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The Impact of Economy-Wide Sentiment on Analysts' Research Activities

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Abstract

In this article, we examine how economy-wide sentiment, measured with the University of Michigan's Consumer Sentiment Index, affects analysts' research activities. Using a firm-fixed effects design, we find that consumer sentiment, especially the component related to economic fundamentals, is negatively associated with analysts' frequency of issuing research reports, but is positively associated with the precision of analysts' idiosyncratic information, our proxy for analysts' engagement in private information discovery. The evidence is more pronounced for firms with larger total assets, higher return on assets, better market performance, lower stock return volatility, and higher institutional ownership. We further document that analyst reports are more informative when consumer sentiment is higher. Taken together, our findings suggest that analysts respond to higher consumer sentiment by allocating more effort to private information discovery, which enhances the informativeness of their reports to investors. Our research reveals the impact of sentiment, a macrolevel factor, on analysts' research activities, and it enriches the knowledge of analysts' decision processes.

Keywords

equity analysts, consumer sentiment, private information discovery

Introduction

Sell-side equity analysts are important financial information intermediaries: They interpret and disseminate public information, and generate their own private insights (Chen, Cheng, & Lo, 2010). Given the prominent role analysts play in capital markets, both academic researchers and practitioners strive to understand analysts' decision processes and the information content of their forecasts and recommendations. Schipper (1991), Ramnath, Rock, and Shane (2008), and Beyer, Cohen, Lys, and Walther (2010) provide comprehensive reviews of this literature.

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Although prior studies have offered important insight, the analyst literature largely focuses on economic determinants at the microeconomic level such as firm characteristics (e.g., Bhushan, 1989) and analyst characteristics (e.g., Clarke & Subramanian, 2006). With few exceptions (e.g., Hribar & McInnis, 2012; Walther & Willis, 2013), the link between analyst research activities and macroeconomic level factors has been underexplored. This study fills this void by investigating how analysts' frequency of issuing research reports and their engagement in private information discovery vary with economy-wide sentiment. Our focus is consistent with Brown, Call, Clement, and Sharp's (2015) survey results that, compared with forecast accuracy, analysts' standing in broker votes and their success at generating trading commissions are more important to their job security, job mobility, and compensation. We measure economy-wide sentiment with consumer sentiment, which, as we discuss below, influences the ways investors use financial information and hence is expected to play an important role in shaping analyst research activities.

Consumer sentiment reflects households' perception of their income and wealth at present and in the near future (Ludvigson, 2004). It has been documented that household wealth is positively associated with equity investment (e.g., Friend & Blume, 1975). Peress (2004) proposes that households having more wealth to invest would acquire more information because the value, but not the cost, of information increases with the amount to be invested. Lewellen, Lease, and Schlarbaum (1977) confirm that expenditures on acquiring financial information are significantly and positively associated with the income level. These findings suggest that consumer sentiment affects the marginal value of analysts' research outputs, as investors search for more information. Besides, the economics literature suggests that economic growth generates a larger amount of more precise information (Van Nieuwerburgh & Veldkamp, 2006; Veldkamp, 2006b). Thus, as consumer sentiment rises and declines along with economic booms and busts (Lemmon & Portniaguina, 2006), the varying amount of information through the business cycles should also have an impact on the marginal value of analysts' research outputs.

As information intermediaries, equity analysts play two primary roles: disseminating and interpreting public information, and discovering and producing private information (Ramnath et al., 2008). They also need to decide whether and when to issue or revise a report and how much information to acquire/produce (Beyer et al., 2010). To the extent that market-wide information production and investors' information acquisition vary with consumer sentiment, we expect equity analysts to respond to consumer sentiment in systematic ways: They will shift more efforts to more valuable research activities. This hypothesis is consistent with the rational inattention theory; that is, under the constraint of time and cognitive capacity, agents rationally allocate efforts among tasks based on each task's marginal benefit (Sims, 2003). This hypothesis is also supported by Brown et al.'s (2015) survey findings that broker votes, which reflect buy-side clients' perceived value of sell-side analysts' research services, are the most important factor in equity analysts' career advancement.

It has also been established in the prior literature that consumer sentiment reflects both consumers' rational expectations of future economic fundamentals and their excessive optimism or pessimism (Lemmon & Portniaguina, 2006). When investors are overly optimistic, stock prices and trading volumes are more likely driven by excessive sentiment than by fundamental information (Baker & Wurgler, 2006), which implies that investors are less inclined to rely on information from analysts. Insofar as equity analysts are incentivized to cover stocks to generate trading commissions (Irvine, 2004; McNichols & O'Brien, 1997), a high level of *excessive* sentiment would discourage analysts' research activities in general, in terms of both the frequency of issuing research reports and the extent of private information discovery.

In our empirical analyses, we measure analysts' frequency of issuing research reports with the total number of one-quarter-ahead earnings forecasts issued by all analysts. We also use the ratio of forecasts per analyst as an additional measure to capture the quantity of analyst research activities. Following prior empirical studies (e.g., Barron, Byard, & Kim, 2002), we use the precision of analysts' idiosyncratic information as a proxy for analysts' effort in private information discovery. Our proxy for consumer sentiment is the University of Michigan's Consumer Sentiment Index (*CSI*), which has been widely used in the prior literature (e.g., Bergman & Roychowdhury, 2008; Seybert & Yang, 2012). Furthermore, we follow Lemmon and Portniaguina (2006) to decompose *CSI* into two components—one related to the economic fundamentals and the other pertinent to investors' residual sentiment. To isolate the temporal effect of consumer sentiment, we adopt a firm-fixed effects approach, following Bergman and Roychowdhury (2008).

Using Institutional Brokers' Estimate System (I/B/E/S) analyst data over 1995-2010, we find significant evidence that analysts' frequency of issuing research reports is negatively associated with consumer sentiment. All else equal, 1 standard deviation increase in *ICS* is associated with a 4% decrease in the total number of analyst forecasts and a 3.5% decrease in the forecast-to-analyst ratio. Moreover, compared with the residual component, the fundamental component of *ICS* has a stronger effect. In contrast to the negative association between consumer sentiment and the quantity of analyst research activities, we find that the precision of analyst idiosyncratic information, our empirical proxy for the extent of analysts' engagement in private information discovery, is positively associated with consumer sentiment. All else equal, increasing *ICS* by 1 standard deviation is associated with an increase of 3.97 in this precision measure, which is an 11% increase relative to its mean. Similar to the results on the number of research reports issued, this effect is primarily driven by the fundamental component of *ICS*. Taken together, our results suggest that during periods of high consumer sentiment, analysts collectively reduce the frequency of issuing research reports but shift more efforts to private information discovery, especially when the consumer sentiment is supported by strong economic fundamentals.

Next, we conduct subsample analyses to investigate variations in the effect of consumer sentiment on analysts' research activities. Consistent with analysts' incentives of generating trading commissions (Irvine, 2004), we find that when sentiment is high, analysts put more efforts in firms where the incremental benefit of analyst research is greater, such as larger firms, firms with higher return on assets (*ROA*) and higher institutional holdings, but with less volatile stock returns.

Finally, we use Frankel, Kothari, & Weber's (2006) ''informativeness'' measure to assess investors' perceived value of analyst reports. The measure captures stock movement on days of analyst revisions relative to all trading days. Our results suggest that analyst reports are more informative to the stock market when consumer sentiment is high; hence, investors seem to appreciate increased efforts that analysts expend in private information discovery during high sentiment periods.

Our study contributes to the literature in several ways: First, our findings contribute to the literature on equity analysts, which has primarily focused on microlevel determinants of analyst activities. We document that consumer sentiment, an important macrolevel factor, has a significant impact on temporal variations in analyst behaviors after controlling for known microlevel determinants. Our study is closely related to, and yet different from, a growing body of research that examines the relation between sentiment and analyst activities. While existing studies in this area largely concern the properties of analyst research outputs (e.g., Bagnoli, Clement, Crawley, & Watts, 2009; Hribar & McInnis, 2012; Walther & Willis, 2013), we take a broader approach and focus on analysts' frequency of issuing research reports and their effort in private information discovery, which are more fundamental aspects of analyst activities (e.g., Barron, Kim, Lim, & Stevens, 1998; Bhushan, 1989) and are more crucial in their career development (Brown et al., 2015).

Second, our results provide valuable insights into the effort allocation decisions made by analysts in their research activities. Prior studies document two important functions of equity analysts—disseminating *public* information and producing *private* insights (Chen et al., 2010; Ramnath et al., 2008). Our results suggest that there exists a substitutive relation between these two key functions—private information discovery appears to be more important for analysts during high sentiment periods where its marginal benefit is possibly higher.

Third, our study enriches the literature on sentiment. Extant studies have provided strong evidence that sentiment affects decisions made by both investors and managers.[1] We extend this literature by considering the impact of consumer sentiment on equity analysts who serve as important information intermediaries in the financial market.

