate our research questions in three parts. We first analyze the impact of boom and bust periods on the timeliness of price discovery at the macro-level. Since the timeliness metric captures how quickly information is incorporated into stock prices, we use a non-stock market measure to classify boom, bust, and steady periods. The measure we use is based on the quarterly University of Michigan Index of Consumer Sentiment (ICS). This allows us to clearly analyze the impact of changes in the economic environment (independent from the stock market) on the timeliness of price discovery.

We next analyze the impact of sentiment on the timeliness metric at the micro-level. We use the firm-specific investor sentiment measure developed by Baker and Wurgler (2006) and test its association with the timeliness of price discovery. This allows us to separate the firm-specific micro-effects from the economy-wide macro-effects during periods of booms and busts. Finally, we test whether the relationship of the timeliness of price discovery of good news versus bad news (micro-level) depends on the level of economy-wide sentiment (macro-level).

Our study most closely related to Baker and Wurgler (2006) who explicitly measure investor sentiment and quantify its impact on stock returns. They find that stocks that are difficult to value and to arbitrage (young, unprofitable, volatile firms with high growth expectations or similar) are more sensitive to investor sentiment. In particular, if sentiment is low (high), subsequent returns for such firms are high (low) compared to stocks that are less difficult to value. Our study differs from Baker and Wurgler (2006) in a number of aspects. First, we analyze the impact of sentiment on the timeliness of price discovery rather than on the cross-section of stock returns. This allows us to understand the price formation process itself during periods of extreme economy-wide sentiment. Our research design is novel in that it uses both macro- and micro-level proxies to disentangle the role market-wide sentiment and firm-specific sentiment plays in the price formation process. Prior research uses the Index of Consumer Sentiment as a proxy for sentiment but does not the link between economy-wide sentiment and firm-specific investor sentiment. At the micro-level we differentiate good news from bad news and provide additional evidence on the timeliness of price discovery for those during boom and bust periods.

Our primary results suggest that at the macro-level, the timeliness of price discovery (i.e the speed of price formation) is significantly faster during periods of extreme economy-wide sentiment than during steady periods. At the micro-level we find the timeliness of price discovery is significantly faster for stocks with higher firm-specific sentiment. By analyzing macro- and micro-level effects simultaneously, our results reveal that during boom and steady periods, price discovery is more timely for stocks with higher values of firm-specific sentiment. During bust periods, the opposite is true; price discovery is more timely for low-sentiment stocks. If firm-specific sentiment runs high, the timeliness of price discovery is slower during bust periods for such stocks than during other periods. Finally, our results suggest that the price discovery of good news is more timely than that of bad news, but this result does not hold during boom periods.

This paper makes a number of contributions. We analyze the impact of periods of extreme economy-wide sentiment on the timeliness of price discovery. Our results help in understanding the impact of investor sentiment on the price formation process, that is, how boom and bust periods can affect the speed at which information is impounded in prices. An in-depth analysis on the impact of sentiment on the timeliness of price discovery is especially interesting since the analysis on the causes and preventions of crashes such as the latest subprime mortgage crisis in the U.S. is ongoing. Our results provide valuable input for both researchers and market participants to understand the impact of such periods of non-normal activities. In addition, unlike prior research we consider both macro-level and micro-level effects and also consider both stock market and non-market measures. Hence, our results are able to provide more comprehensive evidence on the impact of unusual market activity on the price formation process.

The remainder of the paper is organized as follows: Prior literature and development of hypotheses are provided in section I. Section II explains our research design. Section III describes the sample selection and presents the main empirical results, while Section IV summarizes and concludes.

I. Prior Literature and Hypothesis Development

This paper draws upon two streams of literature: that of the timeliness of price discovery and also of investor sentiment. Beekes and Brown (2006) develop a measure of timeliness which reflects the speed of price discovery throughout the year. They show that information is impounded in share price on a more timely base for ‘better-governed’ firms in Australia. Beekes and Brown (2007) review the relevant literature and conclude that observable relationships exist between the timeliness of price discovery and characteristics of a financial market’s reporting and information trading environment. We conjecture that sentiment reflects investors’ cognitive biases during specific periods, and as such can impact on the timeliness of price discovery and therefore the price formation process.

Baker and Wurgler (2007, p. 129) describe investor sentiment as “a belief about future cash flows and investment risks that is not justified by the facts at hand”. In other words, that feelings influence investment choices and judgment are made and hence, may impact stock market movements. Akerlof and Shiller (2009) call these feelings ‘animal spirits’ and suggest that significant economic events can only be grasped by such people’s feelings.[3] Underlying prior work on investor sentiment is the notion that sentiment reflects errors in investors’ expectations about future payoffs (Hribar and McInnis 2012). Seybert and Yang (2012) argue that during periods of high sentiment, investors may engage in a more detailed thought process that involves unrealistic expectations of future firm earnings, where there is more potential to overestimate future earnings for uncertain firms.

We argue that cognitive biases can be used to explain why investors’ decision-making processes would result in unrealistic expectations of future firm prospects in periods of extreme sentiment. Theoretical frameworks show that overconfidence by investors (and variations in confidence due to biased self-attribution) can explain the observed market over- and underreactions (Daniel et al. 1998). Overconfidence is characterized by investors believing that their private information is more precise than it actually is, causing speculative bubbles (Scheinkman and Xiong 2003). Barberis et al. (1998) develop a model that explains how investors actually form their beliefs that lead to market over- and underreactions. Their formal model of investor sentiment based on psychological attributes (conservatism and representativeness) is able to explain mispricing. They refer to psychological evidence by Edwards (1968) and conclude that conservatism causes investors update models too slowly when new information is released. Similarly, based on further psychological evidence by

[3] In psychology, the phenomenon is also called ‘affect heuristic’, when people tend to rely on their intuition more than on hard facts (Shefrin, 2009, p. 232).

Griffin and Tversky (1992) they show that representativeness causes investors to expect future earnings growth mainly based on earnings growth in the past.[4]

People's attributes reflect uncertainty which is especially high during speculative bubbles (Baker and Wurgler 2007). When the market underreacts, good news will be incorporated slowly into prices; that is, current good news is not built into current prices but may predict future positive returns (Barberis et al. 1998). Hence, we posit that during periods of extreme economy-wide sentiment, psychological attributes (overconfidence, increasing conservatism, and representativeness) may impact on the interpretation of information coming from traditional sources. We expect this to affect the timeliness of price discovery. For example, during periods of extreme economy-wide sentiment, the timeliness of price discovery will be slower. During boom and bust periods, increased conservatism (i.e., the tendency to put more weight on past than current information) as proposed by Edwards (1968) can be a catalyst for slow or hesitant reactions to news. Jackson (2011) finds that timeliness between 1998 and 2002 was significantly slower than in the years before and after. This period coincided with general market uncertainty, including the dot.com bubble, a wave of corporate collapses and regulatory responses.

However, an alternate argument could predict that boom and bust periods are associated with more timely price discovery. First, if investors are acting on an overly-confident belief that their private information is superior (Scheinkman and Xiong 2003), then price may reach terminal value faster during boom periods, than if there was no overconfidence in the market.[5]

Second, Hirshleifer and Teoh (2003) show that when there is limited attention in the market, investors may miss or misinterpret certain information disclosures. During periods

[4] In a prior study, Slovic (1973) also refers to these two psychological studies relating those to investment decision making. Besides, Hirshleifer (2001) provides a general survey on how investor psychology influences asset pricing.
[5] This implies that we do not make any assumptions about the 'correctness' of the terminal value, but rather take it as the observable price at the end of a reporting period.

when investors are paying more attention, there is likely to be a greater precision in the interpretation of signals. Assuming that investors are able to recognize boom and bust periods, the expectation is that they would act earlier to avoid being caught out in adverse trading positions and therefore price discovery would be more timely during those periods.

Finally, Shefrin (2009) outlines a number of other 'psychological pitfalls' that may have contributed to the financial crisis in the late 2000s. Narrow framing is defined as people's tendency to simplify a complex decision by splitting the task into smaller packages, and interactions between these smaller packages may not be considered. However, the increased simplicity is likely to incorporate 'simple' information such as accounting-related information faster. Especially during periods of extreme sentiment the increase of multidimensional judgments is likely to increase, enforcing the 'narrow framing' phenomenon. To the extent that accounting related information can be defined as less complex information compared to other information (e.g., statements about future prospects anduncertain estimates) the 'narrow framing' argument suggests an increase in the timeliness of price discovery during boom and bust periods.

Another 'psychological pitfall' that Shefrin (2009) refers to is groupthink, which describes people's tendency to prefer making decisions consistent with one's group or the group leaders. To the extent that the timeliness metric is not premised on whether the share price at the end of the period is 'correct' or not, groupthink may increase the speed of the price formation process by herding and hence, avoiding conflicts.

