The Journal of Financial Research • Vol. XXXVI, No. 2 • Pages 175–214 • Summer 2013

PRESS COVERAGE AND STOCK PRICE DEVIATION FROM FUNDAMENTAL VALUE

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Abstract

We find that excessively high levels of press coverage can significantly exaggerate stock price deviation from fundamental value. We show that being "in the news" a lot is associated with both greater liquidity and more information risk. When we examine signed mispricing, we find that the effect of abnormal press coverage is significant only for stocks with high relative valuations, consistent with the concurrent existences of media-induced sentiment and media bias. Indeed, we uncover that the sentiment effect is attenuated when firms with low valuations receive heavy coverage in the local press.

JEL Classification: G12, G14, L82

I. Introduction

Media coverage affects stock prices. A recent study by Fang and Peress (2009) shows that stocks with no print media coverage outperform stocks with high print media coverage, especially among small firms with concentrated ownership and low analyst following. They interpret their evidence of a no-media premium as consistent with the notion that breadth of information dissemination affects stock returns (Merton 1987), a phenomenon perpetuated by liquidity constraints. In spite of a recent emphasis on media-related issues in the finance literature (see, e.g., Tetlock 2007, 2011; Bushee et al. 2010; Hirshleifer, Lim, and Teoh 2009) important fundamental questions about the role of the press in financial markets remain unanswered. For example, does newspaper coverage improve or reduce market efficiency? And what are the underlying reasons for the effect of newspaper coverage on asset prices? We provide answers to these questions by analyzing the cross-sectional relation between size- and industry-adjusted levels of firm coverage by major print media outlets (hereafter, abnormal press coverage) and several measures of divergence from stocks' intrinsic value.

As mentioned in Tetlock (2007), "It is unclear whether the financial news media induces, amplifies, or simply reflects investors' interpretations of stock market

We would like to thank an anonymous referee and the *JFR* editors for their helpful comments and suggestions.

performance" (p. 1139). Bushee et al. (2010) argue that the press may play a variety of roles including "broad dissemination of information, packaging information from multiple sources, and creating new information through journalism practices" (p. 17). Typically though, the information provided by newspapers is largely repackaged information that is publicly available before the publication date, and therefore, its effect on stock prices should be limited.[1] Nevertheless, stock prices often move following press articles, and sometimes they even respond to stories about events that have occurred well in the past (Tetlock 2011).[2] The finance literature has offered several explanations on why stock prices can be affected by press coverage. These explanations are based on alternative views of the press as (1) an information intermediary, (2) a corporate governance tool, (3) a biased transmitter of favorable information, and (4) a generator of investor sentiment. In this study we test the validity of the aforementioned views of print media.

The information intermediary hypothesis views press coverage as a critical source of disclosure about firms that may help reduce information asymmetry problems (see Healey and Palepu 2001). In this context, the press engages in information production, which helps reduce managers' superior information advantage over outside investors. According to Dyck and Zingales (2002), the media can influence managerial decisions. Thus, the corporate governance hypothesis posits that the media can have an effect on the balance between the private benefits and costs associated with managerial actions that deviate from shareholder value maximization. Both the information intermediary and corporate governance hypotheses imply that greater levels of press coverage should make it easier for investors to value firms, and therefore both hypotheses predict a negative relation between the intensity of media coverage and stock price deviation from fundamental value (mispricing).[3]

In contrast, the following two alternative hypotheses predict a positive relation between the extent of press coverage and mispricing. The biased media hypothesis claims that media tend to report information that is biased in favor of the companies covered. For example, Dyck and Zingales (2003) show that media outlets' spin often tends to follow the spin promoted by companies they cover. Their evidence supports the notion that there exists a quid pro quo relation between journalists and their corporate sources, especially when there are few alternative information sources about the company covered. Similarly,

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[1] Berry and Howe (1994), for example, develop a measure of public information flow to financial markets and use it to document the patterns of information arrival, with an emphasis on the intraday flows. They suggest a positive, moderate relation between public information and trading volume, but an insignificant relation with price volatility.

[2] For example, Tetlock (2011) shows that investors tend to overreact to stale news stories, leading to temporary movements in stock prices. In a recent article, Hirshleifer, Lim, and Teoh (2009) show that extraneous news inhibits reaction to relevant news. Huberman and Regev (2001) point out that a Sunday *New York Times* article on the potential development of new cancer-curing drugs caused EntreMed's stock (ENMD) price to rise from a Friday close price of $12.063 per share to $85 on Monday morning and finally to settle at $52 at the close of trading on Monday. It closed above $30 in the three following weeks. Similar information to that contained in the Sunday *New York Times* article was publicly available five months before the article was published. Huberman and Regev offer a hypothetical question in their conclusion: What would have been the price of ENMD if the editor of the *Times* had chosen to kill this story?

[3] In this article we use the terms "mispricing" and "deviation from fundamental value" interchangeably.

Gurun and Butler (2012) show that local media coverage has a more positive slant toward local firms because they tend to have substantial local advertising expenditures.

If we gauge investor sentiment by the relative amounts of noise traders (individual investors that are less informed) to arbitrageurs (professional investors that are better informed) in the market, it is easy to establish a link between press coverage and sentiment. For example, Barber and Odean (2008) find that individual investors tend to be net buyers when firms are in the news. According to Hong and Stein (2007), abnormal news coverage can systematically drive prices away from fundamental values because it can endogenously raise the level of effective sentiment in the market. In line with their argument, Tetlock (2007), using a qualitative measure of pessimistic press coverage, shows that high media pessimism predicts downward price pressure. Thus, we should observe a positive relation between abnormal news coverage and volume, as well as a positive relation between abnormal news coverage and mispricing. There is an alternative scenario, described in DeLong et al. (1990), where abnormal press coverage can cause prices to move away from fundamentals. This scenario entails the possibility that intense media coverage may trigger positive feedback trading rooted in extrapolative expectations resulting from judgment biases under uncertainty and provide an opportunity for price-destabilizing rational speculation.[4] We label both of the preceding scenarios the "media-induced sentiment hypothesis."

Given the conflicting predictions of the hypotheses presented, the answer to the question of whether press coverage improves or hinders investors' efforts to correctly price stocks is an empirical issue, for which there is little direct evidence. We devise a method that allows us to determine which of the aforementioned views of the press is most accurate. We first examine the potential link between abnormal press coverage and several mispricing measures. We then test the relation between press coverage and measures of risk associated with the information environment of the firm, that is, information risk.[5] This secondary investigation allows us to obtain a clearer picture of the informational efficiency role of press coverage, because evidence of a negative relation between abnormal news coverage by press media and measures of information risk would be in line with the information intermediary and corporate governance hypotheses, whereas evidence of a nonnegative relation would be consistent with the biased media and media-induced sentiment hypotheses.

We use a large sample of publicly traded U.S. firms. We count the number of news articles about every firm that appeared each calendar year from 1995 to 2004 in the four major U.S. newspapers (*Los Angeles Times, New York Times, Wall Street Journal*, and *Washington Post*) and then obtain a measure of abnormal press coverage as the residual from a regression of the article count on firm size and industry indicators. Our proxies for mispricing are based on relative valuation ratios that contrast actual prices to imputed values derived from median industry value multiples as well as future abnormal returns. We provide evidence against the information intermediary and corporate

[4] As noted in Hong and Stein (2007), the main difference between their approach and that of DeLong et al. (1990) is that they endogenize the degree of investor sentiment, while DeLong et al. take sentiment as exogenous.