The remainder of this article is organized as follows: We review the related literature and motivate our hypotheses in Section "Literature Review and Hypothesis Development." Section "Research Design" describes our research designs. We present and discuss empirical results in Section "Results," and Section "Conclusion" concludes the article.

Literature Review and Hypothesis Development

Consumer Sentiment, Macroeconomy, and Information Production

Consumer sentiment (e.g., the University of Michigan's Consumer Sentiment Index) is compiled based on household survey results concerning consumers' assessment of their financial conditions, their expectations regarding the national economy, and their propensity to consume major items. A high reading of consumer sentiment indicates consumers' positive perception of their income and wealth at present and in the near future.

Research on consumer sentiment is extensive. One of the most important implications of consumer sentiment is households' tendency to participate in equity investment, which requires income and wealth (Mankiw & Zeldes, 1991). Ben-Rephael, Kandel, and Wohl (2012) show that increases in consumer sentiment are positively associated with a net flow from bond funds to equity funds, and Chalmers, Kaul, and Phillips (2013) report that high consumer sentiment predicts excess flows into equity funds. Both findings demonstrate consumers' higher interest in participating in equity markets during high sentiment periods. When investors are more engaged in risky investment, they likely demand more information. This intuition is borne out in both analytical models (e.g., Peress, 2004) and survey results (e.g., Lewellen et al., 1977). These studies suggest a positive relation between consumer sentiment and investors' demand for value-relevant information.

Prior research finds that the supply of information also varies with the macroeconomy. Veldkamp (2006a) notes that increases in demand for information result in more information being provided at a lower price because, unlike physical assets, information has large fixed costs and exhibits significant economy of scale. Besides, consumer sentiment is correlated with market-wide information production, as they both covary with economic booms and busts. New development in this line of research suggests that not only a larger amount of information (e.g., Veldkamp, 2006b) but information of higher precision (e.g., Van Nieuwerburgh & Veldkamp, 2006) is also generated with economic growth.[2] This prediction fits empirical data well. Using the number of news articles on *Financial Times*, Veldkamp (2006b) confirms that asset market movements generate news. Brockman, Liebenberg, and Schutte (2010) find an inverse relation between stock return comovement and aggregate economic activities, implying a larger quantity of firm-specific information during economic expansions. These studies suggest a positive relation between consumer sentiment and the market supply of public information.

Because this study aims to examine how a macroeconomic factor influences analyst research activities, we focus on ''consumer'' sentiment, which relates to more constituents in the economy than just ''investor'' sentiment. While all investors are consumers, not all consumers are necessarily current investors but may be potential investors. In addition, many prior studies have used the Michigan ''consumer'' sentiment index in various settings and established useful methods to differentiate the effects of sentiment that are related to economic fundamentals from those potentially associated with behavioral biases (e.g., Lemmon & Portniaguina, 2006).

Equity Analyst Activities

Equity analysts gather public information and acquire private information to generate earnings forecasts, price targets, stock recommendations, and other information about the companies they cover. One of the key benefits that analysts and their employers reap from providing research reports is generating trading commissions (e.g., Irvine, 2004).

Equity analysts also face fierce competition. Both anecdotal and large sample evidence suggest that analysts' compensation and career advancement are closely tied to the quality of their services (e.g., Groysberg, Healy, & Maber, 2011). According to Brown et al. (2015), broker votes, by which buy-side portfolio managers and buy-side analysts assess the value of sell-side brokerage houses' research services, are rated by surveyed sell-side analysts as having a first-order impact on the commission allocated to their employer and, in turn, their compensation. Therefore, it is crucial for these sell-side equity analysts to evaluate investors' information needs, so that their research reports could be incrementally informative and useful to their clients.

While prior studies generally focus on microlevel determinants of analyst research such as firm and analyst characteristics, few recent studies seek to understand the impact of sentiment, a macrolevel factor, on analysts' research outputs. For example, Bagnoli et al. (2009) show that the profitability of analysts' stock recommendations decreases when they change recommendations according to investor sentiment measured by Baker and Wurgler's (2006) index. Hribar and McInnis (2012) show that sentiment-based anomalies documented in Baker and Wurgler can be partially explained by analyst forecast optimism. In contrast to their primary focus on investors' excessive sentiment, we focus on the impact of consumer sentiment, which largely reflects investors' rational expectations of economic fundamentals (e.g., Lemmon & Portniaguina, 2006).

Our article also differs from that of Walther and Willis (2013) who report that analysts are more accurate in their quarterly earnings forecasts when the fundamental component of consumer sentiment is higher, but they are more optimistic and less accurate when the residual component of consumer sentiment (i.e., the portion of sentiment unrelated to underlying economic factors) is higher. While Walther and Willis enrich our understanding of the relation between sentiment and one particular property of analysts' research outputs, namely forecast accuracy, we investigate two fundamental aspects of analyst research activities: the number of research reports issued and the extent of engagement in private information discovery. Our perspective is consistent with the notion that, instead of accuracy, buy-side clients' perceived value of analyst research, such as measured by broker votes, is of first-order importance to sell-side analysts. Furthermore, both types of research activities consume analysts' time and cognitive capacity. If consumer sentiment has different influences on the marginal value of these two activities, as we hypothesize below, then rational analysts should reallocate their effort accordingly. Our article provides an economics-based explanation that could potentially unpack the ''Black Box'' of analysts' decision processes.

Hypothesis Development

Perceiving strong economic fundamentals, confident consumers are not only more willing to spend but also more willing to invest, which increases their demand for financial information (e.g., Friend & Blume, 1975; Lewellen et al., 1977). At the same time, economic expansions stimulate the proliferation of information (Veldkamp, 2005). The quality of information on both the economy and individual firms also improves during economic booms, further lowering the cost to produce information and its price to investors (Van Nieuwerburgh & Veldkamp, 2006).[3] All of these forces likely affect both the supply and the demand of analyst research.

Prior studies suggest that equity analysts play two important roles in the capital market: as interpreters of public information and as developers of private information (e.g., Chen et al., 2010). Analysts are likely to trade-off these two roles based on each role's expected net benefits. To the extent that the way investors use information varies with consumer sentiment, we expect analysts to perceive the changing marginal benefit of their research activities in different sentiment regimes and to adjust their efforts accordingly. Sell-side equity analysts are incentivized to do so because it helps them better cater to the information needs of their clients, which are primarily institutional investors whose votes will determine the distribution of trading commissions and affect analyst compensation (Brown et al., 2015; Groysberg et al., 2011). This shift in analysts' focus is also consistent with Sims's (2003) rational inattention theory, which suggests that facing time and cognitive constraints, rational agents would shuffle their effort among tasks according to each task's marginal value.

In our setting, the abundance of information during high sentiment periods could elevate the marginal net benefit of analysts' role in interpreting public information, if ''information overload'' weakens investors' ability to adequately process the amount of information into useful investment decisions.[4] Thus, analysts could add value for their clients by issuing more research reports that mainly interpret existing public information as opposed to spending more effort on private information discovery during high sentiment period.

Alternatively, analysts' primary clients—institutional investors—may be sophisticated enough to digest the proliferation of public information during high sentiment periods, in which case the marginal benefit of private information discovery likely exceeds that of disseminating public information. Hence, it is also possible that, during high sentiment periods, analysts seek to establish their comparative advantage by exerting greater effort to private information discovery, a more challenging and time-consuming task that requires reducing frequency of issuing reports.

In addition to affecting analysts' supply of research reports, consumer sentiment could have two counteracting effects on investors' demand for analyst research. With higher consumer sentiment, investors are more willing to invest and increase their general demand for financial information, including analyst reports. However, investors' demand for analysts' research may also be reduced by the proliferation in quantity and amelioration in quality of other information during economic expansions. This tension in the effect of sentiment on investors' demand for analyst research echoes its effect on analysts' supply-side trade-off between interpreting public information and discovering private information.

Besides the trade-off between interpreting public information and discovering private information, another factor of analysts' consideration is trading commission (Irvine, 2004). During high sentiment periods, stock trading is also likely more driven by investors' *excessive* sentiment; that is, the component of sentiment unjustified by economic fundamentals (Baker & Wurgler, 2006; Odean, 1998). In particular, retail investors buy or sell stocks in concert, which exacerbates price comovement and mispricing during extreme sentiment periods (Kumar & Lee, 2006). Sophisticated institutional investors are also likely engaged in sentiment-driven trading to profit from equity mispricing. For example, Brunnermeier and Nagel (2004) find that hedge funds profited from the sentiment-driven tech bubble in the late 1990s. As more trading activities are driven by excessive sentiment, investors are less likely to base their trading decisions on analyst reports. Therefore, when the excessive component of consumer sentiment is high, the marginal benefit for analysts to generate trading commissions through research, in terms of both the frequency of issuing research reports and the engagement in private information discovery, is likely to diminish.

The above discussions suggest that consumer sentiment likely affects analyst behaviors; however, *how* analyst research activities vary with consumer sentiment boils down to an empirical question. Therefore, below we state our main hypotheses in the null form:

Hypothesis 1 (H1): *Ceteris paribus*, analysts' frequency of issuing research reports is not associated with consumer sentiment.