Our timeliness metric does not predict whether, why, or which stocks are under- or overvalued but rather measures how quickly prices reach the terminal value in general.[6] We expect the psychological phenomena as described (overconfidence, limited attention, narrow framing, and groupthink) to be more pronounced during periods of extreme economy-wide

[6] See Beekes and Brown (2006), Beekes et al. (2006), Brown and Hsu (2008), Bushman et al. (2010), and Jackson (2011).

sentiment, comprising both boom and bust periods. The phenomena are all likely to result in investors incorporating current information into stock prices in a more timely manner. Hence, our first hypothesis is stated as follows:

H1: During boom and bust periods, price discovery is more timely than during steady periods.

Our first hypothesis addresses the macro-level impact of extreme economy-wide sentiment on price discovery. We next analyze the impact of sentiment on price discovery at the micro-level. Glushkov (2006) provides firm-specific measures of investor sentiment, and finds that the relationship between this sentiment beta and stock returns has an inverse U-shape. His results suggest that variation in firm characteristics drive the sensitivity of stock prices to sentiment. Companies that are 'hard-to-value' and 'difficult-to-arbitrage' are more sentiment-sensitive. Similar impacts of investor sentiment on stock returns are documented by Baker and Wurgler (2006, 2007). They find that when sentiment is low, smaller, more volatile, unprofitable, non-dividend-paying, extreme growth and distressed stocks earn higher subsequent returns, whereas the patterns largely reverse when sentiment is high.

Hribar and McInnis (2012) analyze the association between analysts' forecast errors and changes in investor sentiment over time. They find that investor sentiment has a direct impact on earnings expectations of more speculative ('difficult-to-value') companies. Their results suggest that part of the forecast errors occur due to an overly optimistic expectation regarding earnings and earnings growth triggered by high sentiment. In this paper, we only consider timeliness of price discovery and abstract from such earnings discovery (by analysts). Shedding light on this topic from another angle, Seybert and Yang (2012) ask which factors may impact investor sentiment in the first place. Their findings suggest that management earnings guidance influences (firm-specific) earnings expectations, and as a consequence, is likely to affect sentiment-driven overvaluation. The perspective taken in this paper is consistent with the ‘top down’ approach to behavioural finance and the stock market as outlined by Baker and Wurgler (2007); we assume the source of investor sentiment to be exogenous and focus on its empirical effects.

Consistent with prior evidence on investor sentiment, we expect that firm-specific sentiment may also impact the timeliness of price discovery. We posit that our timeliness metric has significant cross-sectional variation that depends on a company’s firm-specific investor sentiment. Following H1 we expect more timely price discovery for stocks with higher sentiment, based on the psychological phenomena outlined. In other words, investors buying stocks with higher sentiment tend to be more overconfident, to pay more attention, to simplify complex sets of information, and to follow groups. This is likely to result in current information being incorporated into stock prices faster. While in H1 we analyze the impact of sentiment at the macro-level, for H2a, we make predictions for deviations from a steady-state at the micro-level, captured by cross-sectional variation in firm-specific sentiment. H2a is stated as follows:

H2a: Price discovery is more (less) timely for stocks with higher (lower) sentiment.

In addition, we predict that the effect of sentiment on timeliness is more pronounced during boom and bust periods compared to steady periods. This is similar to our first hypothesis which posits a significant impact of boom and bust periods on the price formation process in general. In our H2b and H2c, we analyze the joint effect of H1 and H2a, which is stated as follows:

H2b: During boom periods, price discovery is more (less) timely for stocks with higher (lower) sentiment.

H2c: During bust periods, price discovery is more (less) timely for stocks with higher (lower) sentiment.

In our final set of hypotheses, we address the impact of good and bad news on the timeliness of price discovery during boom and bust periods. We expect that during periods of differing market-wide sentiment, the reaction to good and bad news will differ. During periods of high market sentiment, that is boom periods, investors are more likely to be over-confident, and good news will be incorporated into price in a more timely manner.

Kothari et al. (2009) indicate price discovery is more timely for good news than for bad news. They show that stock prices react more to bad news than they do to good news. Their findings suggest that managers withhold bad news, by not disclosing it to investors in as timely a manner as good news. However, Barberis et al. (1998) show that when markets overreact, good news can tend to become overpriced leading to low average subsequent returns. Similarly, Easterwood and Nutt (1999) find that analysts tend to overreact to good news and underreact to bad news (i.e. there is systematic optimism towards new information).

We expect that a finding of good news being more timely will not necessarily hold for both boom and bust periods. It is expected that good news is incorporated into prices in a more timely manner than bad news only during boom periods, i.e., when market exuberance is high. On the other hand, during bust periods when bad news is more pertinent, we would expect price discovery for bad news to be more timely. Our third set of hypotheses is:

H3a: During boom periods, price discovery is less timely for bad news relative to good news.

H3b: During bust periods, price discovery is less timely for good news relative to bad news.

II. Sample Selection and Methodology

A. Dependent Variable

Intra-period timeliness measures have long been used in accounting research. We utilise a timeliness construct based on that of Beekes and Brown (2006), who extend Ball and

Brown (1968), Alford et al. (1993) and Brown et al. (1999) in measuring the speed with which a firm's share price reflects the net effect of all value-relevant information impounded in share price over the quarter. The quarter is defined to be the period of 95 calendar days ended two days after the quarterly earnings announcement date. The Beekes and Brown (2006) timeliness metric, M^2, is defined as:

$$M^2 = \frac{\sum_{t=-95}^{t=0} \left| \ln(P_0) - \ln(P_t) \right|}{95} \quad , \tag{1}$$

where P_t is the market-adjusted share price, which is observed at daily intervals from day −95 until day 0, where day 0 is two days after the earnings announcement date. As described by Beekes and Brown (2006), the speed of adjustment is at its maximum when M^2 is identically zero; so the lower the value of M^2, the more timely the speed of price discovery. This measure is not without its shortcomings, specifically in that the metric has no upper bound and its value increases with volatility.

We adapt the metric in a similar manner to that described by Beekes et al. (2011). From our market-adjusted log returns (r_t^*), we create two series defined as the "Good News" and "Bad News" series.[7] Good (bad) news returns are where the market-adjusted returns are positive (negative) as expressed in equation (2a) and (2b), respectively:

$$r_t^G = r_t^* \text{ if } r_t^* \geq 0 \text{, otherwise } r_t^G = 0 . \tag{2a}$$

$$r_t^B = r_t^* \text{ if } r_t^* \geq 0 \text{, otherwise } r_t^B = 0 . \tag{2b}$$

The market-adjusted log return series for good and bad news are then used to create two market-adjusted cumulative log return series, defined as the "Good News" and "Bad News" cumulative returns series as expressed in equations (3a) and (3b) respectively. Here *s*

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[7] We take market-adjusted returns, r_t^*, where $r_t^* \equiv r_t - r_{Mt}$, and r_t is the log return for the firm on day *t* and r_{Mt} is the market index log return on day *t*.

is the starting date of the cumulative return series, in our quarterly calendar time s is day -94 for a timeliness measure that covers 95 days ending on day $t = 0$.

$$C_t^G = C_{t-1}^G + r_t^G, t = s,...,0. \tag{3a}$$

$$C_t^G = C_{t-1}^B + r_t^B, t = s,...,0. \tag{3b}$$

The timelines measures for the good (T^G) and bad news (T^B) time series are then estimated from equations (4a) and (4b), respectively. Basically, for a given measure (e.g., "Good News") we calculate the average distance between the Good news cumulative return over the whole period, C_0^G, and the Good news cumulative return to the end of day t, then scale the average by the Good news cumulative return over the whole period.

$$T^G = \left(\sum_{t=s}^{t=0} \left(C_0^G - C_t^G \right) / (1 - s) \right) / C_0^G. \tag{4a}$$

$$T^B = \left(\sum_{t=s}^{t=0} \left(C_0^B - C_t^B \right) / (1 - s) \right) / C_0^B. \tag{4b}$$

Our timeliness metric, *TIME*, is then calculated as a weighted average of the timeliness of good news and bad news, as expressed in equation (5):

$$TIME = \omega \cdot T^G + (1 - \omega) \cdot T^B, \tag{5}$$

where the weights are the extent of the good and bad news, i.e., the cumulative return over the whole window for good news, and for bad news:

$$\omega = C_0^G / \left(C_0^G - C_0^B \right). \tag{6}$$

B. Independent Variables

Our primary variables of concern are the cycles of boom (*Boom*) and bust (*Bust*). We differentiate such periods of extreme economy-wide sentiment from periods of normal activity (i.e., steady periods) using the University of Michigan Index of Consumer Sentiment