[5] In this article, we define information risk as the risk that arises when some investors are better informed than others (see Aslan et al. 2008).

governance hypotheses. In particular, time-series asset pricing tests show that abnormal returns of arbitrage portfolios formed based on our mispricing measures are enhanced when these portfolios are formed using firms with high abnormal press coverage. Our cross-sectional tests show that (1) mispricing significantly rises with abnormal news coverage and (2) information risk measures are significantly and positively related to abnormal news coverage. These two pieces of evidence, together with the fact that abnormal news coverage is associated with greater volume (i.e., more disagreement among investors), are consistent with the predictions of the biased media and the media-induced sentiment hypotheses.[6]

We empirically discriminate between the biased media and media-induced sentiment hypotheses by investigating the effects of abnormal press coverage separately for firms with negative and positive relative valuations, that is, for firms with prices below and above fundamental value, respectively. In line with the media sentiment hypothesis, we find that abnormal press coverage increases the magnitude of mispricing only for overvalued firms. This finding of an asymmetric response to negative and positive news coverage is consistent with a combination of media-induced sentiment and binding short-selling constraints. Alternatively, this finding is also in line with the concurrent existence of media-induced sentiment and media bias.[7]

In the final part of our analysis we assess whether media bias exists. This is done by examining the relation between relative valuation-based mispricing proxies and two separate measures of press coverage, one based on national newspapers and one based on local newspapers. We find that there is an asymmetric effect of local media coverage on mispricing; whereas local press coverage has a weak positive effect on mispricing of overvalued (good news) firms, it has a negative effect on mispricing of undervalued (bad news) firms. Taken together with the findings of Gurun and Butler (2012) wherein local press coverage tends to be relatively less negatively slanted toward local firms, these results can be interpreted as being in line with the existence of bias in the media coverage of local firms. Overall our results indicate that abnormal news coverage leads to mispricing that is rooted primarily in the fact that press coverage creates sentiment among investors. This effect is partly offset by media bias leading to a weaker relation between coverage and relative valuation in the case of bad news than in the case of good news.

II. Related Literature and Hypothesis Development

The cost of becoming informed may exceed the benefit individuals can personally derive from information, giving rise to a rational ignorance paradox (see Downs 1957). Information intermediaries, such as security analysts and the media, that reduce individuals' cost of collecting and evaluating information, provide an opportunity for

[6]The results on the relation between abnormal news coverage and trading volume are not tabulated in this article but available upon request.

[7]The media-induced sentiment hypothesis implies that abnormal print news coverage should increase mispricing for both under- and overpriced firms, whereas the media bias hypothesis predicts that the relation between mispricing and abnormal coverage should be negative for undervalued firms. Thus, the combined effect would be weaker for undervalued firms.

them to overcome rational ignorance. In particular, print media select, certify, and repackage information for a low fee (the price of a newspaper), thereby dramatically reducing the cost that individuals would have to bear to become informed. Hence, what individuals learn from press coverage depends on what information is selected and how it is packaged. If the information included in press articles is selected randomly, or based on honest, reliable, and unbiased criteria, then the press becomes a means of achieving high levels of public disclosure, that is, an information intermediary. In this capacity press coverage is expected to enhance market efficiency and investors become relatively confident that any stock transactions based on press-generated information occur at a "fair price" (see Diamond and Verrecchia 1991). Thus, the information intermediary hypothesis predicts a negative association between press coverage and mispricing.

Credibility is an important objective of journalists' and press editors' choices with respect to what and how to publish because readers of business news are looking for reliable information on which they can base their investment decisions. Thus, truthful and independent reporting and analysis can enhance newspaper reputation and secure readers in the long run. In turn, reputation and credibility allow the press to assume a corporate governance role (see, e.g., Dyck and Zingales 2002), because by publishing corporate news it can add weight to information provided through other sources and spread the information among a large number of individuals. As a result, when negative news is reported, firms or managers suffer reputational costs and, in some cases, become more likely to be punished. Dyck, Volchkova, and Zingales (2008) describe four ways in which the media can influence the balance between private benefits and costs associated with managerial actions that deviate from shareholder value maximization. First, the media can affect the probability that a given managerial action will become known to a certain audience. Second, it can increase the reputational cost of managers' actions. Third, it can affect the probability that punishment will be enforced on the managers. And fourth, the media can affect the size of the punishment, especially if the case goes to trial. Thus, press coverage can also have an effect on market prices, channeled through its role as a managerial disciplinary mechanism. In this context press coverage may enhance market efficiency, albeit in an indirect way, that is, because it reduces agency costs. Because lower agency costs are also associated with less mispricing (see Pantzalis and Park 2008), the corporate governance hypothesis predicts that if the press media play a corporate governance role, press coverage should be negatively related to mispricing.

In spite of its importance, credibility may sometimes be sacrificed when newspapers abandon objectivity in favor of reporting that is geared toward readers' preference for positive news about firms they own or that may help journalists to maintain and nourish relationships with their sources of corporate news. For example, in light of readers' inclination to believe articles that confirm their priors and to discount others (Mullanaithan and Shleifer 2002), it may pay for reporters to "follow the herd." Moreover, Dyck and Zingales (2003) argue that a quid pro quo relation between journalists and their corporate sources is common, especially when there is a shortage of alternative information sources about the company in question. They find that media outlets' spin often tends to follow the spin promoted by the companies they cover. Based on the preceding, the biased media hypothesis predicts that if investors are unable to correctly account for the degree of bias in media reporting, abnormal press coverage is expected to have a detrimental effect on market efficiency. In other words, if abnormally high press coverage is associated with biased information, it may lead to mispricing because investors are unable to correctly account for the extent of bias in reporting.

Alternatively, one can argue that abnormal news coverage may result in mispricing because it may trigger investor sentiment, that is, levels of optimism or pessimism that are not justified by information about fundamentals (Baker and Wurgler 2006).[8] Optimism (pessimism) can result in over- (under)valuation when (1) there is a subset of investors known as noise or sentiment traders that has biased beliefs about cash flows and/or risk, and (2) arbitrage is costly; that is, there are limits to arbitrage. There are at least two scenarios where media-induced investor sentiment can cause mispricing. First, intense media coverage may trigger positive feedback trading rooted in investors' extrapolative expectations resulting from judgment biases under uncertainty.[9] In this case, abnormal press coverage may contribute to mispricing by providing an opportunity of price-destabilizing rational speculation.[10] This process where markets are likely to overreact to abnormal news coverage is described in detail in the model of DeLong et al. (1990). They show that in the presence of positive feedback, rational speculators may be inclined not to counter the irrational drift in prices. Instead, because they anticipate that noise traders will continue buying in the future, rational speculators will buy now in the hope of selling at higher prices later. Consequently, rational speculators may intensify positive feedback trading and thereby move prices further away from their intrinsic values, until ultimately, they revert to fundamental values.