Hypothesis 2 (H2): *Ceteris paribus*, analysts' effort in private information discovery is not associated with consumer sentiment.

Finally, we explore whether and how the informativeness of analyst reports varies with consumer sentiment. We evaluate the informativeness of analyst reports based on the market reaction to them. In the preceding two hypotheses, we conjecture that equity analysts adjust their reporting frequency and effort in private information discovery as a response to consumer sentiment. In this supplemental analysis, we further our understanding on how analysts' shifting efforts are ultimately valued by investors.

Research Design

Measuring Analyst Activities

We measure the quantity of analyst research activities with two proxies: The first is the number of one-quarter-ahead earnings forecasts that analysts issue for the firm during a fiscal quarter, transformed by natural logarithm (*NFORECAST*). The second is the ratio of analysts' forecast frequency to the number of analyst following (*RATIO*), which teases out the effect of analyst following on the number of analyst forecasts. We choose analysts' one-quarter-ahead earnings forecasts for four reasons: First, they are commonly used in the prior literature to examine the effect of sentiment on analyst behavior (e.g., Walther & Willis, 2013). Using the same setting ensures comparability with these prior studies. Second, as our hypotheses concern both analysts' frequency in issuing research reports and their engagement in private information discovery, using quarterly earnings forecasts achieves both purposes at the same time (e.g., Mohanram & Sunder, 2006). Third, because most analyst reports typically include one-quarter-ahead earnings forecasts, it serves as a good proxy for the quantity of analyst research activities. Finally, as sentiment affects stock price movement more in the shorter run (e.g., Baker & Wurgler, 2006; Stambaugh, Yu, & Yuan, 2012), quarterly forecasts are more suitable than annual forecasts or long-term growth forecasts for our purpose of examining the effect of sentiment.

We follow the approach developed by Barron et al. (1998) to measure the extent of analysts' engagement in private information discovery. Barron et al. (1998) argue that analysts have two primary sources of information: The first is public information through channels such as firms' public disclosures and news media (Lang & Lundholm, 1996), which is available to all analysts and other market participants. The second source is analysts' own research and analyses, and is thus specific to each individual analyst. Barron et al. (1998) derive the precision of common information (h) and the precision of idiosyncratic information (s) as follows: $h = SE - D/N/[(1 - 1/N)D + SE]^2$ and $s = D/[(1 - 1/N)D + SE]^2$, where SE is the squared error of the mean forecast, measured as $(EPS_{actual} - EPS_{consensus})^2$, D is the standard deviation of analyst forecasts, and N is the number of analysts issuing forecasts.[5] Following prior empirical studies (e.g., Barron et al., 2002; Byard & Shaw, 2003; Mohanram & Sunder, 2006), we interpret h as the quality of common information available to all analysts and s as analysts' effort in private information discovery. Both s and h are calculated using analysts' one-quarter-ahead earnings forecasts from I/B/E/S Detail History file and are deflated by 100 for ease of exposition. We label s and h as *IDIOSYNC* and *COMMON*, respectively.

Measuring Informativeness of Analyst Reports

Following Frankel et al. (2006), we measure the informativeness of analyst research as $AIDF = \frac{\sum_{t = 1 to NREVS} |R_{t,s} - RSIZE_{t,s}|}{\sum_{t = 1 to Q} |R_{t,s} - RSIZE_{t,s}|} \times \frac{1}{NREVS}$, multiplied by 100 for ease of exposition. For a firm in New York Stock Exchange (NYSE) size decile s, $R_{t,s}$ is its stock return on day t; $RSIZE_{t,s}$ is decile-portfolio return; $NREVS$ is the number of days at which at least one analyst issues/revises forecasts; and Q is the number of trading days in a calendar quarter (we require at least 45 daily returns for each firm quarter).

Measuring Consumer Sentiment

Our primary measure of consumer sentiment is the University of Michigan's Consumer Sentiment Index (*ICS*). We follow Lemmon and Portniaguina (2006) to decompose *ICS* into a fundamental component (*PICS*) that is explained by a series of macrovariables and a residual component (*RICS*) that relates to consumers' excessive sentiment. Details of the decomposition procedure are elaborated in the online appendix.

Control Variables and Regression Models

In testing H1 and H2, we include a set of control variables that prior literature has found to affect analyst activities. We control for firm size (*SIZE*) because it is strongly associated with analyst following (e.g., Bhushan, 1989). As analysts are more likely to cover firms with more favorable future prospects (McNichols & O'Brien, 1997), we include market-to-book ratio (*MB*) as a proxy for growth opportunities, *ROA* as a proxy for accounting performance, and size-adjusted abnormal returns (*SARET*) as a proxy for market performance. An indicator variable (*LOSS*) is added to distinguish loss firms, and we further control for R&D expenses (*RD*), capital intensity (*PPE*), dividend payout (*DIV*), and age (*AGE*). Both stock return volatility (*STD_RET*) and turnover (*TURN*) are included as proxies for uncertainties because prior studies suggest that *STD_RET* is likely driven by new information (French & Roll, 1986) and *TURN* is mainly due to divergence of opinions (Shalen, 1993). Following Bhushan (1989), we control for institutional ownership (*INST*). We include a proxy for management forecast precision (*MFPREC*) because more disclosure leads to greater analyst following (Lang & Lundholm, 1996) and management forecast varies with sentiment (Bergman & Roychowdhury, 2008).[6] Wu and Zang (2009) document a wave of mergers and acquisitions of brokers during 1997-2001 that exogenously affects analyst research activities. Thus, we include an indicator (*WZ*) to account for this period, which coincides with most of the pre-Reg FD era in our sample. To avoid multicollinearity, we do not control for Reg FD. Another indicator for the fourth quarter (*Q4*) is added to account for extraordinary analyst activities around year ends.

We estimate the following models to test H1 and H2 (firm and time subscripts omitted):

$$\begin{aligned}\mathbf{H1}: NFORECAST\ (orRATIO) = {} & \alpha_0 + \alpha_1 SIZE + \alpha_2 MB + \alpha_3 ROA + \alpha_4 LOSS \\ & + \alpha_5 RD + \alpha_6 PPE + \alpha_7 DIV + \alpha_8 AGE + \alpha_9 SARET + \alpha_{10} STDRET \\ & + \alpha_{11} TURN + \alpha_{12} INST + \alpha_{13} MFPREC + \alpha_{14} WZ + \alpha_{15} Q4 + \alpha_{16} ICS + \varepsilon.\end{aligned} \tag{1}$$

$$\begin{aligned}\mathbf{H2}: IDIOSYNC\ (orCOMMON) = {} & \beta_0 + \beta_1 SIZE + \beta_2 MB + \beta_3 ROA + \beta_4 LOSS \\ & + \beta_5 RD + \beta_6 PPE + \beta_7 DIV + \beta_8 AGE + \beta_9 SARET + \beta_{10} STDRET \\ & + \beta_{11} TURN + \beta_{12} INST + \beta_{13} MFPREC + \beta_{14} WZ + \beta_{15} Q4 + \beta_{16} ICS + \varepsilon.\end{aligned} \tag{2}$$

In our supplemental examination of analyst report informativeness (*AIDF*), we remove market-based control variables (*SARET, STD_RET*, and *TURN*) as they are likely to be jointly determined with *AIDF*. The regression model used in this analysis is as follows:

$$\begin{aligned}AIDF = {} & \gamma_0 + \gamma_1 SIZE + \gamma_2 MB + \gamma_3 ROA + \gamma_4 LOSS + \gamma_5 RD + \gamma_6 PPE + \gamma_7 DIV \\ & + \gamma_8 AGE + \gamma_9 INST + \gamma_{10} MFPREC + \gamma_{11} WZ + \gamma_{12} Q4 + \gamma_{13} ICS + \varepsilon.\end{aligned} \tag{3}$$

As in H1 and H2, we are interested in whether and how analysts *respond to* sentiment, *ICS* (*PICS* and *RICS*) is read (estimated) immediately before the end of each fiscal quarter in which analysts' activities are measured. In the supplemental analysis, however, we are interested in whether and how investors' reactions to analyst research *vary with* sentiment, and therefore *ICS* (*PICS* and *RICS*) is read (estimated) in the same quarter as the informativeness measure. Finally, following Bergman and Roychowdhury (2008), we use firm-fixed effects models and cluster all standard errors at the quarterly level to address the possible effect of cross-sectional dependence (Petersen, 2009). All continuous variables are winsorized at the 1st and 99th percentiles to alleviate the influences of outliers.

Table 1. Sample Selection.

	No. of observations (analyst firm quarter)	No. of firms	No. of observations (firm quarters)
All analyst forecasts in I/B/E/S	65,703,575	17,093	
Require observations to have matched PERMNOs and GVKEYs	57,025,883	14,125	
Retain forecasts issued between 1995 and 2010	45,699,732	11,205	
Calculate *AIDF* for supplemental analysis		10,639	218,889
Final sample for supplemental analysis after requiring control variables		8,627	175,523
Retain *EPS* forecasts issued for the upcoming fiscal quarter	1,406,974	10,092	
Calculate *NFORECAST* and *RATIO* for H1		10,092	193,921
Final sample for H1 after requiring control variables		8,445	163,754
Calculate *COMMON* and *IDIOSYNC* for H2		8,525	153,215
Final sample for H2 after requiring control variables		7,259	130,242

Note. The table presents the sample selection procedure.