(*ICS*).[8] We first calculate the five-quarter moving-averages of the *ICS*. Boom (bust) periods are defined as those periods where the value increases (decreases) by a certain percentage, i.e. the percentage by which *ICS* deviates from a steady period. A priori we expect a portion of 20-30% of the 124 quarters during 1980 to 2010 to be classified as steady periods. The remaining quarters are expected to be more or less equally distributed over boom and bust periods.[9] We obtain an expected portion of 25% of the quarters as steady periods when using ±0.6% as the cut-off point. In other words, those quarters during which the five-quarter moving-average of *ICS* increases or decreases by 0.6% are defined as boom or bust periods. The remaining quarters represent steady periods. In sensitivity analyses, we alter the cut-off points to ±0.5% and ±0.7% allowing the portion of steady periods to range between 20% and 30%. Figure 1 depicts the quarterly movements of *ICS* during 1980 to 2010. The benefit of using the *ICS* is its independence of any direct stock market measure since the timeliness metric itself is based on stock market information. This allows us to avoid the problem of a circular relationship between the dependent and independent variable.[10]

[Insert Figure 1 about here]

In addition, we require a measure of firm-specific investor sentiment. We follow Baker and Wurgler (2006) for estimating *Sent*. Consistent with Glushkov (2006), we take the change in sentiment as the priced factor, with sentiment beta ($\beta_{SENT,i}$) our firm-specific measure. The following model is estimated to generate firm specific beta measures:

[8] Bergman and Roychowdhury (2008) use this index as a proxy for investor sentiment itself. In our study, we use the index in order to define explicit periods of booms, busts, and steady state.
[9] More specifically, boom periods are expected to make up a slightly larger proportion of the quarters compared to bust periods consistent with the notion that historically bull markets last longer than bear markets.
[10] We acknowledge that some association between *ICS* and the stock market may exist nonetheless. For example, Qiu and Welch (2006) analyze different measures for investor sentiment and find for the consumer index a significant relationship with financial market pricing.

$$R_{i,t} = \alpha_i + \beta_{MRKT,i} R_t^{MRKT} + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \beta_{MOM,i} MOM_t + \beta_{SENT,i} \Delta SENT_t^{\perp} + \varepsilon_{i,t},$$
$$\varepsilon_{i,t} \sim N\left(0, \sigma_\varepsilon^2\right) \quad (7)$$

The model equals the Cahart four-factor model, with the inclusion of a change in sentiment variable. $R_{i,t}$ is denoted as excess returns of the stock i at time t, R_t^{MRKT}, SMB_t, HML_t, and MOM_t are the Cahart factors, and $\Delta SENT_t^{\perp}$ equals the change in sentiment, orthogonalized with respect to a set of macroeconomic conditions. All the factors are taken monthly to estimate equation (7) over a rolling 60-month period.

As well as the variables *Boom* and *Bust*, we use the estimated results for $\beta_{SENT,i}$ (firm-specific investor sentiment *Sent*) as an independent variable in our main model (equation 8). To test whether the speed of the price formation process is affected by boom and bust periods (H1), firm-specific sentiment (H2a), and both (H2b)[11], we estimate the following equation:

$$TIME_{i,t} = \alpha + \beta_1 Boom_t + \beta_2 Bust_t + \beta_3 Sent_{i,t} + \beta_4 ICS_t + \beta_5 Liquid_{i,t} + \beta_6 Size_{i,t} + \beta_7 Surprise_{i,t} + \beta_8 OperCyc_{i,t} + \beta_9 SalesVol_{i,t} + \beta_{10} Lev_{i,t} + \beta_{11} CapFix_{i,t} + \beta_{12} RD_{i,t} + \beta_{13} BTM_{i,t} + \beta_{14} Vol_{i,t} + \varepsilon_{i,t} \quad (8)$$

Alongside the micro-economic measures of investor sentiment (*Sent*) we also take the raw value of *ICS* to control for macro-economic sentiment. Inextricably linked to the timeliness of price discovery is liquidity (*Liquid*). This issue is also likely to be especially pertinent during periods of boom and bust. Indeed, many consider the recent financial crisis to have been a crisis of liquidity (Asness et al. 2009). As such we control for liquidity using the Amihud (2002) measure of illiquidity.

We also include other variables which have been found to be associated with the timeliness of price discovery (Beekes and Brown 2006; Beekes et al. 2006; Jackson 2011). Firm size (*Size*) is measured as the natural logarithm of the market value of equity; an

[11] For testing H2b, we split the pooled sample into boom and bust periods and run regression (3) for each subsample separately excluding the variables *Boom* and *Bust*.

earnings surprise is taken as the absolute value of the mean analyst forecast errors (*Surprise*); the firm's operating cycle (*OperCyc*) is the logarithm of the sum of days accounts receivable and days inventory; Sales volatility (*SalesVol*) is the standard deviation over years *t-5* to *t-1* of the ratio of sales to average total assets; the debt to equity ratio (*Lev*); the ratio of capital expenditure to fixed assets (*CapFix*); research and development expenditures scaled by sales (*RD*); the book to market ratio (*BTM*); and the standard deviation of daily market-adjusted returns over the quarter (*Vol)*.

In an additional step we include *Good* in the regression, which is a dummy variable that indicates whether the share's price rose relative to the market. Interacting *Good* with our main variables *Boom* and *Bust* allows us to analyze the timeliness of good versus bad news dependent on periods of high versus low market exuberance (H3a and H3b). The extended model is shown in equation (9)

$$\begin{aligned} TIME_{i,t} &= \alpha + \beta_1 Boom_t + \beta_2 Bust_t + \beta_3 Sent_{i,t} + \beta_4 Good_{i,t} + \beta_5 Boom * Good_{i,t} \\ &+ \beta_6 Bust * Good_{i,t} + \beta_7 ICS_t + \beta_8 Liquid_{i,t} + \beta_9 Size_{i,t} + \beta_{10} Surprise_{i,t} + \beta_{11} OperCyc_{i,t} \\ &+ \beta_{12} SalesVol_{i,t} + \beta_{13} Lev_{i,t} + \beta_{14} CapFix_{i,t} + \beta_{15} RD_{i,t} + \beta_{16} BTM_{i,t} + \beta_{17} Vol_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{9}$$

We cluster the error terms by firm, quarter, and industry. If macro-level extreme sentiment is associated with more timely price discovery, then β_1 and β_2 should be negative (H1), as *TIME* is decreasing in timeliness. Likewise, if firms with higher sentiment are associated with more timely price discovery, then β_3 should be. Consistent with prior research, β_4 should be negative indicating that in general good news is more timely relative to bad news. Consistent with H3a and H3b, we expect β_5 and β_6 to be negative, i.e. good news are expected to be more timely relative to bad news during boom periods, which reverses during bust periods though.

To provide a ready interpretation of our regression analyses, we normalize all of our independent variables so that the intercept equals the sample mean of the timeliness variable for that model and the coefficient of each explanatory variable indicates the change in the predicted value of the dependent variable for a one standard deviation change in that explanatory variable, all else equal. We report the raw variable values for the descriptive statistics.

C. Data

We obtain data over the period 1975 to 2010 for a sample of U.S. firms to estimate equation (8) and (9). This allows us to present results for the period 1980-2010. All price data is sourced from the *CRSP* Daily Stock File, with accounting data sourced from the merged *CRSP/Compustat* Fundamental Quarterly files, and analyst data from *I/B/E/S*. Factors to estimate sentiment beta are obtained from Kenneth French[12] and Jeffrey Wurgler.[13] After removing observations with missing data, we are left with 96,792 firm-quarter observations on which to perform our analysis.

III. Empirical Results

A. Descriptive Statistics

Table I presents descriptive statistics of the full sample. All variables are winsorized at the 1% extremes to reduce spurious effects from outliers. *TIME*, which captures the timeliness of price discovery, has a mean (median) of 0.513 (0.5134). The values are inconsistent with prior literature (e.g. Beekes and Brown 2006) due to the modification to the timeliness metric. *Boom*, *Bust*, and *Steady* are dummy indicator variables for each quarter based on the University of Michigan Index of Consumer Sentiment (*ICS*) in order to pick up economy-wide sentiment. *Boom* (*Bust*) takes the value 1, if the five-quarter moving-average of *ICS* increases (decreases) by 0.6%, and zero otherwise. *Steady* is coded as 1 if the change

[12] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[13] http://people.stern.nyu.edu/jwurgler/

in the five-quarter moving-average of *ICS* is between [-0.6%, +0.6%], and zero otherwise. The mean values in Table I for *Boom* (0.3554), *Bust* (0.3841), and *Steady* (0.2605) show that on average, boom and bust periods occur almost equally over our sample period (37.9% and 37.1% of the 124 quarters respectively). The distribution changes when using alternative thresholds while keeping the portion of steady periods within the expected range of 20% to 30% of the quarters. Based on 0.7%, and hence, allowing for a larger deviation, we obtain relatively more steady periods (29.8%) and relatively less boom periods (36.3%) and bust periods (33.9%). On the contrary, using 0.5% as a threshold, the portion of steady quarters decreases down to 22.6%, and the remaining quarters are distributed evenly across boom periods (38.7%) and bust periods (38.7%).