Second, when prices and sentiment are endogenously determined, abnormal news coverage can lead to disagreement among investors, systematically driving prices away from fundamental value (see Hong and Stein 2007).[11] For example, when there is gradual flow of information (Hong and Stein 1999) combined with investors' lack of understanding about the structure of the environment or failure to realize that they are at an informational disadvantage (i.e., overconfidence), the effect of news coverage on stock prices can be permanent.[12] Overconfident investors weigh their own information too heavily when updating their beliefs (Odean 1998) and may be slow to do so in face of new evidence (Edwards 1968). If during periods of positive (negative) abnormal press coverage investor

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[8] For example, Bonner, Hugon, and Walther (2007) show that market participants overreact (underreact) to large positive forecast revisions issued by analysts with high (low) media coverage.

[9] See, for example, survey evidence in Frankel and Froot (1988) and Case and Shiller (1988), and experimental evidence in Andreassen and Kraus (1988).

[10] Rational speculators are traditionally thought of as stabilizing powers in financial markets that promote market efficiency by "bucking the trend," thereby driving prices closer to their fundamental values. Figlewiski (1979) argues that in the presence of risk aversion, the effectiveness of rational speculation in promoting market efficiency is compromised. DeLong et al. (1990) add that the unpredictability of irrational traders' behavior can also diminish the effectiveness of rational speculation.

[11] Hong and Stein (2007) outline three sentiment mechanisms: (1) gradual information flow combined with investor overconfidence, (2) new information appearing in an "attention-grabbing" manner when investors have limited attention, and (3) investors having heterogeneous priors in combination with lack of sophisticated updating of beliefs. Hong and Stein argue that any of these three sentiment mechanisms combined with the existence of short-selling constraints yields the prediction that abnormal news coverage has a systematic tendency to drive prices up.

[12] An example of this effect is carefully outlined in Huberman and Regev (2001). Other studies that provide similar evidence are Menzly and Ozbas (2006), Cohen and Frazzini (2006), and Hong, Torous, and Valcanov (2007).

sentiment runs high (low), investors will generally expect good (bad) news. If, however, there is new information (e.g., an earnings announcement) that is contrary to these expectations, investors may initially underreact and prices may not fully adjust to reflect the new and conflicting information. Similarly, Livnat and Petrovits (2008) argue that drift returns may be greater for bad (good) news following periods of high (low) investor sentiment than following periods of low (high) investor sentiment as the belief updating process occurs and investors are able to confirm the direction of the initial (contradictory) news using subsequent information. They provide evidence that holding extreme good news firms following pessimistic sentiment periods earns significantly higher excess returns than holding extreme good news firms following optimistic sentiment periods.

In addition to its effect on prices, if abnormal news coverage induces sentiment, it should be also associated with high volume. Thus, according to the media-induced sentiment hypothesis, we should observe a positive relation between abnormal news coverage and mispricing, as well as a positive relation between abnormal news coverage and volume. Based on the preceding discussion, our first hypothesis is:

Hypothesis 1: Firms with high press coverage are more likely to display high levels of mispricing.

An alternative way of assessing the relative validity of the different views of press coverage is to examine the link between abnormal press coverage and information risk. Information risk arises when some investors have more and/or better information than others about a firm's prospects, that is, when the quality of the firm's information environment is poor. Aslan et al. (2008) document that the size of such risk depends on a variety of factors such as the quality of a firm's accounting information, the availability of public information sources about the firm, the frequency of new information events, and the fraction of investors who have better information. Because a firm's information risk emanates from a multitude of sources, we use several alternative measures, such as the quality of earnings attributes, analyst forecast accuracy, stock return volatility, and so on, to capture information risk. The information intermediary and the corporate governance hypotheses predict a negative relation between abnormal press coverage and information risk. The biased media and media-induced sentiment hypotheses predict a positive relation. Thus, our second hypothesis is:

Hypothesis 2: Abnormal press coverage increases information risk.

Past research in psychology and political science has emphasized that individuals do not respond to positive and negative information in a symmetric fashion. Collectively, that literature (e.g., Soroka 2006) suggests that increases in bad news may matter more than increases in good news. Whereas the political science evidence is characterized by a focus on political issues and implications, the psychology literature's focus has been on attitude formation and on providing evidence on the process of the asymmetric responsiveness at the individual level. The evidence from the psychology literature suggests that negative information has a greater effect on impressions than does positive information (e.g., Ronis and Lipinski 1985; Singh and Teoh 2000; Van der Pligt and Eiser 1980; Vonk 1993, 1996; Soroka 2006).

In economics, prospect theory (Kahneman and Tversky 1979) suggests a similar asymmetric response to positive and negative information. In this context, asymmetry is considered the process of reacting differently to positive and negative perceptions. Because people care more about a loss in utility than they do about a gain of equal magnitude, reactions to negative information are greater than reactions to positive information.

In general, news coverage tends to be more tilted toward negative than positive information. This well-established fact[13] may be driven by the same individual-level theories discussed previously. According to this view, the media's emphasis on negative news may be in response to the asymmetric preference of individuals toward negative news. It may also indicate that the media plays a "surveillance" role, as outlined in the corporate governance hypothesis.

Based on the preceding, we extend our investigation to examine whether the effect of press coverage on mispricing is asymmetric, that is, different for firms that are overvalued and likely to have experienced good news versus firms that are undervalued and likely to have experienced bad news. According to the literature on psychology, politics, and economics discussed earlier, and if media coverage indeed induces sentiment, we will find larger effects of press coverage on mispricing for undervalued firms. However, if press coverage is also strongly favorably biased toward firms' management, we may find an insignificant relation between press coverage and mispricing for undervalued firms but a significant relation for overvalued firms. Our third hypothesis is:

Hypothesis 3: The effect of press coverage on mispricing is asymmetric.

III. Data and Measures

We collect news articles on our sample firms that appeared in the four major U.S. newspapers (*Los Angeles Times, New York Times, Wall Street Journal*, and *Washington Post*) from 1995 to 2004 as follows. We first collect company names through the Center for Research in Securities Prices (CRSP) where NYSE, AMEX, and NASDAQ stocks are listed. We identify 6,053 company names and 28,492 firm-years after omitting regulated utilities (Standard Industrial Classification [SIC] codes 4910–4949), depository institutions (SIC codes 6000–6099), and holding or other investment companies (SIC codes 6700–6799), and dropping the firms if their SIC codes are missing.

Next, we merge the sample with Compustat data to extract accounting and financial information. We exclude any observations if such information is not available in Compustat. We require that the firm have the essential data in the computation of mispricing measures and the firm's total assets be greater than 10 million to avoid cases of firms with distorted valuation multiples used to derive the mispricing measures. These

[13] Several studies document that media tends to highlight violence (e.g., Altheide 1997; Davie and Lee 1995; Smith 1984) and events involving conflict or crisis (Bagdikian 1987; Herman and Chomsky 1988; Paraschos 1988; Patterson 1997; Shoemaker, Danielian, and Brendlinger 1991).

requirements reduced our sample to 19,290. We finally require that firms have all information on size, book-to-market (B/M) ratio, earnings volatility, business segments, and dividend policy. Consequently, our final sample includes 12,789 firm-years during the sample period. In the Appendix, we provide detailed descriptions of the variables used in this article.