Data

Our sample period spans from 1995 to 2010. We require firms to have common shares listed at NYSE, American Stock Exchange (AMEX), or National Association of Securities Dealers Automated Quotations (NASDAQ) and covered by analysts. We retrieve data on analyst-related variables from I/B/E/S, financial data from COMPUSTAT, market information from Center for Research in Security Prices (CRSP), management forecast from First Call, and institutional holdings from Thomson-Reuters S34 file.

Our sample starts with all available analyst forecasts in I/B/E/S (65,703,575 forecasts for 17,093 unique firms). We obtain a total of 45,699,732 forecasts (for 11,205 unique firms) issued between 1995 and 2010 with matched identifiers (PERMNOs and GVKEYs). After removing missing values for required variables, 175,523 firm-quarter observations for our supplemental analysis remain. We then keep 1,406,974 one-quarter-ahead earnings forecasts (of 10,092 unique firms). After dropping missing values for additional variables, 163,754 firm-quarter observations for testing H1 remain, and 130,242 for testing H2. Table 1 summarizes the sample selection.

Results

Descriptive Statistics

As our sample size varies across different tests, we present the summary statistics for the entire sample with available data. Our sample firms are followed by a mean (median) of 3.7 (4.0) analysts or 1.29 (1.39) in natural logarithm (untabulated). As Table 2 Panel A shows, these analysts issue a mean (median) of 4.6 (5.0) one-quarter-ahead earnings forecasts or 1.52 (1.61) in natural logarithm, resulting in a mean (median) forecast-analyst ratio (*RATIO*) of 1.26 (1.00).

Table 2. Descriptive Statistics.

Panel A: Summary Statistics.

Name	*N*	*M*	*SD*	*Q1*	Median	*Q3*
Dependent variables						
NFORECAST	163,754	1.52	1.01	0.69	1.61	2.30
RATIO	163,754	1.26	0.37	1.00	1.00	1.42
COMMON	130,242	14.24	50.83	0.08	1.33	8.00
IDIOSYNC	130,242	36.12	116.97	0.10	1.30	12.00
AIDF	175,523	2.01	1.14	1.39	1.75	2.36
Control variables						
SIZE	175,523	6.26	1.85	4.89	6.13	7.47
MB	175,523	3.16	4.07	1.36	2.18	3.69
ROA	175,523	0.00	0.05	0.00	0.01	0.02
LOSS	175,523	0.27	0.45	0	0	1
RD	175,523	0.05	0.10	0	0	0.06
PPE	175,523	0.47	0.37	0.16	0.37	0.70
DIV	175,523	0.34	0.47	0	0	1
AGE	175,523	4.65	1.16	3.87	4.77	5.55
INST	175,523	0.55	0.28	0.32	0.55	0.77
MFPREC	175,523	0.58	0.97	0	0	1.50
WZ	175,523	0.33	0.47	0	0	1
Q4	175,523	0.25	0.43	0	0	1
SARET	163,754	0.01	0.33	−0.18	−0.02	0.15
STD_RET	163,754	0.03	0.02	0.02	0.03	0.04
Sentiment variables						
ICS	65	89.59	13.73	82.40	92.40	97.40
PICS	65	89.28	12.99	84.42	91.41	96.74
RICS	65	0.32	5.19	−3.19	0.92	3.22

(*continued*)

Both the common and idiosyncratic components (*COEMMON* and *IDIOSYNC*) of analyst information exhibit substantial cross-sectional variations. The means are higher than the medians, consistent with the prior literature (e.g., Barron et al., 1998, 2002; Mohanram & Sunder, 2006). Informativeness of analysts' research (*AIDF*) varies mildly across firms. Summary statistics of our control variables are consistent with those reported in prior studies. Our sample firms incur losses in about 27%, and pay dividends in 34% of the quarters. On average, about 55% of our sample firms' outstanding shares are held by institutional investors, and the majority of sample firms do not provide management forecasts. The means (medians) of *ICS, PICS*, and *RICS* are 89.59, 89.28, and 0.32 (92.40, 91.41, and 0.92), respectively.

Table 2 Panel B reports pairwise correlations of firm-level variables used for testing H1 and H2, with Spearman's (Pearson's) correlations above (below) the diagonal. The quantity measures of analyst research (*NFORECAST* and *RATIO*) are positively correlated (Pearson's $\rho = .542$). Consistent with prior research, analysts tend to conduct more research for larger firms (*SIZE*), growth firms (*MB*), and firms with better performance (*ROA*; for example, Bhushan, 1989; Lang & Lundholm, 1996; McNichols & O'Brien, 1997). Moreover, more precise management forecasts (*MFPREC*) are associated with more analyst

Table 2. (continued)

Panel B: Pairwise Correlations for H1/2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
1. *NFORECAST*		**.542**	**−.062**	**−.078**	**.542**	**.058**	**.130**	**−.116**	**−.098**	**.116**	**.156**	**.239**	*−.001*	**−.149**	**.303**	**.349**	**.181**	**−.134**	**.018**
2. *RATIO*	**.590**		**−.114**	**−.125**	**.225**	**−.046**	**.072**	**−.055**	**−.134**	**.195**	**.116**	**.108**	**−.009**	**−.031**	**.126**	**.112**	**.006**	**−.046**	**.033**
3. *COMMON*	**−.015**	**−.165**		**.165**	**−.076**	**.097**	**.088**	**−.082**	**.005**	**−.051**	**−.044**	**−.050**	**.063**	**−.010**	**−.018**	**−.053**	*−.004*	**.099**	**−.014**
4. *IDIOSYNC*	*.004*	**−.146**	**.029**		**−.050**	**.063**	**.082**	**−.086**	**−.019**	**−.046**	**−.018**	**−.017**	**.024**	**−.037**	**−.058**	**−.043**	*−.003*	**.088**	**−.011**
5. *SIZE*	**.530**	**.267**	**−.089**	**−.026**		**−.106**	**.209**	**−.224**	**−.385**	**.195**	**.499**	**.462**	**−.019**	**−.395**	**−.024**	**.329**	**.166**	**−.094**	*−.004*
6. *MB*	**.106**	**−.039**	**.175**	**.165**	**−.134**		**.023**	**−.011**	**.196**	**−.090**	**−.057**	**−.098**	**.190**	**.037**	**.093**	**−.081**	**−.011**	**.085**	**−.007**
7. *ROA*	**.113**	**.050**	**.154**	**.134**	**.057**	**.324**		**−.672**	**−.454**	**.101**	**.187**	**.159**	**.140**	**−.357**	**−.037**	**.151**	**.115**	**−.010**	**.005**
8. *LOSS*	**−.115**	**−.070**	**−.120**	**−.121**	**−.228**	**−.107**	**−.737**		**.346**	**−.082**	**−.233**	**−.179**	**−.127**	**.391**	**.094**	**−.142**	**−.125**	**.007**	*−.005*
9. *RD*	**−.054**	**−.143**	**.079**	**.026**	**−.332**	**.256**	**−.108**	**.240**		**−.248**	**−.286**	**−.169**	**.029**	**.296**	**.147**	**−.145**	**−.076**	*.000*	**.010**
10. *PPE*	**.092**	**.168**	**−.073**	**−.025**	**.202**	**−.082**	**.076**	**−.091**	**−.258**		**.243**	**.250**	**.018**	**−.171**	**−.123**	*.004*	**−.055**	**.009**	*−.001*
11. *DIV*	**.152**	**.131**	**−.066**	**−.008**	**.499**	**−.059**	**.146**	**−.233**	**−.254**	**.239**		**.452**	**−.021**	**−.381**	**−.228**	**.102**	**.047**	**−.027**	**−.010**
12. *AGE*	**.223**	**.125**	**−.040**	*−.002*	**.474**	**−.084**	**.112**	**−.184**	**−.080**	**.278**	**.474**		*−.003*	**−.338**	**−.055**	**.355**	**.160**	**−.114**	*−.001*
13. *SARET*	**.018**	**−.007**	**.083**	**.041**	**.037**	**.234**	**.191**	**−.164**	**−.013**	**.033**	**.026**	**.034**		**−.029**	**.043**	**−.072**	**−.039**	**−.007**	**−.025**
14. *STD_RET*	**−.164**	**−.054**	**−.019**	**−.080**	**−.476**	**−.055**	**−.262**	**.363**	**.258**	**−.181**	**−.456**	**−.373**	**−.096**		**.367**	**−.218**	**−.110**	**.208**	*.002*
15. *TURN*	**.332**	**.140**	**−.017**	**−.085**	**−.011**	**.116**	**.015**	**.082**	**.189**	**−.148**	**−.265**	**−.054**	**.010**	**.363**		**.250**	**.080**	**−.106**	*−.002*
16. *INST*	**.357**	**.132**	**−.020**	**−.020**	**.347**	**−.067**	**.099**	**−.141**	**−.063**	**.009**	**.095**	**.302**	**−.032**	**−.207**	**.350**		**.255**	**−.244**	*−.004*
17. *MFPREC*	**.191**	**.028**	**.091**	**.051**	**.171**	**.014**	**.104**	**−.124**	**.013**	**−.027**	**.048**	**.151**	**−.023**	**−.113**	**.138**	**.257**		**−.128**	*−.003*
18. *WZ*	**−.134**	**−.044**	**.040**	**.076**	**−.093**	**.075**	*.003*	**.007**	*.004*	**.017**	**−.027**	**−.114**	**−.038**	**.211**	**−.153**	**−.250**	**−.126**		*.003*
19. *Q4*	**.017**	**.033**	**−.019**	**−.027**	*−.004*	**−.014**	**.011**	*−.005*	*.001*	*−.001*	**−.010**	*.000*	**−.027**	**.015**	*−.002*	*−.003*	*−.003*	*.003*	