[Insert Table I about here]

B. Univariate correlations

Table II presents both Pearson (above the diagonal) and Spearman (below) correlations between all variables. The correlation between *TIME* and *Boom* is negative (Pearson correlation -0.051, *p*-value <.0001) suggesting that if economy-wide sentiment is high, accounting information is incorporated faster into stock prices. On the contrary, during bust and steady periods, timeliness decreases (Pearson correlation is positive with 0.014 for *Bust* and 0.040 for *Steady*, both *p*-value <.0001). This is consistent with the notion that during periods of market exuberance, market participants appear to react faster and hence, reach the stock price at the end of the period more quickly. On the other hand, during steady periods and bust periods, the price formation process takes longer. This is consistent with increasing conservatism during those periods, which may slow the incorporation of news into prices.

By construction, the variables *Boom*, *Bust*, *Steady*, and *ICS* show significant and high correlations (up to -0.587 for *Boom* and *Bust*). In our multivariate analyses, we calculate variance inflation factors to make sure that multicollinearity is not an issue. Apart from those variables, the results do not show further concerns of high correlation. The results of the correlations for the remaining variables with *TIME* are consistent with prior literature (e.g. Beekes and Brown 2006, Jackson 2011).

[Insert Table II about here]

Stock return volatility (*Vol*) is not highly correlated with *TIME*, with a Pearson coefficient of 0.066 (p-value <.0001). This is in contrast to the correlation with the timeliness metric employed by Beekes and Brown (2006), M^2, which has a correlation with volatility of 0.540 in our sample. This reduction in correlation between the timeliness metric and stock return volatility highlights that the original metric, M^2, is biased with volatility, whereas our modification, *TIME*, is not.

Table III presents the mean and median values of the variables portioned by the boom, bust, and steady periods using the 0.6% change in the five-period moving average of *ICS*. From the means, price discovery (*TIME*) is the most (least) timely during boom (steady) periods. Firm-specific sentiment (*Sent*) is lowest (highest) during bust (steady) periods. However, the mean sentiment is negative during boom periods as well. For the most part, the mean values of the variables are significantly different across all periods. A similar pattern is exhibited with the median values, and setting the threshold for boom (bust) periods at ±0.5% and ±0.7%. Given there are systematic differences in firm characteristics across the three different periods, it is important that we control for these in our multivariate analysis.

[Insert Table III about here]

C. Multivariate Analysis

The main results of our multivariate analyses based on equation (3) are summarized in Table IV. The dependent variable is the timeliness of price discovery measured by *TIME.* All variables have been normalized providing ready interpretations of the figures. Error terms are clustered by firm, quarter, and industry. The first column provides results based on the pooled sample. The second and third row both show a negative regression coefficient for *Boom* (−0.0025) and *Bust* (−0.0007), both significant at the 1% level.

[Insert Table IV about here]

The results support H1 showing that during boom and bust periods the timeliness of price discovery significantly increases relative to steady periods. The univariate analyses already suggest this relationship between *Boom* and *Time*, i.e. periods of market exuberance increase the timeliness of price discovery. Multivariate analyses show that this also holds for *Bust* and *Time* when controlling for micro-economic sentiment (*Sent*), macro-economic sentiment (*ICS*), and other factors that have been shown to be related to the timeliness metric. All control variables are statistically significant and directionally consistent with prior findings.

While we highlight that our timeliness measure is not likely to be biased due to volatility, the arrival rate of information is still likely to be an important facet of the price discovery process. Hence, we control for the standard deviation of the daily market-adjusted returns (*Vol*) in our models. Indeed, we find that higher stock return volatility is associated with less timely price discovery (pooled sample coefficient 0.0043, p-value <.0001).

An F-test shows that the difference between the coefficients on *Boom* and *Bust* are significantly different (F-test 96.20, p-value <.0001). We obtain the same result if we consider boom and bust periods only (second column). The regression coefficient for *Bust* (0.0017) is not significant at less than the 1% level (p-value <.0001).

During periods of market exuberance (*Boom*) and downturns (*Bust*) stock prices seem to reach their terminal values faster. Consistent with explanations from psychology and behavioral finance, over-confidence (which is high during boom periods) induces investors to believe their private information is more precise letting them react faster and hence, may cause an increase in the timeliness of price discovery. For bust periods, the inverse of the limited attention hypothesis by Hirshleifer and Teoh (2003) suggests that investors may be paying more attention during bust periods. That way signals may be interpreted more precisely, and consequently information impounded into stock prices faster. Our finding is also consistent with arguments based on the psychological pitfalls of 'narrow-framing' and 'groupthink'. For both of them, we predicted that they may lead to an increase in the timeliness of price discovery during boom and bust periods. During periods of extreme economy-wide sentiment, investors tend to simplify complex information making it easier to incorporate them quickly into stock prices (narrow framing). They also tend to follow groups or exhibit 'herding' (groupthink).

The results for our second set of hypotheses are displayed in the fourth and fifth row of Table IV. Hypothesis 2a posits that price discovery is more timely for stocks with higher sentiment. *Sent* is estimated by $\beta_{SENT,i}$ of equation (2) and proxies for firm-specific sentiment. For H2a, our findings support our prediction for the pooled sample, with a significantly negative regression coefficient on *Sent* (-0.0004). Hence, our previous findings of H1 (macro-level) are confirmed at the micro-level by results of testing H2a: deviations from steady state firm-specific sentiment lead to more timely price discovery.

For H2b we posit that price discovery is more timely for stocks with higher values of firm-specific sentiment during periods of high economy-wide sentiment (boom periods). For the sample of boom periods (BOOM), the coefficient on *Sent* is -0.0011 (and statistically significant at the 1% level). The results hold when we examine steady periods, with the coefficient on *Sent* is -0.0013. Hence, the results for boom and steady periods suggest that stocks with higher values of sentiment are more timely in their price discovery.

For H2c, we posit that price discovery is more timely for stock with lower values of firm-specific sentiment during periods of low economy-wide sentiment (bust periods). For the sample of bust periods (BUST), the coefficient on *Sent* is 0.0012 (*p*-value <.0001). The results suggest that during bust periods, stocks with low firm-specific sentiment are related to a low value of the timeliness metric, which equals a more timely price discovery.

The different results for bust periods are consistent with the notion that investors are more conservative during bust periods with respect to stocks with high firm-specific sentiment. They are likely to rely more on their past than current information. In addition, the representativeness argument suggests that during bust periods, investors may expect future earnings growth from high-sentiment stocks still mainly based on earnings growth in the past. In both cases, as a consequence, price discovery becomes less timely.

Overall, H2b and H2c are supported. During boom periods, price discovery is more timely for stocks with higher sentiment; and during bust periods, price discovery is more timely for stocks with low sentiment. Both conservatism and representativeness are possible explanations for these results.

The results for our third set of hypotheses estimated by equation (9) are shown in rows of six to eight in Table V. Specifically we predict that during boom (bust) periods, the price discovery of good news will be more (less) timely. The coefficient on *Good* suggest that price discovery is more timely for good news in general (pooled sample *Good* coefficient of

−0.0020, p-value <.0001). Interacting *Good* with our dummy indicator variables *Boom* and *Bust* allows us to analyze the impact of these periods on the relationship between good news and the timeliness metric. The coefficient on our interaction terms, *Boom**Good* and *Bust**Good* are not statistically significantly different from zero.

[Insert Table V about here]

The coefficients on *Good* in the separate boom, bust and steady samples are consistent with the results on the pooled sample. Specifically, good news is more timely than bad news in general. We find that the magnitude of the result is consistent across boom, bust and steady periods with coefficients of -0.0024, -0.0022 and -0.0020, respectively (all p-values <.0001).

We then address this issue in an alternate manner. Specifically, we use the estimates of the timeliness of good news, T^G, and bad news, T^B, from equations (4a) and (4b), respectively, to compare the mean and medians. Table VI presents the mean and median values of the timeliness of good and bad news across boom, bust and steady periods. Consistent with *TIME*, both good and bad news is the most timely in boom periods. Good news is slightly more timely in steady periods compared to bust periods at the mean, but vice versa at the median. We then compare the timeliness of good and bad news within the different periods. We find, consistent with the results reported in Table V, good news is more timely than bad news within each of the three periods. However, we do not find any statistically significant difference between the means and medians in the boom periods.

[Insert Table VI about here]

When controlling for good news as in equation (9), an *F*-test shows that the difference between the coefficients on *Boom* and *Bust* remains significant (*F*-test 96.20, *p*-value <.0001). This suggests that information is incorporated into stock prices in a more timely manner during boom periods compared to bust periods. We obtain the same result if we consider boom and bust periods only (second column) with a significantly positive regression coefficient for *Bust* (0.0017, *p*-value <.0001).