Measure of Press Coverage

We obtain a count of the number of newspaper articles on a particular firm for each calendar year by typing the company name in the ProQuest search engine. The articles provide various types of information including firm performance, new products, editors' opinions, managers' personality, customer reviews, government regulations on the firm, and so on. Some articles contain overall positive content, others negative content, and more often than not, mixed content. In this study we refrain from classifying articles as containing good or bad news based on press article content for a couple of reasons. First, judging whether an article is positive or negative is subjective. Indeed, in the early stages of this research project we closely scrutinized a randomly selected number of articles and realized it was often difficult to unequivocally classify articles into good news or bad news groups. Thus, using subjective judgment to distinguish between good and bad news nature of articles would not only substantially reduce the sample size but also potentially inject sample selection bias in our empirical results. Second, using keywords in textual analysis software is problematic. As noted in Loughran and McDonald (2011) and Henry and Leone (2009), textual analysis is not an exact science. They argue that reliance on "negative" and "positive" word counts based on word lists developed for other disciplines to measure the tone of a financial text can lead to misclassifications.[14] Instead, we indirectly refer to press coverage of good (bad) news when valuation is higher (lower) than stock intrinsic value.

Given the importance of local (home) bias in finance and the potential role of local media (see, e.g., Gurun and Butler 2012), we also account for local press coverage. However, because of the tremendous collection effort associated with the nature of our data, we restrict the analysis that accounts for local press coverage to a smaller data set comprising the S&P 500 firms.

An important characteristic of our press coverage measure is that it is an "abnormal" press coverage measure, that is, one that captures deviation from what is expected given the firm's size and industry. The use of an abnormal press coverage measure is motivated by the observation that the raw number of press articles is highly skewed. As shown in Panel A of Table 1, out of 12,789 sample firm-year observations, 7,392 (about 58%) involve firms not covered by any of the four major newspapers. After

[14] Loughran and McDonald (2011) use a large sample of 10-Ks during 1994–2008. They discover that almost three-fourths of the word count was wrongly identified as negative by the commonly used *Harvard Dictionary*. For example, words such as "tax," "board," "foreign," "vice," and "liability" that may sound negative in other disciplines are perfectly "neutral" in a finance context. Henry and Leone (2009) note that using general word lists may also give rise to problems associated with polysemy. They mention, for example, that the word "division" is considered "negative" in the word list from the General Inquirer (GI) program, which was developed by Philip Stone, a specialist in social psychology.

TABLE 1. Distribution of Press Coverage.

Panel A. Distribution of Press Coverage in Decile Groups of Firm Size

	Number of Firm-Years	Number of Covered Firm-Years	Number of Noncovered Firm-Years	Total Number of Articles	Average Number of Articles
D1 (Smallest)	1,276	156	1,120	249	0.1951
D2	1,278	228	1,050	454	0.3552
D3	1,278	320	958	824	0.6448
D4	1,279	348	931	966	0.7553
D5	1,281	452	829	1,396	1.0898
D6	1,278	578	700	1,740	1.3615
D7	1,278	624	654	2,424	1.8967
D8	1,280	749	531	3,414	2.6672
D9	1,276	911	365	7,298	5.7194
D10 (Largest)	1,285	1,031	254	33,740	26.2578
Total	12,789	5,397	7,392	52,505	4.105

Panel B. Distribution of Press Coverage in Fama–French 49 Industries

Code	Industry	Number of Firms	Number of Covered Firms	Number of Noncovered Firms	Total Number of Articles	Average Number of Articles
1	Agriculture	21	11	10	104	4.9524
2	Food Products	270	137	133	1713	6.3444
3	Candy and Soda	77	41	36	689	8.9481
4	Beer & Liquor	37	14	23	167	4.5135
5	Tobacco Products	4	0	4	0	0.0000
6	Recreation	128	53	75	334	2.6094
7	Entertainment	156	82	74	2,748	17.6154
8	Printing & Publishing	184	116	68	1,875	10.1902
9	Consumer Goods	260	132	128	2,173	8.3577
10	Apparel	191	77	114	321	1.6806
11	Healthcare	289	122	167	944	3.2664
12	Medical Equipment	384	130	254	636	1.6563
13	Pharmaceutical Products	498	230	268	2,580	5.1807
14	Chemicals	288	134	154	767	2.6632
15	Rubber & Plastic Products	135	44	91	101	0.7481
16	Textiles	44	15	29	24	0.5455
17	Construction Materials	252	118	134	544	2.1587
18	Construction	193	92	101	283	1.4663
19	Steel Works Etc.	233	85	148	248	1.0644
20	Fabricated Products	57	26	31	54	0.9474
21	Machinery	493	216	277	981	1.9899
22	Electrical Equipment	446	126	320	403	0.9036
23	Automobiles & Trucks	212	118	94	652	3.0755
24	Aircraft	68	30	38	734	10.7941
25	Shipbuilding & Railroad Equipment	21	12	9	362	17.2381
26	Defense	38	22	16	219	5.7632
27	Precious Metals	81	32	49	122	1.5062
28	Non-Metallic & Industrial Metal Mining	52	27	25	70	1.3462
29	Coal	25	6	19	17	0.6800
30	Petroleum & Natural Gas	593	260	333	1,703	2.8718

(Continued)

Table 1. Continued.

Panel B. Distribution of Press Coverage in Fama–French 49 Industries

Code	Industry	Number of Firms	Number of Covered Firms	Number of Noncovered Firms	Total Number of Articles	Average Number of Articles
32	Communication	306	145	161	1,483	4.8464
33	Personal Services	145	43	102	288	1.9862
34	Business Services	764	293	471	1,963	2.5694
35	Computers	395	171	224	2,986	7.5595
36	Computer Software	849	357	492	11,672	13.7479
37	Electronic Equipment	880	378	502	3,050	3.4659
38	Measuring & Control Equipment	299	97	202	532	1.7793
39	Business Supplies	180	93	87	775	4.3056
40	Shipping Containers	62	21	41	54	0.8710
41	Transportation	356	123	233	919	2.5815
42	Wholesale	841	282	559	938	1.1153
43	Retail	704	380	324	3,356	4.7670
44	Restaurants, Hotels, & Motels	329	155	174	757	2.3009
45	Banking	124	37	87	552	4.4516
46	Insurance	439	157	282	1,035	2.3576
47	Real Estate	97	38	59	134	1.3814
48	Trading	137	64	73	213	1.5547
49	Other Miscellaneous	152	55	97	230	1.5132
Total		12,789	5,397	7,392	52,505	4.1055

Note: This table shows the distribution of the sample that contains 12,789 firm-year observations (2,575 firms) from 1995 to 2004. Panel A provides the distribution of press coverage for decile groups classified on size (total assets). Panel B reports the distribution for Fama–French 49 industries. We collect newspaper articles related to the firm and reported in four major newspapers: *Los Angeles Times, New York Times, Wall Street Journal*, and *Washington Post*. Industry codes are obtained from Kenneth R. French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

classifying firms into decile groups based on size (measured by the total assets), we observe that there are only 249 articles about firms in the bottom decile group (smallest firms), corresponding to an average number of articles per firm-year for the group of just 0.195. This average number monotonically increases in firm size and reaches 26.258 for the top decile group, that is, a number 135 times greater than that of the bottom decile group. Panel A provides another interesting result. The number of covered firm-years also monotonically increases in firm size whereas the number of uncovered firm-years decreases in firm size. The average number of articles for a firm per year is 4.105 but the standard deviation is greater than 25 (see Table 2). In addition to firm size, the extent of press coverage is significantly related to industry affiliation. Panel B reports the distribution of press coverage across 49 industries defined based on the Fama–French classification. We observe substantial differences in coverage across industries, indicating the need to control for industry effects in our subsequent multivariate tests.