Note. The table presents summary statistics (Panel A) and pairwise correlations (Panel B). See the appendix for variable definitions. Spearman's (Pearson's) correlations are presented above (below) the diagonal. The correlations marked in bold are significant at least at the 5% level, and those marked in italics are statistically insignificant (two-sided *p* value greater than .10)

Table 3. The Effect of Sentiment on the Number of Analyst Forecasts. Dependent Variable: *NFORECAST.*

Variables	(1) Model	(2) Model	(3) Model
SIZE	0.3347*** (0.008)	0.3366*** (0.008)	0.3459*** (0.010)
MB	0.0107*** (0.001)	0.0106*** (0.001)	0.0105*** (0.001)
ROA	0.2119*** (0.075)	0.2112*** (0.078)	0.1978** (0.078)
LOSS	−0.0676*** (0.007)	−0.0676*** (0.006)	−0.0673*** (0.007)
RD	0.3395*** (0.058)	0.3429*** (0.057)	0.3552*** (0.059)
PPE	−0.1601*** (0.017)	−0.1612*** (0.017)	−0.1547*** (0.017)
DIV	0.0793*** (0.008)	0.0787*** (0.008)	0.0829*** (0.009)
AGE	0.0029 (0.008)	0.0043 (0.007)	0.0125* (0.006)
SARET	−0.0516*** (0.010)	−0.0518*** (0.010)	−0.0477*** (0.010)
STD_RET	−4.2046*** (0.484)	−4.1066*** (0.489)	−3.5886*** (0.546)
TURN	0.0198*** (0.001)	0.0197*** (0.001)	0.0200*** (0.001)
INST	0.4005*** (0.022)	0.4053*** (0.023)	0.4267*** (0.025)
MFPREC	0.0150*** (0.003)	0.0154*** (0.003)	0.0146*** (0.003)
WZ	0.0081 (0.023)	0.0028 (0.023)	−0.0301 (0.021)
Q4	0.0530*** (0.013)	0.0528*** (0.013)	0.0472*** (0.014)
ICS	−0.0030*** (0.001)		
PICS		−0.0027*** (0.001)	
RICS			−0.0016 (0.001)
Constant	−0.6057*** (0.123)	−0.6549*** (0.120)	−1.0158*** (0.083)
Firm fixed effects	Yes	Yes	Yes
Cluster year quarter	Yes	Yes	Yes
Observations	163,754	163,754	163,754
Adj. *R*-square	.7043	.7041	.7036

Note. The table presents regression results of the effect of sentiment on the number of analyst forecasts. All variables are defined in the appendix. All continuous variables are winsorized at 1% and 99%. Robust standard errors are reported in parentheses.
$^{*}p < .10$. $^{**}p < .05$. $^{***}p < .01$. (two-sided)

forecasts; however, during the broker consolidation period (*WZ*), the quantity measures of analyst activities (*NFORECAST* and *RATIO*) declined.

We observe a positive correlation between the common and idiosyncratic components (*COMMON* and *IDIOSYNC*) of analyst information precision (Pearson's ρ = .029).[7] These two variables are correlated with most firm characteristics in the same direction; for example, both are positively correlated with performance (*ROA*) but negatively with uncertainty (*STD_RET* and *TURN*). Although more precise management forecasts foster more frequent analyst forecasts, the univariate correlation between management forecast precision and analyst information precision is unclear in a pooled sample (Spearman's ρ is positive, whereas Pearson's ρ is negative).[8]

Regression Analysis of the Effect of Sentiment on Analyst Research Activities

Table 3 reports the multivariate analysis of the effect of consumer sentiment (*ICS*) on the number of one-quarter-ahead earnings forecasts issued by analysts (*NFORECAST*). We find that *ICS* is significantly and negatively associated with *NFORECAST* (p value < .01). In terms of economic magnitude, 1 standard deviation increase in *ICS* leads to a 4% reduction in the number of analyst forecasts. This magnitude is comparable with other significant firm-level factors (e.g., a 4% increase in the number of analyst reports results from 1 standard deviation change in the market-to-book ratio), and is also consistent with moderate changes in the quantity of analyst forecasts documented in recent studies (e.g., Lehavy, Li, & Merkley, 2011).

Consistent with the prior literature, an increase in firm size, growth opportunities, accounting performance, and disclosure transparency is associated with an increase in analyst forecasts. The effect of stock return volatilities (*STD_RET*) on the total number of analyst forecasts is significantly negative, whereas the effect of stock turnovers (*TURN*) is significantly positive, even though both measures are included as controls for uncertainties. Finally, the coefficient on *Q4* is significantly positive, suggesting that analysts issue more forecasts in the last fiscal quarter.

Moving from Column 1 to Columns 2 and 3, we replace *ICS* with its two components, *PICS* and *RICS*, respectively. We find that *PICS* remains significantly negative (p value $< .01$) while *RICS* is insignificant (p value $> .10$); therefore, the significant effect of *ICS* on the number of analyst forecasts is solely driven by the fundamental component of consumer sentiment.

Table 4 presents the regression results of the forecast-to-analyst ratio (*RATIO*), which captures the *average* analyst activity rather than the *total* activity. In Column 1, we continue to find a significantly negative effect of *ICS* on the forecast-to-analyst ratio (p value $< .01$); 1 standard deviation increase in *ICS* leads to a 3.5% reduction in this ratio. The adjusted R^2 drops to about 26.62% from 70.43% in the analysis of *NFORECAST*. Results in Columns 2 and 3 of Table 4 suggest that both *PICS* and *RICS* are negatively correlated with the forecast-to-analyst ratio (p value $< .01$ and $< .05$, respectively), even though *RICS* is insignificant in Table 3. Therefore, the residual component of *ICS* has a relatively large effect on the total number of forecasts (the numerator of *RATIO*) than on the number of analyst following (the denominator of *RATIO*), as analyst coverage tends to be sticky (Brown et al., 2015).[9] Overall, our results in Tables 3 and 4 suggest that analysts reduce their frequency of issuing research reports (measured with earnings forecast frequency) in response to high consumer sentiment.[10]

To test H2, we first investigate the association between *ICS* and the precision of analysts' common information (*COMMON*) to verify the notion that public information proliferates and tends to have higher quality during economic expansions (Veldkamp, 2005, 2006a, 2006b). After controlling for other factors, we find *ICS* to be positively associated with *COMMON* with a marginal significance (p value $< .10$, Table 5, Column 1); however, neither *PICS* nor *RICS* has a significant effect on *COMMON* (p value $> .10$, Columns 2 and 3).