D. Sensitivity analyses

In Tables VII and VIII we present sensitivity analyses using alternate definitions for *Boom*, *Bust*, and *Steady*. Our main results are based on the five-quarter moving-averages of the University of Michigan Index of Consumer Sentiment (*ICS*) identifying *Boom* and *Bust* if the value increases (decreases) by 0.6%. For sensitivity analyses, we re-estimate equations (8) and (9) using the change as ±0.5% which classifies a smaller portion of steady periods compared to our main analyses. Our results remain unchanged with this altered specification of boom and bust periods. The only minor difference is that for the subsample BUST the control variable *RD* turns marginally significant in the ±0.5% specification -(0.0003, *p*-value 0.0498). When allowing for a larger portion of steady periods by choosing the cut-off point at ±0.7% (in untabulated results), our main results also remain almost unchanged. Overall, we only use alternate specifications that result in a portion of 20% to 30% of the quarters for steady periods since further deviations may lead to misspecifications of the periods and as such to spurious conclusions.

[Insert Table VII about here]

[Insert Table VIII about here]

We then consider that the impact of sentiment may not be a linear relation. As such, we allow for a quadratic form by including the squared value of *Sent* ($Sent^2$). This approach is consistent with the findings of Glushkov (2006) that finds an inverse U-shape returns on firm-specific sentiment. Re-estimating equations (8) and (9) with the inclusion of $Sent^2$ do not alter our reported results. Indeed, the coefficient on $Sent^2$ is consistently negative.[14] This implies that the relation between sentiment and the timelines of price discovery is indeed linear. However, the exception to this is during bust periods; that is, price discovery is less timely in bust periods for firms with more extreme sentiment. Upon further analysis, we find that the turning point is at a value of 0.0055 (0.0112) where boom and bust periods are identified by a change in the moving-average of the University of Michigan Index of Consumer Sentiment of ±0.6% (±0.5%). This turning point occurs in the second quartile of the distribution of *Sent*.

Next, instead of imposing cut-off points of the change in *ICS* to define our boom and bust periods, we re-estimate the main results with the continuous value of the change in the five-period moving average of *ICS* captured by *BBS*, and its squared value (BBS^2). Hence, we rerun regression (3) and replace *Boom* and *Bust* by *BBS* and BBS^2. To be consistent with our main analysis, we would expect the extreme values of *BBS* to be negative, indicating that where there is a greater change in investor sentiment, price discovery is more timely. Indeed, the results presented in Table IX confirm this. The coefficient on *BBS* is negative (−0.0007, *p*-level 0.0022), and the quadratic functional form, BBS^2, is positive (0.0012, *p*-level <.0001). These results show that the findings are robust to this alternate specification, and that during more extreme periods of economy-wide investor sentiment, price discovery is more timely. The results for *Sent* (-0.0011, *p*-level <.0001) and $Sent^2$ (0.0010, *p*-level <.0001) are also consistent with our prior findings suggesting that price discovery is more timely for more

[14] For a quadratic relation to hold, the sign on $Sent^2$ would need to be opposite to that of *Sent*.

extreme firm-specific sentiment. When including *Good* into the regression (second column), the results remain qualitatively unchanged. The significantly negative coefficient for *Good* (−0.0025, *p*-level <.0001) confirms prior findings that price discovery for good news is relatively more timely than for bad news.

[Insert Table IX about here]

We then consider a different criteria in assessing boom and bust periods. Consistent with Bushman and Williams (2011), we define bust periods with reference to the NBER Business Cycle Reference Dates.[15] Specifically, a bust period are those defined by the NBER as being in a recession, where a recession is where the economy is contracting, or in other words, the period from peak to trough. All non-bust periods are defined as boom periods. This results in 23 bust quarters, equating to 18.55% of our sample. When we re-estimate equation (3) with the alternate definitions of boom and bust we find qualitatively similar results. Consequently, we are confident that the main results reported are not sensitive to the empirical identification of boom and bust periods.

Finally, we consider market-wide volatility. In our main results we include controls for firm-specific stock return volatility (*Vol*). However, it is possible that market-wide volatility will differ during boom, bust and steady-state periods. Indeed, market-wide is lower during steady-state periods than in boom and bust periods, where market-wide volatility is taken as the VIX implied volatility of the S&P 500 reported by the CBOE. We also include the VIX as an additional control variable in estimating equations (8) and (9). In doing so, we find that as the VIX increases, price discovery, on average, is more timely, consistent with

[15] The NBER Business Cycle Reference Dates are available from http://www.nber.org/cycles.html.

boom and bust periods being more timely than steady-state periods. Overall, however, the inclusion of VIX does not alter any of our main results reported.

IV. Conclusions

The aim of this paper is to contribute to the literature on the timeliness of price discovery considering periods of extreme economy-wide and firm-specific sentiment. We provide evidence that sentiment at both the macro- and micro-levels affects how timely information is impounded into stock prices. Our results provide important insights into the price formation process. They are useful for researchers analyzing the speed at which terminal value is reached and the underlying reasons for it. Our findings may help market participants obtain a deeper understanding of the consequences of periods of non-normal market activity.

Using a large sample based on U.S. firms with 99,715 observations, we show that at the macro-level during both boom and bust periods, information is impounded into stock prices at a faster rate. We base our analyses on prior behavioral finance evidence that uses psychological phenomena as explanations for certain stock market movements. At the micro-level, our results suggest that during boom periods, price discovery for stocks with higher sentiment is more timely. However, during bust periods, price discovery is more timely for stocks with low sentiment. Finally, incorporating good news and bad news into our analyses, we find that in general, price discovery of good news is more timely than that of bad news.

We contribute to the literature in numerous ways. This study is the first to analyze how periods of extreme economy-wide sentiment impact the timeliness of price discovery. Amid discussions on the recent financial crisis, our paper provides insight into the consequences of such periods on the price formation process. In addition, our research design includes both macro-level and micro-level effects, as well as both stock market and non-stock market measures of sentiment. This allows us to provide more comprehensive evidence on how boom and bust periods and firm-specific investor sentiment affect timeliness.

We acknowledge some limitations in our study. An inherent problem when analyzing non-normal market activity is to define those periods correctly. Ex-ante it is hard to predict those per se. Ex-post, we can still not be absolutely certain whether the periods we identified separate the sample periods into boom, bust, and steady periods accurately. However, the University of Michigan Index of Consumer Sentiment (ICS) is a common measure to capture overall sentiment. Hence, we are confident that despite some remaining uncertainties, our quarterly periods reflect periods of different levels of economy-wide sentiment in a refined manner enough to analyze the impact on the price formation process.

Our results can be used in future research analyzing the impact of economy-wide sentiment on the timeliness of price discovery in different settings. Comparing the U.S. setting with an environment that was not as strongly affected by the recent financial crisis and investigating how the timeliness metric differs during those years may be a useful avenue for future research.

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Figure 1: Economy-wide proxy for sentiment

This figure depicts the quarterly movements of the University of Michigan Index of Consumer Sentiment (*ICS*) over the period Q1/1980-Q4/2010. *ICS* is used as a proxy for economy-wide sentiment and for identifying boom, bust, and steady periods independent from stock market movements.