Based on the evidence from Table 1, we conclude that it is imperative to create a "pure" measure of press coverage that would net out the significant effects of size and industry. Thus, we compute abnormal press coverage as the difference between expected and actual counts of press articles, that is, the residual value ($e_{i,t}$) in the following

TABLE 2. Descriptive Statistics.

	N	Mean	Standard Deviation	5th Percentile	Median	95th Percentile
			Press Coverage			
PRESS	12,789	4.1055	25.8717	0	0	15
APRESS	12,789	−0.0036	0.7823	−1.1184	−0.0814	1.4183
			Mispricing			
MP	12,736	0.4833	0.4400	0.0187	0.3688	1.3506
AR3	11,909	0.0398	0.0581	0.0000	0.0204	0.1459
AR6	11,909	0.0274	0.0386	0.0000	0.0138	0.1017
AR12	11,909	0.0203	0.0280	0.0000	0.0103	0.0747
			Analyst Coverage			
AF	12,789	5.2619	6.7661	0	3	20
EAF	12,789	−0.0020	0.7233	−1.2596	0.0602	1.0695
			Information Risk			
EQ1	11,801	0.3237	0.5757	0.0140	0.1634	1.0671
EQ2	10,722	0.1683	0.2161	0.0113	0.1134	0.4743
EQ3	10,722	0.1793	0.2507	0.0109	0.1045	0.6095
AFE	8,369	0.6587	4.0066	0.0050	0.1200	2.0455
AFD	7,736	0.1611	0.6772	0.0000	0.0370	0.5556
RVOL	12,787	0.0380	0.0204	0.0150	0.0335	0.0761
			Liquidity			
VOLUME	12,789	13.2344	2.7006	8.9929	13.2194	17.6043
SVOLUME	12,784	−6.1238	1.1810	−8.1256	−6.0398	−4.3149
ILLIQ	12,788	−17.2452	2.9763	−21.9705	−17.3346	−12.3329
SILLIQ	12,783	2.1164	1.3079	0.2850	1.9102	4.4995
			Other Firm Characteristics			
SIZE	12,789	19.4902	1.8118	16.8052	19.3541	22.7867
B/M	12,789	0.7009	0.3651	0.1778	0.6748	1.3126
EVOL	12,789	0.1814	1.4871	−2.1443	0.2580	2.6336
NSEG	12,789	1.5264	0.9221	1	1	3
DIV	12,789	0.3166	0.4652	0	0	1

Note: Reported are descriptive statistics for our sample firms. The sample contains 12,789 firm-year observations (2,575 firms) from 1995 to 2004. Refer to the Appendix for detailed variable descriptions.

regression equation, which we estimate every year rather than using the whole sample, to avoid look-ahead bias.

$$\mathrm{Ln}\left(1 + PRESS_{i,t}\right) = \beta_0 + \beta_1 SIZE_{i,t} + \Sigma\beta_S IND_{i,t} + e_{i,t}, \quad (1)$$

where *PRESS* is the raw number of newspaper articles related to firm *i* and reported in four major newspapers in a calendar year. Because *PRESS* is highly skewed, we use a log-transformed measure as a dependent variable. *SIZE* is the log of total assets and *IND* is a vector of 49 industry dummy variables. In the reminder of this article, our empirical tests focus on the linkage of abnormal press coverage to mispricing.

Valuation Measures

We contend that the likelihood of mispricing increases when a firm's current value deviates substantially from an empirical benchmark that stands for the (unobservable) fundamental value. We follow past studies (e.g., Doukas, Kim, and Pantzalis 2005, 2010) that adopt relative valuation measures based on the Berger and Ofek (1995) approach to capture the degree of deviation of the current stock price from its fundamental (intrinsic) value. We label this difference the excess price, that is, the degree of under- or overvaluation relative to the (fundamental) benchmark value. Excess price (*EP*) is computed as:

$$EP_{i,t} = \mathrm{Ln}\left[CAPITAL_{i,t}/Imputed\left(CAPITAL_{i,t}\right)\right], \tag{2}$$

where i indexes firms and t is a yearly time index, $CAPITAL_{i,t}$ is the market value of common equity plus book value of debt, and $Imputed(CAPITAL_{i,t})$ is computed as the product of the firm's total assets and the firm's primary industry-median ratio of total capital to total assets. We assign firms to industries based on the Fama–French 49-industry classification. A positive (negative) value of *EP* indicates that the market assigns a price for the stock that is higher (lower) than what the industry benchmark-based price would indicate. Because mispricing can be reflected in both positive and negative values of *EP*, we define our mispricing measure (*MP*) as the absolute value of *EP*. In addition, we use an indicator variable (*MPD*), that is, mispricing dummy, as an alternative mispricing measure. $MPD_{i,t}$ equals 1 if the *EP* value of firm i is in the top quartile (high positive) or in the bottom quartile (high negative values) after sorting all firms based on *EP* in year t, and 0 otherwise.

Average Excess Monthly Future Returns

One may argue that the deviations from fundamentals-related benchmarks could be inconsistent with "true" mispricing because the benchmarks are measured with error. To alleviate this concern, we use future stock returns as dependent variables. If *MP* and *MPD* are indeed capturing mispricing, they should give rise to high (absolute) future returns. Because *MP* and *MPD* are constructed at the end of calendar year t, we compute abnormal future returns over the 3-, 6-, and 12-month periods starting from the beginning of calendar year t+1 (i.e., *AR3*, *AR6*, and *AR12*, respectively). More specifically, *AR3* is measured as the difference between the average monthly return of firm i from January to March in year t+1 and the median monthly return of a matching firms' benchmark portfolio that consists of all sample firms that belong to the same industry and in the same size and B/M ratio quintiles as firm i. The summary statistics of abnormal press coverage, mispricing measures, and other firm variables are reported in Table 2.

IV. Abnormal Press Coverage and Mispricing

Abnormal Press Coverage and Mispricing

Table 3 illustrates how firms with high *APRESS* differ from firms with low *APRESS*. It reports mean values of several firm characteristics' variables for quintile groups formed

TABLE 3. Mean Comparisons: Univariate Analysis.