In contrast to Table 5, where the effect of consumer sentiment on the precision of analysts' common information is weak, we find a strong effect on the precision of analysts' idiosyncratic information, as shown in Table 6 where *IDIOSYNC* is the dependent variable. The coefficient estimates of *ICS* and *PICS* are 0.2891 and 0.3014, respectively; both are statistically significant (p value $< .01$). A 1 standard deviation increase in *ICS* is associated with an increase of 3.97 in *IDIOSYNC*. This effect is also economically significant as it represents an 11.0% increase over the sample mean precision of idiosyncratic information (36.12 in Table 2). Similar inference can be drawn for *PICS*: 1 standard deviation increase in *PICS* is associated with an increase of 3.92 in *IDIOSYNC*, a 10.8% change above its sample mean, indicating analysts' increasing effort in uncovering private information when

Table 4. The Effect of Sentiment on the Ratio of Forecasts to Analyst Following. Dependent Variable: *RATIO.*

Variables	(1) Model	(2) Model	(3) Model
SIZE	0.0450*** (0.003)	0.0474*** (0.003)	0.0542*** (0.004)
MB	0.0009*** (0.000)	0.0008*** (0.000)	0.0007** (0.000)
ROA	0.0675 (0.045)	0.0658 (0.047)	0.0555 (0.044)
LOSS	−0.0211*** (0.003)	−0.0210*** (0.003)	−0.0208*** (0.003)
RD	0.1394*** (0.026)	0.1433*** (0.026)	0.1523*** (0.028)
PPE	−0.0300** (0.014)	−0.0305** (0.014)	−0.0252* (0.013)
DIV	0.0195*** (0.006)	0.0193*** (0.006)	0.0226*** (0.006)
AGE	−0.0167*** (0.003)	−0.0149*** (0.003)	−0.0087*** (0.003)
SARET	−0.0090 (0.006)	−0.0089 (0.006)	−0.0056 (0.005)
STD_RET	−0.2935 (0.202)	−0.1707 (0.233)	0.2173 (0.258)
TURN	0.0046*** (0.000)	0.0045*** (0.000)	0.0047*** (0.000)
INST	0.0146** (0.007)	0.0202*** (0.007)	0.0361*** (0.009)
MFPREC	0.0013 (0.001)	0.0016 (0.002)	0.0009 (0.002)
WZ	0.0138 (0.012)	0.0068 (0.012)	−0.0180* (0.011)
Q4	0.0302*** (0.008)	0.0296*** (0.009)	0.0253*** (0.009)
ICS	−0.0025*** (0.001)		
PICS		−0.0021*** (0.001)	
RICS			−0.0018** (0.001)
Constant	1.2320*** (0.077)	1.1632*** (0.065)	0.8891*** (0.034)
Firm fixed effects	Yes	Yes	Yes
Cluster year quarter	Yes	Yes	Yes
Observations	163,754	163,754	163,754
Adj. R^2	.2662	.2648	.2634

Note. The table presents regression results of the effect of sentiment on the ratio of the number of analyst forecasts divided by the number of analysts following. All variables are defined in the appendix. All continuous variables are winsorized at 1% and 99%. Robust standard errors are reported in parentheses.
$^*p < .10$. $^{**}p < .05$. $^{***}p < .01$. (two-sided)

high consumer sentiment is supported by strong macrofundamentals. The coefficient estimate of *RICS* is insignificantly positive, suggesting that analysts choose not to cater to irrational investors whose trading decisions are driven by excessive sentiment unrelated to economic fundamentals.[11]

Given our earlier finding that the quantity of analysts' research is negatively correlated with consumer sentiment, the results here show that analysts collectively shift their efforts from disseminating more research reports to discovering and acquiring more idiosyncratic private information during high sentiment periods, consistent with analysts' strong incentives to establish and maintain their comparative advantage as information intermediaries. Our evidence suggests that consumer sentiment, especially the fundamental component, plays a significant role in analysts' decisions on where to allocate their effort.

Regarding the control variables, we find that both *ROA* and *INST* are positively associated with *IDIOSYNC*, suggesting that increases in firm performance and institutional holdings within firm encourage analysts to explore more private information. However, factors such as occurrence of loss (*LOSS*), firm size (*SIZE*), market-to-book ratio (*MB*), R&D intensity (*RD*), and stock return volatilities (*STD_RET*) are negatively associated with

Table 5. The Effect of Sentiment on the Precisions of Analyst Common Information. Dependent Variable: *COMMON*.

Variables	(1) Model	(2) Model	(3) Model
SIZE	−24.3744*** (1.085)	−24.4504*** (1.091)	−24.5606*** (1.056)
MB	−0.1941*** (0.067)	−0.1911*** (0.067)	−0.1907*** (0.068)
ROA	26.9197*** (4.625)	26.9823*** (4.648)	27.1937*** (4.561)
LOSS	−0.7474* (0.425)	−0.7504* (0.425)	−0.7501* (0.424)
RD	−22.9440*** (4.218)	−23.0778*** (4.234)	−23.2564*** (4.269)
PPE	−16.1570*** (1.555)	−16.1628*** (1.544)	−16.2787*** (1.529)
DIV	−2.8706*** (0.743)	−2.8802*** (0.745)	−2.9402*** (0.745)
AGE	−1.3912*** (0.413)	−1.4499*** (0.411)	−1.5466*** (0.411)
SARET	0.7014 (0.677)	0.6846 (0.681)	0.6102 (0.673)
STD_RET	−53.7509** (22.676)	−58.0149** (22.802)	−64.1596*** (20.434)
TURN	0.1254*** (0.035)	0.1255*** (0.035)	0.1216*** (0.035)
INST	4.4049*** (1.393)	4.2287*** (1.383)	3.9976*** (1.399)
MFPREC	−1.2712*** (0.270)	−1.2773*** (0.270)	−1.2624*** (0.269)
WZ	4.1600*** (1.103)	4.3829*** (1.111)	4.7492*** (0.965)
Q4	−1.1260** (0.500)	−1.0970** (0.496)	−1.0282** (0.472)
ICS	0.0480* (0.025)		
PICS		0.0317 (0.027)	
RICS			0.0532 (0.048)
Constant	188.3158*** (8.683)	190.7245*** (8.947)	195.0116*** (7.641)
Firm fixed effects	Yes	Yes	Yes
Cluster year quarter	Yes	Yes	Yes
Observations	130,242	130,242	130,242
Adj. R^2	.2187	.2186	.2186

Note. The table presents regression results of the effect of sentiment on the precision of the common component of analyst information. All variables are defined in the appendix. All continuous variables are winsorized at 1% and 99%. Robust standard errors are reported in parentheses.
$^*p < .10$. $^{**}p < .05$. $^{***}p < .01$. (two-sided)

IDIOSYNC, for the same firm over time. We find that *MFPREC* is negatively associated with *IDIOSYNC*; therefore, more precise management forecasts seem to discourage analysts from discovering private information.

Subsample Analyses of Cross-sectional Variations

If analysts compete with mounting public information in economic expansions (Veldkamp, 2006b) and rationally cater to investors' demand for better quality information during high sentiment period, we would expect analysts to exert more efforts in firms where more trading commissions can be generated. In particular, we expect the effect of consumer sentiment to be more pronounced for larger firms with better accounting and capital market performance (McNichols & O'Brien, 1997), more institutional holdings (Bhushan, 1989), and less volatile stock returns (Chang, Sudipto, & Gilles, 2006). For each partitioning variable, we calculate the median for each firm over the sample period, and then we use the firm-level medians to split sample firms into two subsamples. This approach ensures that observations from each subsample are not clustered in either the high or the low sentiment

Table 6. The Effect of Sentiment on the Precisions of Analyst Idiosyncratic Information. Dependent Variable: *IDIOSYNC*.

Variables	(1) Model	(2) Model	(3) Model
SIZE	−45.6298*** (3.118)	−45.6550*** (3.143)	−46.8204*** (3.029)
MB	−0.8101*** (0.156)	−0.8004*** (0.155)	−0.7795*** (0.156)
ROA	45.5644*** (10.321)	45.3175*** (10.436)	47.0445*** (10.394)
LOSS	−4.0440*** (0.932)	−4.0557*** (0.932)	−4.0721*** (0.919)
RD	−78.1495*** (11.111)	−78.2282*** (10.978)	−80.1825*** (11.051)
PPE	−32.0087*** (3.517)	−31.7721*** (3.500)	−32.5443*** (3.423)
DIV	−9.9696*** (1.466)	−9.8704*** (1.453)	−10.3108*** (1.497)
AGE	0.2009 (1.055)	0.2071 (1.067)	−0.7668 (0.974)
SARET	−6.2049*** (1.688)	−6.0996*** (1.675)	−6.6753*** (1.672)
STD_RET	−105.4483*** (38.366)	−106.9595*** (37.179)	−172.1206*** (34.536)
TURN	0.0667 (0.064)	0.0754 (0.065)	0.0511 (0.066)
INST	8.7716*** (3.222)	8.6582*** (3.181)	6.1103* (3.303)
MFPREC	−3.7823*** (0.678)	−3.8371*** (0.673)	−3.7796*** (0.683)
WZ	6.1741** (2.984)	6.1531* (3.163)	9.8456*** (2.698)
Q4	−2.5802** (1.212)	−2.6301** (1.257)	−2.0150* (1.046)
ICS	0.2891*** (0.077)		
PICS		0.3014*** (0.104)	
RICS			0.0445 (0.115)
Constant	340.6078*** (26.135)	339.6482*** (27.711)	381.6452*** (22.782)
Firm fixed effects	Yes	Yes	Yes
Cluster year quarter	Yes	Yes	Yes
Observations	130,242	130,242	130,242
Adj. R^2	.1772	.1771	.1767

Note. The table presents regression results of the effect of sentiment on the precision of the idiosyncratic component of analyst information. All variables are defined in the appendix. All continuous variables are winsorized at 1% and 99%. Robust standard errors are reported in parentheses.
*$p < .10$. **$p < .05$. ***$p < .01$. (two-sided)

period, which would likely happen if we alternatively partition the full sample by the sample median. For instance, to the extent that firms tend to perform poorly when the economy is contracting and consumer sentiment is low, the low *ROA* subsample would contain more observations from the low sentiment period if we partition the full sample by the median of *ROA* of all observations.