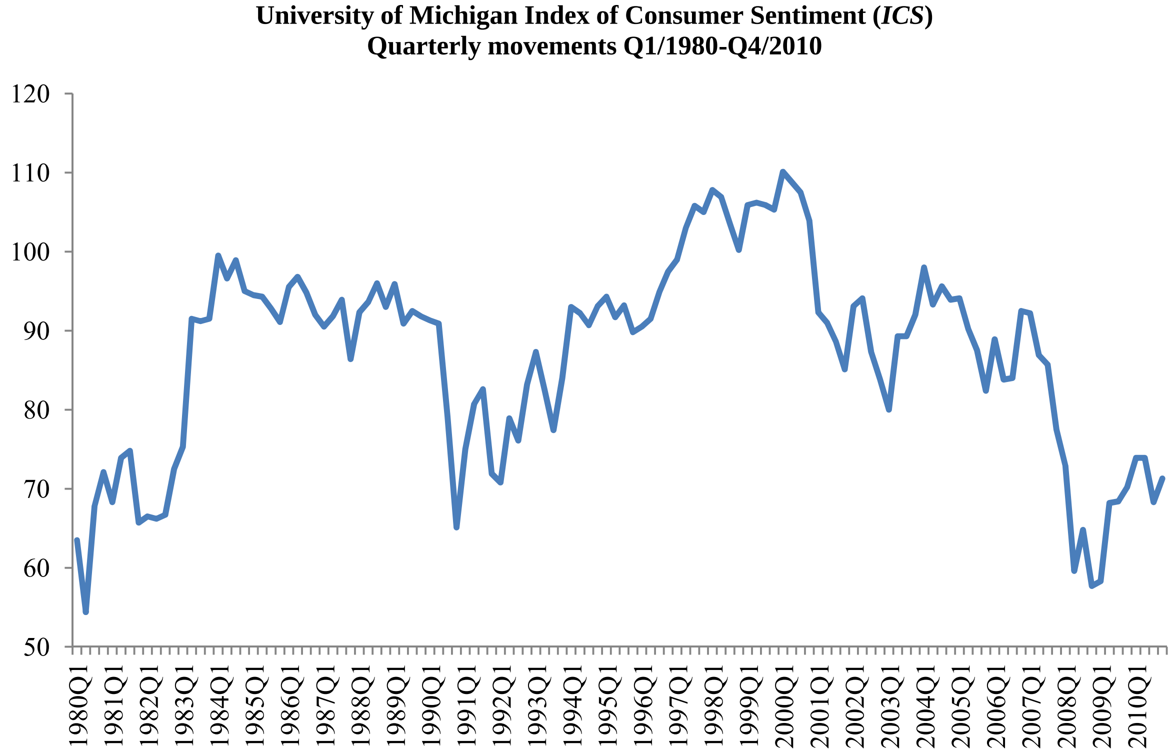

Table I: Descriptive Statistics

This table presents the descriptive statistics of the full sample (N = 96,792). *TIME* is the timeliness metric as expressed in equation (5); *Boom* (*Bust*) periods are defined as where the five-month moving average of the University of Michigan Index of Consumer Sentiment (*ICS*) increases (decreases) by 0.6%, and all other periods are set as *Steady*; *Sent* is the firm-specific sentiment beta estimated as in equation (2) over a 60-month period; *Good* is a dummy variable for if the firm out-performed the market in the quarter; *ICS* is the level of the University of Michigan Index of Consumer Sentiment; *Liquid* is the Amihud (2002) measure of illiquidity; *Size* is measured as the natural logarithm of the market value of equity; *OperCyc* is the firm's operating cycle estimated as the natural logarithm of the sum of days of accounts receivables and days of inventories; *SalesVol* is the sales volatility measured as the standard deviation of sales (scaled by average total assets) over years *t-1* to *t-5*; *Lev* is leverage measured as the debt to equity ratio; *CapFix* is the ratio of capital expenditures to fixed assets (property, plant and equipment); *RD* is the level of research and development expenditure (scaled by the log of sales), with research and development expenditures assumed to be zero if missing; *BTM* is the book to market ratio; and *Vol* is the standard deviation of daily market adjusted returns over the timeliness specification period.

	Mean	**Std Dev**	**Q1**	**Median**	**Q3**
TIME	0.5143	0.0481	0.4817	0.5134	0.5458
Boom	0.3554	0.4786	0.0000	0.0000	1.0000
Bust	0.3841	0.4864	0.0000	0.0000	1.0000
Steady	0.2605	0.4389	0.0000	0.0000	1.0000
Sent	-0.0025	0.0283	-0.0213	-0.0048	0.0151
Good	0.4148	0.4927	0.0000	0.0000	1.0000
ICS	89.14	11.68	83.80	91.50	94.90
Liquid	0.2922	1.0695	0.0018	0.0112	0.0814
Size	6.3281	1.7434	5.0345	6.2412	7.4940
Surprise	0.0107	0.0338	0.0004	0.0017	0.0059
OperCyc	6.2711	1.0642	5.7209	6.2025	6.6326
SalesVol	0.0287	0.0316	0.0090	0.0183	0.0359
Lev	0.5262	0.9470	0.0442	0.2117	0.5671
CapFix	0.0632	0.0550	0.0277	0.0484	0.0809
RD	1.7231	5.6283	0.0000	0.0000	0.7164
BTM	0.5884	0.4369	0.3060	0.4904	0.7491
Vol	0.0226	0.0125	0.0136	0.0194	0.0280

Table II: Correlation Matrix

This table presents the Pearson (Spearman) correlations above (below) the diagonal of the full sample (N = 96,792). Correlations significant at the 1% (5%) level are presented in bold (italic) typeface. All variables are defined as in Table 1.

	TIME	*Boom*	*Bust*	*Steady*	*Sent*	*Good*	*ICS*	*Liquid*	*Size*	*Surprise*	*OperCyc*	*SalesVol*	*Lev*	*CapFix*	*RD*	*BTM*	*Vol*
TIME		**-0.051**	**0.014**	**0.040**	-0.001	**-0.045**	**0.020**	**-0.031**	**0.020**	**0.014**	**-0.020**	**0.015**	-0.006	**0.032**	**0.011**	**-0.017**	**0.066**
Boom	**-0.048**		**-0.586**	**-0.440**	**0.028**	*0.007*	**0.190**	**-0.028**	**0.025**	**-0.046**	0.002	-0.005	**-0.049**	0.003	0.005	**-0.067**	**-0.150**
Bust	**0.010**	**-0.586**		**-0.469**	**-0.168**	-0.001	**-0.437**	**0.026**	-0.005	**0.042**	**0.026**	**-0.024**	**0.052**	**-0.016**	**0.014**	**0.075**	**0.099**
Steady	**0.041**	**-0.441**	**-0.469**		**0.156**	-0.006	**0.278**	0.002	**-0.022**	0.004	**-0.031**	**0.032**	-0.004	**0.014**	**-0.021**	**-0.011**	**0.054**
Sent	0.001	**0.031**	**-0.172**	**0.157**		-0.003	**0.240**	0.005	**-0.055**	0.001	**-0.093**	**0.053**	**-0.053**	**0.043**	**-0.031**	**-0.045**	0.003
Good	**-0.042**	*0.007*	-0.001	-0.006	-0.006		**0.026**	**-0.028**	**0.049**	**-0.066**	**-0.036**	-0.001	**-0.048**	0.002	**-0.009**	**-0.082**	**-0.039**
ICS	**0.034**	**0.265**	**-0.498**	**0.262**	**0.213**	**0.032**		**-0.068**	**0.032**	**-0.067**	**-0.097**	**0.061**	**-0.101**	**0.048**	**-0.020**	**-0.145**	**-0.046**
Liquid	**-0.045**	**-0.028**	**-0.009**	**0.040**	**0.090**	**-0.040**	**0.016**		**-0.409**	**0.176**	**0.093**	**0.026**	**0.174**	**-0.035**	**-0.074**	**0.282**	**0.312**
Size	**0.021**	**0.024**	-0.002	**-0.024**	**-0.052**	**0.051**	**0.020**	**-0.929**		**-0.266**	**-0.088**	**-0.158**	**-0.188**	**-0.041**	**0.367**	**-0.385**	**-0.431**
Surprise	**0.019**	**-0.043**	**0.054**	**-0.013**	**-0.032**	**-0.078**	**-0.096**	**0.345**	**-0.402**		**0.065**	**0.054**	**0.374**	**-0.043**	**-0.039**	**0.294**	**0.356**
OperCyc	-0.005	*-0.007*	**0.009**	-0.002	**-0.044**	**-0.035**	**-0.022**	**0.105**	**-0.108**	**0.030**		**-0.183**	**0.200**	**-0.039**	**0.016**	**0.164**	0.003
SalesVol	**0.022**	**-0.014**	**-0.032**	**0.051**	**0.088**	*0.007*	**0.091**	**0.146**	**-0.191**	**0.117**	**-0.148**		**-0.070**	**0.088**	**-0.063**	**-0.038**	**0.127**
Lev	**-0.020**	**-0.035**	**0.022**	**0.013**	**-0.041**	**-0.043**	**-0.018**	**0.113**	**-0.078**	**0.252**	**0.044**	**-0.140**		**-0.178**	**-0.085**	**0.477**	**0.208**
CapFix	**0.041**	0.005	**-0.020**	**0.017**	**0.059**	0.002	**0.058**	**-0.071**	**0.024**	**-0.118**	**-0.014**	**0.114**	**-0.325**		**0.049**	**-0.190**	**0.123**
RD	**0.030**	**0.009**	**0.028**	**-0.040**	**-0.045**	0.000	**-0.048**	**-0.197**	**0.127**	**-0.046**	**0.180**	-0.005	**-0.316**	**0.167**		**-0.131**	**-0.028**
BTM	**-0.027**	**-0.052**	**0.059**	-0.008	**-0.034**	**-0.086**	**-0.100**	**0.376**	**-0.381**	**0.359**	**0.120**	**-0.068**	**0.446**	**-0.239**	**-0.222**		**0.211**
Vol	**0.060**	**-0.158**	**0.101**	**0.060**	**0.009**	**-0.019**	**-0.018**	**0.370**	**-0.461**	**0.352**	**0.028**	**0.188**	**-0.057**	**0.097**	**0.160**	**0.076**	

Table III: Means (Medians) of Variables by Boom, Bust, and Steady state periods.

This table presents the mean (median) values of the descriptive statistics by boom, bust, and steady state periods. Boom (bust) periods are defined as where the five-month moving average of the University of Michigan Index of Consumer Sentiment (*ICS*) increases (decreases) by 0.6%. The differences in means (medians) are tested using a student *t*-test (wilcoxon *z*-test), with differences significant at the 1% (5%) level are presented in bold (italic) typeface. All variables are defined as in Table I.