	Sorted on *APRESS*						
	Lowest Q1	Q2	Q3	Q4	Highest Q5	Q5–Q1	(*t*-stat.)
				Press Coverage			
PRESS	0.0714	0.2939	0.5832	1.5860	18.2428	18.1713***	(16.45)
APRESS	−0.9693	−0.4159	−0.0865	0.2858	1.1735	2.1428***	(158.62)
SD_PRESS	1.5034	0.9294	1.0159	1.4854	9.0763	7.5730***	(16.00)
SD_APRESS	0.4776	0.3774	0.3589	0.4052	0.5562	0.0785***	(10.38)
				Mispricing			
MP	0.4199	0.4689	0.4872	0.5140	0.5266	0.1067***	(8.61)
AR3	0.0336	0.0411	0.0433	0.0432	0.0377	0.0041***	(2.83)
AR6	0.0223	0.0294	0.0288	0.0298	0.0265	0.0042***	(4.35)
AR12	0.0170	0.0213	0.0224	0.0214	0.0194	0.0023***	(3.28)
SD_MP	0.2426	0.2742	0.2808	0.2856	0.2893	0.0466***	(10.30)
SD_AR3	0.0369	0.0436	0.0474	0.0482	0.0421	0.0053***	(5.76)
SD_AR6	0.0257	0.0302	0.0319	0.0313	0.0284	0.0027***	(4.61)
SD_AR12	0.0187	0.0219	0.0238	0.0232	0.0202	0.0016***	(4.01)
				Analyst Coverage			
AF	6.7783	3.8166	3.1932	3.8639	8.7243	1.9459***	(8.65)
EAF	−0.0434	−0.0571	−0.0608	0.0211	0.1310	0.1743***	(8.21)
				Information Risk			
EQ1	0.2852	0.3156	0.3431	0.3463	0.3263	0.0410***	(2.84)
EQ2	0.1457	0.1650	0.1772	0.1799	0.1732	0.0274***	(4.59)
EQ3	0.1626	0.1763	0.1933	0.1837	0.1804	0.0178**	(2.44)
AFE	0.3917	0.9147	0.7976	0.6107	0.6497	0.2580**	(2.50)
AFD	0.1427	0.1682	0.1889	0.1762	0.1463	0.0035	(0.17)
RVOL	0.0307	0.0373	0.0420	0.0429	0.0371	0.0064***	(12.80)
				Liquidity			
VOLUME	14.2290	12.8141	12.2963	12.4151	14.4531	0.2241***	(3.05)
SVOLUME	−6.0316	−6.2592	−6.2906	−6.2444	−5.7868	0.2448***	(7.49)
ILLIQ	−18.4420	−16.8184	−16.1896	−16.2927	−18.5229	−0.0809	(−1.02)
SILLIQ	1.8206	2.2579	2.4009	2.3708	1.7207	−0.0999***	(−2.90)
				Other Firm Characteristics			
SIZE	20.4558	19.2867	18.7417	18.7836	20.2120	−0.2437***	(−4.81)
B/M	0.6914	0.7497	0.7284	0.7048	0.6305	−0.0610***	(−6.66)
EVOL	−0.1111	0.1301	0.3262	0.3214	0.2352	0.3464***	(8.27)
NSEG	1.5773	1.4312	1.4380	1.4834	1.7040	0.1268***	(4.43)
DIV	0.4542	0.2850	0.2274	0.2497	0.3687	−0.0855***	(−6.22)

Note: Reported are mean values of variables for the quintile subsamples sorted on abnormal news coverage (*APRESS*). Also reported are the differences in mean values between highest and lowest *APRESS* firms and the corresponding *t*-statistics in parentheses. *SD_* represents the within-firm standard deviation of the variable. Refer to the Appendix for detailed variable descriptions.

***Significant at the 1% level.

**Significant at the 5% level.

based on the level of *APRESS* and mean differences across the two extreme groups (top- vs. bottom-*APRESS* quintiles) as well as the corresponding *t*-statistics for the mean difference tests. All mispricing measures are, on average, significantly larger for firms in the top-*APRESS* quintile (Q5) compared to those in the bottom-*APRESS* quintile (Q1). This evidence is in line with the predictions of both the biased media hypothesis and media sentiment hypothesis. Average *MP* is about 25% larger for the Q5 *APRESS* group compared to the Q1 *APRESS* group. Additionally, future returns' differentials between Q5 and Q1 reveal that markets take up to a year to correct mispricing caused by abnormal press coverage. The difference in *AR* is 0.41% per month for the first 3 months and drops to 0.23% for the 12-month period following the end of calendar year. Q5 *APRESS* firms are also covered by more analysts and are larger than the Q1 *APRESS* firms. Yet, consistent with the mispricing evidence, they display a poorer information environment (greater level of information risk) than Q1 *APRESS* firms. The mean values of five out of six measures of information risk are significantly higher for high-*APRESS* firms than for low-*APRESS* firms.

Based on the univariate results presented in Table 3, we have preliminary evidence supporting the notion that abnormal coverage by news articles is positively related to mispricing. To also provide risk-adjusted evidence in an asset pricing context, we estimate time-series regressions and examine abnormal returns of different portfolios formed after sorting independently on both excess firm value and abnormal press coverage at the end of each calendar year. A firm is included into the highest (lowest) *APRESS* group if its *APRESS* value is classified in the top (bottom) *APRESS* quartile. Similarly, a firm is included in the most overpriced (underpriced) group if its relative valuation is classified in the top (bottom) quartile of *EP*. Thus, at the end of every calendar year, we form four portfolios of firms.

Assuming markets are behaving efficiently over the medium term by correcting the level of mispricing, it is expected that our *EP* measure is negatively related to future risk-adjusted returns. In addition, if abnormal news coverage leads to investor sentiment, this effect should be exaggerated in cases where there is abnormal news coverage. To test whether the possible different return patterns are consistent with the above expectations, we construct two arbitrage portfolios. In the first portfolio, we buy the highest *APRESS* firms and simultaneously sell the lowest *APRESS* firms, and in the second portfolio, we buy the most overpriced firms and sell the most underpriced firms. If one group outperforms the other in the arbitrage portfolio, the estimated alpha in the asset pricing model should be significant. Conversely, if the return difference between the two groups is a manifestation of confounding effects (i.e., differences in market beta, size, B/M, and momentum), the alpha should be economically and statistically indistinguishable from zero.

Table 4 reports the intercepts (alphas) from the asset pricing model regressions. Consistent with our prior evidence and with the notion that the extreme values of relative valuation measures capture mispricing, the alpha of firms in the top *EP* quartile (overpriced firms) is negative and that of firms in the bottom *EP* quartile (underpriced firms) is positive. More important, the return difference between underpriced and overpriced firms depends on the level of abnormal coverage. For the lowest *APRESS* group, the most underpriced firms outperform the most overpriced firms by 0.60% per

TABLE 4. Time-Series Tests of Four-Factor Models for the High- and Low-*APRESS* Firms and the Arbitrage Portfolios.

	Constant	R_m^M–R_m^F	*SMB*	*HML*	*UMD*	R^2
			Most Overpriced			
Highest *APRESS*	−0.0053***	1.0366***	0.4920***	−0.0438	−0.0993**	0.9101
	(−3.19)	(22.60)	(9.65)	(−0.67)	(−2.11)	
Lowest *APRESS*	−0.0006	1.0046***	0.4638***	0.0956	−0.0443	0.8443
	(−0.25)	(19.95)	(5.77)	(1.11)	(−0.67)	
Arbitrage portfolio	−0.0047**	0.0320	0.0282	−0.1393	−0.0549	0.0616
(highest – lowest)	(−2.01)	(0.51)	(0.37)	(−1.39)	(−0.76)	
			Most Underpriced			
Highest *APRESS*	0.0062**	0.8181***	0.9190***	0.3795***	−0.0317	0.7796
	(2.01)	(10.53)	(8.54)	(3.60)	(−0.35)	
Lowest *APRESS*	0.0055**	0.9805***	0.9769***	0.5666***	0.0547	0.8217
	(1.98)	(15.54)	(9.20)	(5.46)	(0.53)	
Arbitrage portfolio	0.0007	−0.1624**	−0.0579	−0.1871*	−0.0864	0.0525
(highest – lowest)	(0.23)	(−2.17)	(−0.63)	(−1.90)	(−1.14)	
			Arbitrage Portfolio (Most Overpriced – Most Underpriced)			
Highest *APRESS*	−0.0115***	0.2185***	−0.4270***	−0.4233***	−0.0675	0.3617
(over – under)	(−3.68)	(2.95)	(−3.85)	(−4.24)	(−0.75)	
Lowest *APRESS*	−0.0060	0.0241	−0.5131***	−0.4711***	−0.0990	0.2251
(over – under)	(−1.49)	(0.30)	(−3.14)	(−3.52)	(−0.68)	