Results from our subsample analyses are reported in Table 7.[12] The findings are largely consistent with our expectations. For the quantity of analyst research activities, the impact of consumer sentiment is generally larger for larger firms and firms with higher *ROA*, better market performance, and lower stock return volatility. While it appears that analysts respond to higher sentiment by reducing the quantity of their research activities across all conditions, their engagement in private information gathering exhibits notable differences between subsamples. For example, when the dependent variable is *IDIOSYNC*, our empirical proxy for analysts' effort in private information discoveries, we find that the effect of consumer sentiment is significant only in the subsamples of larger firms, firms with higher *ROA*, higher institutional holdings, and less volatile stock returns. These results complement our earlier findings in two ways: First, the subsample analyses provide further

Table 7. Subsample Analysis.

	NFORECAST			*RATIO*			*IDIOSYNC*		
	(1) *ICS*	(2) *PICS*	(3) *RICS*	(4) *ICS*	(5) *PICS*	(6) *RICS*	(7) *ICS*	(8) *PICS*	(9) *RICS*
SIZE									
Large	−0.0033***	−0.0031***	−0.0014	−0.0029***	−0.0024***	−0.0020**	0.3249***	0.3551***	0.0096
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.087)	(0.113)	(0.128)
Small	−0.0025***	−0.0019***	−0.0020	−0.0011***	−0.0007**	−0.0012**	0.1544**	0.1282	0.0951
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.069)	(0.091)	(0.104)
ROA									
High	−0.0031***	−0.0031***	−0.0007	−0.0026***	−0.0022***	−0.0017*	0.3454***	0.3600***	0.0492
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.098)	(0.131)	(0.146)
Low	−0.0028***	−0.0019**	−0.0029*	−0.0023***	−0.0018***	−0.0020**	0.0676	0.0788	−0.0096
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)	(0.048)	(0.055)	(0.095)
SARET									
High	−0.0037***	−0.0036***	−0.0012	−0.0027***	−0.0023***	−0.0017**	0.2919***	0.3169**	0.0136
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.091)	(0.121)	(0.139)
Low	−0.0013	−0.0006	−0.0021	−0.0022***	−0.0016***	−0.0021**	0.1748***	0.1559**	0.0896
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)	(0.055)	(0.073)	(0.101)
STD_RET									
High	−0.0022**	−0.0008	−0.0037***	−0.0017***	−0.0010*	−0.0020**	0.0949	0.0675	0.0873
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.064)	(0.073)	(0.118)
Low	−0.0033***	−0.0035***	−0.0005	−0.0027***	−0.0023***	−0.0017*	0.2958***	0.3264***	−0.0059
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.086)	(0.116)	(0.134)
INST									
High	−0.0029***	−0.0025**	−0.0016	−0.0027***	−0.0022***	−0.0020**	0.3204***	0.3431***	0.0275
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.083)	(0.114)	(0.134)
Low	−0.0032***	−0.0029***	−0.0014	−0.0017***	−0.0013***	−0.0012**	0.1148	0.0890	0.0833
	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)	(0.077)	(0.084)	(0.117)

Note. The table presents regression results of subsample analyses. All variables are defined in the appendix. Firm-specific median of each condition variable is used to partition the full sample. All continuous variables are winsorized at 1% and 99%. Robust standard errors are reported in parentheses.
$^{*}p < .10$. $^{**}p < .05$. $^{***}p < .01$. (two-sided)

evidence that analysts cater to investors' information needs, consistent with the view that analysts are rational on average. Second, the subsample analyses also highlight the unique effect of consumer sentiment. If consumer sentiment is merely a proxy for general macroeconomic conditions with no differential impact on investors' information needs, we would expect to observe similar effects across all subsamples.

Supplemental Analysis on Investors' Response to Analyst Reports

We use Frankel et al.'s (2006) ''informativeness'' measure to evaluate the extent to which investors respond to analyst reports. This measure essentially captures the stock price reactions on days when analysts release research reports relative to the total stock price movement on all trading days during the quarter. Table 8 presents the results from this analysis. Column 1 shows that consumer sentiment (*ICS*) has a significant and positive effect on the informativeness of analyst reports (p value $< .01$). Moreover, such an effect is primarily driven by the fundamental component of sentiment (*PICS;* p value $< .05$). A 1 standard deviation increase in *ICS* is associated with an increase of 0.0463 in *AIDF*, which is 2.8% of its average level (2.01; see Table 2). Similarly, 1 standard deviation increase in *PICS* is associated with an increase of 0.0390 in *AIDF*. In contrast, the residual component of consumer sentiment (*RICS*) is statistically insignificant at conventional levels. In our main analyses, we demonstrate that analysts seek to maintain their comparative advantage during high sentiment periods by reducing forecast frequency but shifting more efforts to private information acquisition and discovery. The results in Table 8 thus suggest that investors seem to appreciate and value the trade-off made by analysts.

Robustness Checks and Additional Analyses

In this section, we summarize robustness test results to rule out alternative explanations. Detailed discussions are available in the online appendix.

We first investigate whether high consumer sentiment is associated with high information asymmetry and/or uncertainty.[13] We find that consumer sentiment is negatively associated with information uncertainty. At the market level, the Pearson correlation between *ICS* and Chicago Board Options Exchange Market Volatility Index (*VIX*) is $-.26$ (p value $< .01$); at the firm level, stock return volatility is also negatively associated with sentiment after controlling for firm-fixed effects (p value $< .1$). However, consumer sentiment is positively associated with probability of informed trade, *PIN* (p value $< .01$; results from the bid–ask spreads are similar, with p values $< .05$).[14] One possible explanation is that more sophisticated investors are likely to benefit more from the abundance of information available in the market during high sentiment periods through ''mosaic'' information gathering, in that they are more adept at collecting and transforming stray information into useful private insights. Taken together, there is inconclusive evidence on the relation between sentiment and uncertainty/information asymmetry.

Next, we explore a specific alternative explanation for our main results. That is, the association we documented between consumer sentiment and analyst research activities might be driven by changes in the information environment caused by firms' product market strategies in response to changes in consumer sentiment. This explanation implies a chain of three links from sentiment to analyst research activities: (a) high consumer sentiment leads firms to engage more in product market expansion, (b) product market

Table 8. The Effect of Sentiment on the Informativeness of Analyst Reports. Dependent Variable: *AIDF*.

Variables	(1) Model	(2) Model	(3) Model
SIZE	0.0229* (0.012)	0.0197 (0.012)	0.0110 (0.013)
MB	−0.0016 (0.001)	−0.0012 (0.001)	−0.0010 (0.001)
ROA	−0.0083 (0.157)	0.0214 (0.162)	0.0422 (0.169)
LOSS	0.0045 (0.012)	0.0024 (0.012)	0.0005 (0.012)
RD	−0.1303 (0.086)	−0.1364 (0.085)	−0.1549* (0.086)
PPE	0.0185 (0.028)	0.0202 (0.029)	0.0144 (0.028)
DIV	−0.0483*** (0.017)	−0.0485*** (0.017)	−0.0535*** (0.016)
AGE	0.1417*** (0.014)	0.1353*** (0.015)	0.1216*** (0.015)
INST	0.1855*** (0.032)	0.1793*** (0.033)	0.1676*** (0.033)
MFPREC	0.0683*** (0.005)	0.0675*** (0.004)	0.0689*** (0.004)
WZ	−0.1681*** (0.033)	−0.1545*** (0.034)	−0.1221*** (0.027)
Q4	−0.0206 (0.017)	−0.0191 (0.019)	−0.0126 (0.020)
ICS	0.0041*** (0.001)		
PICS		0.0030** (0.001)	
RICS			0.0039 (0.003)
Constant	0.7819*** (0.211)	0.9229*** (0.206)	1.3105*** (0.132)
Firm fixed effects	Yes	Yes	Yes
Cluster year quarter	Yes	Yes	Yes
Observations	175,523	175,523	175,523
Adj. R^2	.1156	.1151	.1149

Note. The table presents regression results of the effect of sentiment on the informativeness of analyst reports. All variables are defined in the appendix. All continuous variables are winsorized at 1% and 99%. Robust standard errors are reported in parentheses.
$^{*}p < .10$. $^{**}p < .05$. $^{***}p < .01$. (two-sided)

expansion leads to more future uncertainty or information asymmetry in the capital market, and (c) analysts respond to higher uncertainty or information asymmetry by discovering more private information while reducing their forecast frequency. Biddle, Hilary, and Verdi (2009) argue that firm-specific investment (as measured by the sum of capital expenditure, R&D expenses, and assets acquisitions) is a function of growth opportunities (as measured by sales growth); therefore, we include both measures in our test.