	Boom	Bust	Steady	Boom – Bust	Boom – Steady	Bust – Steady
TIME	0.5110	0.5152	0.5175	**-0.0042**	**-0.0065**	**-0.0024**
	(0.5105)	(0.5137)	(0.5171)	**(-0.0033)**	**(-0.0066)**	**(-0.0033)**
Sent	-0.0014	-0.0085	0.0050	**0.0071**	**-0.0063**	**-0.0134**
	(-0.0030)	(-0.0102)	(0.0037)	**(0.0072)**	**(-0.0067)**	**(-0.0139)**
ICS	92.12	82.67	94.60	**9.45**	**-2.48**	**-11.93**
	(93.60)	(85.10)	(93.20)	**(8.50)**	**(0.40)**	**(-8.10)**
Liquid	0.2517	0.3271	0.2958	**-0.0754**	**-0.0441**	**0.0313**
	(0.0102)	(0.0104)	(0.0141)	**(-0.0002)**	**(-0.0039)**	**(-0.0037)**
Size	6.3872	6.3176	6.2629	**0.0696**	**0.1243**	**0.0547**
	(6.3015)	(6.2370)	(6.1610)	**(0.0645)**	**(0.1405)**	**(0.0760)**
Surprise	0.0086	0.0125	0.0109	**-0.0039**	**-0.0023**	**0.0016**
	(0.0015)	(0.0019)	(0.0016)	**(-0.0004)**	**(-0.0001)**	**(0.0003)**
OperCyc	6.2740	6.3063	6.2153	**-0.0324**	**0.0586**	**0.0910**
	(6.1945)	(6.2032)	(6.2114)	**(-0.0087)**	(-0.0170)	***(-0.0082)***
SalesVol	0.0285	0.0277	0.0304	**0.0007**	**-0.0019**	**-0.0027**
	(0.0179)	(0.0176)	(0.0199)	**(0.0004)**	**(-0.0019)**	**(-0.0023)**
Lev	0.4637	0.5886	0.5193	**-0.1250**	**-0.0557**	**0.0693**
	(0.1944)	(0.2230)	(0.2196)	**(-0.0286)**	**(-0.0251)**	(0.0035)
CapFix	0.0635	0.0622	0.0645	**0.0013**	*-0.0010*	**-0.0023**
	(0.0486)	(0.0474)	(0.0496)	**(0.0012)**	**(-0.0010)**	**(-0.0022)**
RD	1.7621	1.8208	1.5257	-0.0587	**0.2364**	**0.2951**
	(0.0000)	(0.0000)	(0.0000)	**(0.0000)**	**(0.0000)**	**(0.0000)**
BTM	0.5493	0.6300	0.5807	**-0.0807**	**-0.0314**	**0.0493**
	(0.4682)	(0.5172)	(0.4866)	**(-0.0490)**	**(-0.0184)**	**(0.0306)**
VOL	0.0201	0.0242	0.0237	**-0.0041**	**-0.0037**	**0.0004**
	(0.0172)	(0.0207)	(0.0205)	**(-0.0035)**	**(-0.0033)**	**(0.0002)**
N	34,399	37,182	25,211			

Table IV: Main results: Boom (Bust) +0.6% (-0.6%) change in *ICS* over five rolling quarters

This table presents the results of estimating equation (8), where the dependent variable is *TIME*, as expressed in equation (5). Boom (bust) periods are defined as where the five-quarter moving average of the University of Michigan Index of Consumer Sentiment (*ICS*) increases (decreases) by 0.6%. All dependent variables have been standardized so that the intercept represents the sample mean, and the coefficients are the impact on *TIME* given a one standard deviation increase in the independent variable. Two-tailed *p*-values are provided in parentheses, based on standard errors clustered by firm, quarter and industry. All variables are defined as in Table I.

		POOLED	BOOM+BUST	BOOM	BUST	STEADY
Intercept		0.5143	0.5132	0.5110	0.5152	0.5175
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Boom	*H1*	-0.0025				
		(<.0001)				
Bust	*H1*	-0.0007	0.0017			
		(0.0017)	(<.0001)			
Sent	*H2*	-0.0004	0.0001	-0.0011	0.0012	-0.0013
		(0.0340)	(0.5133)	(<.0001)	(<.0001)	(0.0001)
ICS		0.0011	0.0004	0.0020	-0.0012	0.0029
		(<.0001)	(0.0949)	(<.0001)	(<.0001)	(<.0001)
Liquid		-0.0018	-0.0016	-0.0014	-0.0017	-0.0024
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Size		0.0022	0.0022	0.0018	0.0022	0.0020
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Surprise		0.0002	0.0001	0.0003	0.0000	0.0008
		(0.3057)	(0.8082)	(0.4245)	(0.9876)	(0.0401)
OperCyc		-0.0003	-0.0004	-0.0013	0.0003	-0.0002
		(0.0463)	(0.0745)	(<.0001)	(0.2300)	(0.4915)
SalesVol		0.0003	0.0003	0.0003	0.0004	0.0004
		(0.0629)	(0.1482)	(0.3230)	(0.2145)	(0.2023)
Lev		-0.0002	-0.0003	-0.0002	-0.0004	0.0000
		(0.2580)	(0.1652)	(0.5159)	(0.2282)	(0.9224)
CapFix		0.0009	0.0014	0.0013	0.0014	-0.0002
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.4993)
RD		-0.0003	-0.0004	-0.0003	-0.0004	-0.0002
		(0.0493)	(0.0619)	(0.3146)	(0.1306)	(0.5098)
BTM		-0.0001	-0.0001	-0.0001	-0.0001	-0.0004
		(0.7983)	(0.8100)	(0.8188)	(0.8492)	(0.3912)
Vol		0.0043	0.0041	0.0034	0.0041	0.0036
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
N		96,792	71,581	34,399	37,182	25,211
Adj R^2		0.0117	0.0096	0.0101	0.0084	0.0146
F-Test		96.20				
Boom = Bust		<.0001				

Table V: Including news (good and bad)

This table presents the results of estimating equation (9), where the dependent variable is *TIME*, as expressed in equation (5). Boom (bust) periods are defined as where the five-quarter moving average of the University of Michigan Index of Consumer Sentiment (*ICS*) increases (decreases) by 0.6%. All dependent variables have been standardized so that the intercept represents the sample mean, and the coefficients are the impact on *TIME* given a one standard deviation increase in the independent variable. Two-tailed *p*-values are provided in parentheses, based on standard errors clustered by firm, quarter and industry. All variables are defined as in Table I.

		POOLED	BOOM+BUST	BOOM	BUST	STEADY
Intercept		0.5143	0.5132	0.5110	0.5152	0.5175
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Boom	*H1*	-0.0024				
		(<.0001)				
Bust	*H1*	-0.0006	0.0017			
		(0.0423)	(<.0001)			
Sent	*H2*	-0.0004	0.0001	-0.0012	0.0012	-0.0013
		(0.0247)	(0.6130)	(<.0001)	(<.0001)	(0.0001)
Good	*H3*	-0.0020	-0.0023	-0.0024	-0.0022	-0.0020
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
*Boom*Good*	*H3a*	-0.0003				
		(0.3759)				
*Bust*Good*	*H3b*	-0.0002	0.0001			
		(0.5836)	(0.7579)			
ICS		0.0012	0.0004	0.0021	-0.0012	0.0030
		(<.0001)	(0.0559)	(<.0001)	(<.0001)	(<.0001)
Liquid		-0.0018	-0.0016	-0.0013	-0.0017	-0.0024
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Size		0.0023	0.0022	0.0020	0.0021	0.0020
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Surprise		0.0001	0.0000	0.0002	-0.0001	0.0007
		(0.5655)	(0.8664)	(0.6358)	(0.7901)	(0.0616)
OperCyc		-0.0004	-0.0004	-0.0014	0.0003	-0.0003
		(0.0227)	(0.0440)	(<.0001)	(0.2401)	(0.3783)
SalesVol		0.0003	0.0003	0.0003	0.0004	0.0004
		(0.0677)	(0.1493)	(0.3402)	(0.2035)	(0.2244)
Lev		-0.0002	-0.0003	-0.0002	-0.0004	0.0000
		(0.2745)	(0.1896)	(0.6489)	(0.2141)	(0.9686)
CapFix		0.0009	0.0013	0.0013	0.0013	-0.0002
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.5089)
RD		-0.0004	-0.0004	-0.0003	-0.0005	-0.0003
		(0.0217)	(0.0309)	(0.2142)	(0.0898)	(0.4265)
BTM		-0.0002	-0.0002	-0.0002	-0.0002	-0.0005
		(0.3646)	(0.4532)	(0.5836)	(0.5484)	(0.2044)
Vol		0.0043	0.0041	0.0034	0.0041	0.0035
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
N		96,792	71,581	34,399	37,182	25,211

Adj R^2	0.0137	0.0118	0.0129	0.0103	0.0163
F-Test *Boom = Bust*	96.20 (<.0001)				

Table VI: Comparison of the Timeliness of Good and Bad News

This table presents the mean (median) values of the timeliness of good and bad news by boom, bust, and steady state periods. Boom (bust) periods are defined as where the five-month moving average of the University of Michigan Index of Consumer Sentiment (*ICS*) increases (decreases) by 0.6%. The differences in means (medians) are tested using a student *t*-test (wilcoxon *z*-test), with differences significant at the 1% (5%) level are presented in bold (italic) typeface. The timeliness of good news, T^G, and bad news T^B, are defined in equations (4a) and (4b) respectively.