Note: This table reports the estimated coefficients in the time-series tests of four-factor models for highest and lowest *APRESS* groups and the arbitrage portfolio. The sample includes 120 monthly observations from January 1996 to December 2005. A firm is included in the highest (lowest) *APRESS* group if its *APRESS* is classified into the top (bottom) quartile, where *APRESS* = abnormal press coverage as the residual value from the annual regressions of press coverage on firm size and industry dummies. A firm is also included in the most overpriced (underpriced) group if its *EP* is classified in the top (bottom), where *EP* is the measure of excess price based on Berger and Ofek (1995), which is computed in equation (2). For the subsamples, we use the following four-factor model:

$$R_m^P - R_m^F = \alpha_0 + \beta_1\left(R_m^M - R_m^F\right) + \beta_2 SMB_m + \beta_3 HML_m + \beta_4 UMD_m + e_m,$$

where R_m^P = a portfolio's monthly return, R_m^F= one-month Treasury bill rate, and R_m^M = value-weighted market return. The arbitrage portfolios are constructed as the difference in returns between the highest and lowest *APRESS* firms or between the most overpriced and the most underpriced firms. We report the estimated coefficients from the regression of return on the arbitrage portfolios:

$$R_m^H - R_m^L\left(\text{or } R_m^O - R_m^U\right) = \alpha_0 + \beta_1\left(R_m^M - R_m^F\right) + \beta_2 SMB_m + \beta_3 HML_m + \beta_4 UMD_m + e_m,$$

where R_m^H (R_m^L) = monthly return of the highest (lowest) *APRESS* group and R_m^O (R_m^U) = monthly return of the most overpriced (underpriced) group. Refer to the Appendix for detailed variable descriptions. The numbers in parentheses are *t*-statistic values.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

month; for the highest *APRESS* group, the return difference strengthens to 1.15% per month, a significant effect in both statistical and economic terms. Results also show that, consistent with the findings of Fang and Peress (2009) who demonstrate that firms with no media coverage earn higher returns than those with media coverage, among the group of most overpriced firms, the alpha for highest *APRESS* and the most overpriced firms is –0.53% and significant at the 1% level whereas the alpha for the lowest *APRESS* firms is only –0.06%, which is 9 times smaller than the alpha of the former group. This result is against the information intermediary and corporate governance hypotheses that predict less mispricing from a stock with high media coverage. However, for underpriced firms, we do not find that abnormal press coverage significantly affects the level of performance. The difference in abnormal return between the highest and the lowest *APRESS* groups in underpriced firms is around 0.07% per month with a *t*-statistic of 0.23. This asymmetric effect of abnormal media coverage on mispricing between underpriced firms and overpriced firms is reported in the following tests and indicates that the positive relation between abnormal news coverage and mispricing is not due to lower information risk.

Abnormal Press Coverage: Risk Factor versus Characteristic?

Before we test the alternative hypotheses about the relation between press coverage and mispricing, we need to establish that press coverage has a substantial nonsystematic effect on stock return performance. Specifically, it is possible that firms receiving abnormal press coverage may have common characteristics that are to some extent systematic. Therefore, mispricing may disappear when a previously unobserved risk factor based on abnormal press coverage (*APC*) is considered. Based on the method of Daniel and Titman (1997), Davis, Fama, and French (2000), Daniel, Titman, and Wei (2001), and Hirshleifer, Hou, and Teoh (2012), we distinguish between the risk explanation and the mispricing concept. First, we classify firms into 27 portfolios based on the 33rd and 67th percentile breakpoints of *SIZE*, *APRESS*, and *EP*. We conduct time-series tests on these portfolios by adding two more factors (*CMA* and *APC*) to the four-factor model used in Table 4, where *CMA* (conservative minus aggressive) is the monthly return difference between the portfolios of high and low accruals (*ACCRUAL*) developed by Hirshleifer, Hou, and Teoh, and *APC* (abnormal press coverage) is the monthly return difference between the portfolios with high and low abnormal press coverage. We present the results in Panel A of Table 5. Consistent with evidence in Table 4, the alpha of firms in the top *EP* tercile (overpriced firms) is low and that of firms in the bottom *EP* tercile (underpriced firms) is high. Abnormal returns are more apparent for small firms. We find an asymmetric effect of *APC*. The estimated coefficient of *APC* is significant and negative for bigger firms, but it is significant and positive for smaller firms.

In Panel B, we estimate factor loadings with monthly returns over the previous 60 months (24-month minimum) using a five-factor model ($R_m^M – R_m^F$, *SMB*, *HML*, *CMA*, *APC*). We then estimate Fama–MacBeth (1973) regressions of monthly returns in the model that includes characteristics, such as size, B/M, previous returns, *ACCRUAL*, and *APRESS*, along with the factor loadings. Because the dependent variable is the monthly stock return and the potential mispricing effect can be manifested in two opposite directions (up and down), it is possible that positive and negative effects of abnormal press coverage on stock returns may cancel each other out. Therefore, we estimate the Fama–MacBeth regressions separately for firms with positive excess price (overpriced firms) and firms with negative excess price (underpriced firms). Consistent with Hirshleifer, Hou, and Teoh (2012), the first regression for overpriced firms in column (1) shows that

TABLE 5. Abnormal Press Coverage: Risk Factor versus Characteristic.

Panel A. Time-Series Tests for the Portfolios Sorted by *SIZE*, *APRESS*, and *EP*