Regarding link (a), we find that consumer sentiment is positively associated with future sales growth (p value < .01) but is not significantly associated with future investment (p value = .40). Thus, the evidence is mixed on the conjecture that higher sentiment is associated with more product market expansions. Regarding link (b), we document strong evidence that product market expansion seems to reduce, rather than increase, future information asymmetry in capital markets; however, we also find weak evidence that product market expansion is associated with higher future uncertainty. The predicted relation in link (c) is inconsistent with results reported earlier. Specifically, test results in Table 6 suggest that when uncertainty is high, analysts' private information discovery is reduced, rather than increased as implied by the alternative explanation. Furthermore, subsample analysis in Table 7 shows that the impact of sentiment on analyst private information discovery is larger for firms with lower stock return volatility. Finally, when considering all three links jointly, the alternative explanation implies that our results should be more pronounced among firms with greater scale of expansions (which we measure by total investment) and more growth opportunities (which we measure by sales growth, following Biddle et al., 2009). To test this, we conduct subsample analyses conditional on each variable. Regarding the impact on analyst private information discovery, our results are actually stronger for firms with *less* expansion or *slower* sales growth; regarding the impact of consumer sentiment on analyst forecast frequency, results are not consistently stronger in either subsample (untabulated). Thus, our findings are inconsistent with the alternative explanation.

In summary, we find no systematic relation between consumer sentiment and information asymmetry or uncertainty. The results from our additional analyses do not support the alternative explanation that analysts are responding to uncertainty or information asymmetry arising from firms' production market expansion during high sentiment periods.

We also conduct a battery of additional analyses. Using data collected from Bloomberg, we first validate the notion that information production and demand is positively associated with consumer sentiment in the U.S. capital market. More specifically, we show that the number of news articles and the level of readership interest both increase with consumer sentiment. Our results are robust to controls for GDP growth, market-wide uncertainty, external financing, and to correcting potential biases in Barron et al. (1998)'s precision measure of analyst idiosyncratic information. We also use Baker–Wurgler Index as an alternative proxy for investors' excessive sentiment, and the results are qualitatively unchanged.

Conclusion

In this study, we explore the impact of consumer sentiment on analyst research activities, namely analysts' frequency of issuing research reports and their effort allocated to private information discovery. Using a firm-fixed effect design, we document that analysts issue fewer earnings forecasts but engage in more extensive private information discovery during high sentiment periods, and that the results are primarily driven by the fundamental component of consumer sentiment. Further analyses suggest that investors perceive analyst reports as more informative during high sentiment periods; therefore, investors appear to value analysts' increased efforts in acquiring and producing private information. Taken together, our results suggest that consumer sentiment plays a significant role in shaping analyst activities. More specifically, in response to high consumer sentiment, analysts appear to shift more effort toward private information discovery.

Our article enriches the literature on equity analysts by demonstrating how analysts collectively respond to consumer sentiment, an important macrolevel factor. Future studies can further explore the relations between analyst-specific characteristics (such as experience and industry expertise) and individual analysts' responses to sentiment. Our findings also shed light on analysts' effort allocation across different research activities. Future research can further explore the mechanism behind this effort allocation for a better understanding of equity analysts' decision process.

Appendix Variable Definitions.

Sentiment-related variables	
ICS	The University of Michigan Consumer Sentiment Index
PICS	Predicted component of *ICS*, measured as the predicted value of *ICS* in a regression in which *ICS* is the dependent variable and a series of macrovariables are the independent variables. See online appendix for more details.
RICS	Residual component of *ICS*, measured as the residual value of *ICS* in a regression in which *ICS* is the dependent variable and a series of macrovariables are the independent variables. See online appendix for more details.
Variables related to analyst activities	
NFORECAST	Natural logarithm of the number of analyst one-quarter-ahead earnings forecasts for a firm.
RATIO	Number of analyst one-quarter-ahead earnings forecasts divided by the number of analysts issuing forecasts for the firm
IDIOSYNC	Precision of analyst idiosyncratic information as in Barron et al. (1998), deflated by 100.
COMMON	Precision of analyst common information as in Barron et al. (1998), deflated by 100.
AIDF	Informativeness of analyst reports as in Frankel et al. (2006), multiplied by 100.
Other firm-level variables	
SIZE	Natural logarithm of total assets (*#ATQ*), measured at the end of previous fiscal quarter.
MB	Market-to-book ratio (*#PRCCQ* × *#CSHOQ* / *#CEQQ*), measured at the end of previous fiscal quarter.
ROA	Income before extraordinary items (*#IBQ*) divided by total assets (*#ATQ*), measured at the end of previous fiscal quarter.
LOSS	Indicator variable that equals 1 if a firm's income before extraordinary items (#IBQ) in the previous fiscal quarter is negative, and 0 otherwise.
RD	Research and development expenses (*XRD*) divided by total assets (*#AT*), measured at the end of previous fiscal year.
PPE	Total gross property, plant and equipment (*#PPEGT*) divided by total assets (*#AT*), measured at the end of previous fiscal year.
DIV	Indicator variable that equals 1 if a firm pays dividend (i.e., *#DVPSX_F* > 0) in the previous fiscal year, and 0 otherwise.
AGE	Natural logarithm of total number of months a firm exists in CRSP, measured at the end of previous fiscal quarter.
SARET	Cumulated daily size-adjusted returns over a 120-day period ending on the earnings announcement of previous fiscal quarter.
STD_RET	Standard deviation of a firm's daily returns calculated over a 120-day period ending on the earnings announcement of previous fiscal quarter.
TURN	Average stock trading volume over a 120-day period ending on the earnings announcement of previous fiscal quarter, divided by the number of shares outstanding (*#CSHOQ*).
INST	Percentage of institutional ownership, measured at the end of previous fiscal quarter.
MFPREC	Precision of management forecasts that takes the value of 3, 2, or 1 for any point, range, or qualitatively guidance issued (following Bamber et al., 2010) over a 120-day period ending on previous fiscal quarter.
WZ	Indicator variable that equals 1 if an observation belongs to the period of high merger and acquisition wave from 1997 to 2001, and 0 otherwise.
Q4	Indicator variable that equals 1 for the fourth fiscal quarter, and 0 otherwise.

Authors' Note

Data used in this study are available from public sources indicated in the text.

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Notes

1. Sentiment has been shown to be related to trading activities in the capital market (e.g., Dichev et al., 2014; Kumar & Lee, 2006; Stambaugh et al., 2012). Prior studies have also found that sentiment has an impact on various corporate decisions, including management voluntary disclosure (Bergman & Roychowdhury, 2008; Seybert & Yang, 2012), *pro forma* earnings disclosures (Brown, Christensen, Elliott, & Mergenthaler, 2012), accrual management (Ali & Gurun, 2009), capital investments (Baker, Stein, & Wurgler 2003), and payout policies (Baker & Wurgler, 2004).
2. Note that these studies suggest that the quantity and quality of information are associated with the level of economic production rather than productivity. Production and productivity are two interrelated but yet distinct economic concepts. According to the Cobb-Douglas production function ($Y = AL^{\beta}K^{\alpha}$), total production output (Y) is a function of labor (L) and capital (K) input, as well as productivity (A). Information could proliferate as production grows, which might be fueled by growth in capital and/or labor without corresponding growth in productivity.
3. Note that in these theoretical models, economic booms are associated with more information, regardless of whether it is public or private. However, their argument does imply that as information gets cheaper, more information becomes available to investors.
4. Prior research suggests that individuals' decision accuracy positively correlates with the amount of information they receive up to a point; however, when further information is provided beyond this point, information overload occurs, and the decision accuracy actually declines (Schroder et al., 1967).
5. In the event where an analyst makes multiple earnings forecasts in one fiscal quarter, we retain the first forecast.
6. The variable is measured following Bamber, Jiang, & Wang (2010). When there are multiple management forecasts, we take the average precision value. Results remain qualitatively the same if we take the highest precision value instead.
7. Mohanram and Sunder (2006) document a negative correlation between *COMMON* and *IDIOSYNC*. We are able to confirm this negative correlation when we only use observations from their sample period.
8. The pairwise correlation among firm characteristics in the supplemental analysis is very similar to that discussed above; hence, we do not tabulate the results for brevity but summarize them as follows: For the dependent variable, analyst report informativeness (*AIDF*) is modestly correlated

with most firm characteristics; most correlations are of small magnitude except between institutional ownership (*INST*) and management forecast precision (*MFPREC*).

9. When we use the total number of analysts as the dependent variable (untabulated), we find an overall weaker impact of consumer sentiment: *ICS* is weakly significant (p value $< .10$).
10. We also replace one-quarter-ahead earnings forecasts with (a) all earnings forecasts regardless of horizons and (b) 1-year-ahead forecasts. Untabulated results from both tests are qualitatively similar to those in Tables 3 and 4.
11. We use the raw value of *IDIOSYNC* in our main analyses following prior studies (e.g., Mohanram & Sunder, 2006), but our results remain qualitatively the same if we use the value in log instead (untabulated).
12. Our results are similar if we interact firm characteristics with consumer sentiment in a pooled regression.
13. We thank an anonymous referee for suggesting additional analyses on this aspect, including the specific alternative explanation we discuss below.
14. We thank Professor Stephen Brown for making his *PIN* measure available online (http://scholar.rhsmith.umd.edu/sbrown/pin-data?destination=node/998).

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