	Boom	Bust	Steady	Boom – Bust	Boom – Steady	Bust – Steady
T^G	0.5104	0.5128	0.5126	**-0.0024**	**-0.0022**	**0.0002**
	(0.5093)	(0.5110)	(0.5121)	**(-0.0018)**	**(-0.0028)**	**(-0.0011)**
T^B	0.5106	0.5175	0.5211	**-0.0069**	**-0.0105**	**-0.0036**
	(0.5098)	(0.5157)	(0.5201)	**(-0.0060)**	**(-0.0104)**	**(-0.0044)**
T^G - T^B	-0.0001	**-0.0046**	**-0.0085**			
	(-0.0005)	**(-0.0047)**	**(-0.0080)**			
N	34,399	37,182	25,211			

Table VII: Sensitivity analysis with Boom (Bust) +0.5% (-0.5%) change in *ICS* over five rolling quarters

This table presents the results of estimating equation (8), where the dependent variable is *TIME*, as expressed in equation (5). Boom (bust) periods are defined as where the five-quarter moving average of the University of Michigan Index of Consumer Sentiment (*ICS*) increases (decreases) by 0.5%. All dependent variables have been standardized so that the intercept represents the sample mean, and the coefficients are the impact on *TIME* given a one standard deviation increase in the independent variable. Two-tailed *p*-values are provided in parentheses, based on standard errors clustered by firm, quarter and industry. All variables are defined as in Table 1.

		POOLED	BOOM+BUST	BOOM	BUST	STEADY
Intercept		0.5143	0.5129	0.5108	0.5149	0.5187
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Boom	*H1*	-0.0034				
		(<.0001)				
Bust	*H1*	-0.0015	0.0016			
		(<.0001)	(<.0001)			
Sent	*H2*	-0.0004	0.0000	-0.0010	0.0008	-0.0010
		(0.0127)	(0.8283)	(0.0002)	(0.0049)	(0.0044)
ICS		0.0011	0.0000	0.0014	-0.0013	0.0041
		(<.0001)	(0.9348)	(<.0001)	(<.0001)	(<.0001)
Liquid		-0.0018	-0.0016	-0.0014	-0.0017	-0.0024
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Size		0.0022	0.0019	0.0015	0.0020	0.0025
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Surprise		0.0002	0.0002	0.0004	0.0000	0.0005
		(0.3452)	(0.5100)	(0.1882)	(0.9008)	(0.2070)
OperCyc		-0.0003	-0.0004	-0.0012	0.0003	-0.0002
		(0.0454)	(0.0548)	(<.0001)	(0.2886)	(0.5542)
SalesVol		0.0003	0.0003	0.0003	0.0003	0.0004
		(0.0669)	(0.1712)	(0.3010)	(0.2806)	(0.1992)
Lev		-0.0002	-0.0004	-0.0003	-0.0005	0.0001
		(0.2623)	(0.1269)	(0.4348)	(0.1741)	(0.7483)
CapFix		0.0009	0.0013	0.0013	0.0013	-0.0002
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.5589)
RD		-0.0003	-0.0003	-0.0001	-0.0004	-0.0005
		(0.0498)	(0.1475)	(0.6268)	(0.1753)	(0.1658)
BTM		0.0000	-0.0001	-0.0002	0.0000	-0.0005
		(0.8220)	(0.8367)	(0.6031)	(0.9134)	(0.2606)
Vol		0.0043	0.0038	0.0029	0.0040	0.0041
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
N		96,792	73,513	35,499	38,014	23,295
Adj R^2		0.0129	0.0089	0.0081	0.0080	0.0206
F-Test		93.82				
Boom = Bust		<.0001				

Table VIII: Sensitivity analysis with Boom (Bust) +0.5% (-0.5%) including news (good and bad)

This table presents the results of estimating equation (9), where the dependent variable is *TIME*, as expressed in equation (5). Boom (bust) periods are defined as where the five-month moving average of the University of Michigan Index of Consumer Sentiment (*ICS*) increases (decreases) by 0.5%. All dependent variables have been standardized so that the intercept represents the sample mean, and the coefficients are the impact on *TIME* given a one standard deviation increase in the independent variable. Two-tailed *p*-values are provided in parentheses, based on standard errors clustered by firm, quarter and industry. All variables are defined as in Table I.

		POOLED	BOOM+BUST	BOOM	BUST	STEADY
Intercept		0.5143	0.5129	0.5108	0.5149	0.5187
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Boom	*H1*	-0.0032				
		(<.0001)				
Bust	*H1*	-0.0014	0.0016			
		(<.0001)	(<.0001)			
Sent	*H2*	-0.0004	-0.0001	-0.0010	0.0008	-0.0010
		(0.0085)	(0.7122)	(0.0001)	(0.0057)	(0.0046)
Good	*H3*	-0.0020	-0.0023	-0.0024	-0.0022	-0.0021
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
*Boom*Good*	*H3a*	-0.0003				
		(0.3330)				
*Bust*Good*	*H3b*	-0.0002	0.0001			
		(0.5939)	(0.6835)			
ICS		0.0011	0.0000	0.0014	-0.0013	0.0042
		(<.0001)	(0.8764)	(<.0001)	(<.0001)	(<.0001)
Liquid		-0.0018	-0.0016	-0.0014	-0.0017	-0.0024
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Size		0.0023	0.0020	0.0016	0.0020	0.0025
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Surprise		0.0001	0.0001	0.0003	0.0000	0.0004
		(0.6207)	(0.7651)	(0.3231)	(0.9256)	(0.2747)
OperCyc		-0.0004	-0.0004	-0.0013	0.0003	-0.0003
		(0.0222)	(0.0315)	(<.0001)	(0.3046)	(0.4318)
SalesVol		0.0003	0.0003	0.0003	0.0003	0.0004
		(0.0721)	(0.1677)	(0.3073)	(0.2662)	(0.2207)
Lev		-0.0002	-0.0004	-0.0002	-0.0005	0.0001
		(0.2794)	(0.1544)	(0.5363)	(0.1780)	(0.8007)
CapFix		0.0009	0.0013	0.0013	0.0013	-0.0002
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.5600)
RD		-0.0004	-0.0003	-0.0002	-0.0004	-0.0005
		(0.0220)	(0.0838)	(0.4820)	(0.1229)	(0.1270)
BTM		-0.0002	-0.0002	-0.0003	-0.0002	-0.0006
		(0.3799)	(0.4601)	(0.3790)	(0.6042)	(0.1337)
Vol		0.0043	0.0038	0.0029	0.0040	0.0040
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
N		96,792	73,513	35,499	38,014	23,295

Adj R^2	0.0150	0.0111	0.0108	0.0099	0.0224
F-Test	62.15				
Boom = Bust	<.0001				

Table IX: Sensitivity analysis with continuous value of change in *ICS*

This table presents the results of estimating equation (8), where the dependent variable is *TIME*, as expressed in equation (5). All dependent variables have been standardized so that the intercept represents the sample mean, and the coefficients are the impact on *TIME* given a one standard deviation increase in the independent variable. Two-tailed *p*-values are provided in parentheses, based on standard errors clustered by firm, quarter, and industry. All variables are defined as in Table 1, except where *BBS* is the change in the five-period moving average of *ICS*; and BBS^2 is the squared value of *BBS*.

			including *Good*
Intercept		0.5143	0.5143
		(<.0001)	(<.0001)
BBS	*H1*	-0.0033	-0.0034
		(<.0001)	(<.0001)
BBS^2	*H1*	0.0005	0.0005
		(0.0269)	(0.0163)
Sent	*H2*	-0.0002	-0.0002
		(0.2411)	(0.1917)
Good			-0.0023
			(<.0001)
ICS		0.0029	0.0030
		(<.0001)	(<.0001)
Liquid		-0.0018	-0.0017
		(<.0001)	(<.0001)
Size		0.0020	0.0020
		(<.0001)	(<.0001)
Surprise		0.0002	0.0001
		(0.2703)	(0.5181)
OperCyc		-0.0003	-0.0004
		(0.0451)	(0.0215)
SalesVol		0.0003	0.0003
		(0.0539)	(0.0585)
Lev		-0.0002	-0.0002
		(0.2938)	(0.3081)
CapFix		0.0009	0.0008
		(<.0001)	(<.0001)
RD		-0.0003	-0.0004
		(0.0615)	(0.0276)
BTM		-0.0001	-0.0003
		(0.5583)	(0.2015)
Vol		0.0038	0.0038
		(<.0001)	(<.0001)
N		96,792	96,792
Adj R^2		0.0135	0.0157