SIZE	*APRESS*	*EP*	Constant	$R_m^M - R_m^F$	*SMB*	*HML*	*UMD*	*CMA*	*APC*	R^2
1	1	1	0.0185***	0.8730***	1.1913***	0.2167	−0.1078	0.3638	0.3898	0.6102
			(3.16)	(6.06)	(7.88)	(1.13)	(−0.73)	(1.29)	(0.83)	
1	1	2	0.0059	0.7707***	1.1609***	0.2032	−0.1384	0.1970	0.3906	0.5540
			(1.01)	(5.78)	(7.68)	(0.98)	(−0.96)	(0.75)	(0.95)	
1	1	3	0.0057	0.9304***	1.3579***	−0.8325***	−0.0209	0.1143	−0.1258	0.6713
			(0.90)	(5.24)	(5.06)	(−3.12)	(−0.13)	(0.63)	(−0.23)	
1	2	1	0.0182***	0.6552***	1.1007***	0.0373	−0.0160	0.3752**	1.0092**	0.6839
			(4.12)	(6.37)	(9.28)	(0.26)	(−0.16)	(2.23)	(2.58)	
1	2	2	0.0038	0.8371***	0.9984***	0.2085**	0.0764	0.2552***	1.1160***	0.8026
			(1.14)	(11.02)	(11.97)	(1.99)	(0.91)	(2.80)	(3.71)	
1	2	3	0.0029	0.8859***	1.2049***	−0.2177	−0.0237	0.0936	0.8559**	0.8072
			(0.74)	(8.59)	(11.40)	(−1.64)	(−0.24)	(0.52)	(2.39)	
1	3	1	0.0126*	0.7274***	1.2449***	0.4617**	0.1848	0.3152**	2.1109***	0.5965
			(1.88)	(5.53)	(9.93)	(2.50)	(1.35)	(2.02)	(4.61)	
1	3	2	0.0039	0.8434***	1.1153***	0.5685***	0.2336**	0.0029	1.5430***	0.6789
			(0.83)	(7.80)	(10.00)	(4.02)	(2.17)	(0.01)	(5.18)	
1	3	3	−0.0020	0.8552***	1.1475***	0.0364	−0.0481	−0.2127**	1.5778***	0.8293
			(−0.59)	(9.50)	(14.40)	(0.33)	(−0.52)	(−2.01)	(5.59)	
2	1	1	0.0086***	0.8675***	1.1072***	0.5056***	0.0493	0.1120	0.0235	0.7928
			(2.92)	(12.10)	(11.61)	(3.47)	(0.42)	(1.12)	(0.08)	
2	1	2	−0.0012	0.9614***	0.8650***	0.5635***	0.1345**	0.0109	−0.4715***	0.8923
			(−0.65)	(20.75)	(16.34)	(7.97)	(2.60)	(0.13)	(−2.85)	
2	1	3	0.0021	0.9682***	0.7708***	0.0443	−0.0275	0.0291	−0.6201**	0.8717
			(0.89)	(17.85)	(11.16)	(0.60)	(−0.45)	(0.41)	(−2.46)	
2	2	1	0.0124***	0.8360***	1.1348***	0.6023***	0.2341***	0.2778**	0.1949	0.7629
			(3.79)	(12.72)	(15.33)	(6.00)	(3.01)	(2.01)	(0.81)	
2	2	2	0.0029	0.9259***	0.8442***	0.6015***	0.2196***	0.0909	−0.0401	0.7922
			(1.04)	(14.16)	(12.48)	(5.54)	(2.72)	(1.12)	(−0.19)	
2	2	3	−0.0022	1.0406***	0.7890***	0.2984***	−0.0688	0.1565*	−0.5878**	0.8100
			(−0.77)	(13.01)	(9.09)	(2.67)	(−0.73)	(1.77)	(−2.33)	
2	3	1	0.0030	0.8310***	1.0723***	0.7150***	0.2310***	0.1837	1.1587***	0.7523
			(0.97)	(11.25)	(12.62)	(6.08)	(2.61)	(1.42)	(4.30)	
2	3	2	0.0022	1.0532***	1.0273***	0.7658***	0.2201***	−0.1389	0.4601**	0.8250
			(0.76)	(15.87)	(11.92)	(7.90)	(3.22)	(−1.19)	(2.15)	
2	3	3	−0.0067**	1.1224***	0.6877***	0.1314	−0.0505	0.1699*	−0.2598	0.8169
			(−2.04)	(13.99)	(6.63)	(1.25)	(−0.58)	(1.96)	(−0.94)	
3	1	1	0.0024	1.1409***	0.6843***	0.7462***	0.1362**	0.1183	−0.2612	0.8756
			(1.00)	(19.94)	(9.61)	(9.05)	(2.00)	(1.56)	(−1.27)	
3	1	2	−0.0011	1.0008***	0.4279***	0.6079***	0.1803***	−0.0243	−0.4518***	0.8692
			(−0.55)	(19.18)	(8.11)	(9.21)	(3.37)	(−0.46)	(−3.22)	
3	1	3	−0.0014	0.9956***	0.2116**	0.2061***	−0.0779	0.2350***	−0.5413**	0.8151
			(−0.56)	(15.00)	(2.21)	(2.78)	(−1.35)	(2.97)	(−2.49)	
3	2	1	0.0021	0.9612***	0.5176***	0.7356***	0.0763	−0.1085	−0.0596	0.6503
			(0.52)	(10.92)	(4.25)	(5.40)	(0.75)	(−0.95)	(−0.20)	
3	2	2	−0.0048*	0.9770***	0.5328***	0.6576***	0.1491*	0.0961	−0.6220***	0.7553
			(−1.66)	(11.07)	(5.67)	(5.86)	(1.75)	(1.15)	(−2.95)	
3	2	3	−0.0027	0.9171***	0.3054***	0.2426**	−0.0463	0.1476**	−0.4109**	0.7803
			(−0.95)	(13.10)	(3.84)	(2.46)	(−0.53)	(2.17)	(−1.99)	
3	3	1	0.0024	1.0966***	0.5332***	0.7023***	0.0526	0.2664***	−0.0250	0.8073
			(0.89)	(15.18)	(5.17)	(6.05)	(0.57)	(3.72)	(−0.11)	
3	3	2	−0.0020	1.0505***	0.3514***	0.5511***	0.0299	0.0624	−0.1612	0.8453
			(−0.90)	(19.26)	(5.18)	(6.51)	(0.44)	(0.83)	(−0.88)	

(Continued)

Table 5. Continued.

Panel A. Time-Series Tests for the Portfolios Sorted by *SIZE*, *APRESS*, and *EP*

SIZE	*APRESS*	*EP*	Constant	R_m^M–R_m^F	*SMB*	*HML*	*UMD*	*CMA*	*APC*	R^2
3	3	3	0.0011 (0.67)	1.0065*** (28.20)	0.1474*** (2.82)	−0.0036 (−0.07)	−0.1597*** (−3.63)	0.1672*** (3.56)	−0.1049 ((0.75)	0.9283

Panel B. Fama–MacBeth (1973) Regressions of Monthly Stock Returns on Characteristics and Factor Loadings

	Overpriced Firms	Underpriced Firms
	(1)	(2)
SIZE	−0.0036***	0.0003
	(−3.48)	(0.25)
B/M	0.0098***	0.0145***
	(6.15)	(6.68)
PRET(–1,–1)	−0.0521***	−0.0803***
	(−4.40)	(−7.87)
PRET(–12,–2)	−0.0001	−0.0080*
	(−0.03)	(−1.90)
PRET(–36,–13)	−0.0020*	−0.0035***
	(−1.91)	(−2.64)
ACCRUAL	−0.0237***	−0.0112*
	(−3.26)	(−1.78)
APRESS	0.0023**	0.0004
	(2.48)	(0.31)
β_{Market}	0.0078**	−0.0013
	(2.08)	(−0.38)
β_{SMB}	0.0036	−0.0004
	(1.60)	(−0.20)
β_{HML}	−0.0026	0.0014
	(−0.90)	(0.50)
β_{CMA}	−0.0004	0.0010
	(−0.35)	(1.20)
β_{APC}	0.0011*	−0.0001
	(1.95)	(−0.19)
Intercept	0.0950***	0.0012
	(4.42)	(0.05)
Number of months	96	96
Average R^2	13.86%	11.15%

Note: Panel A reports the time-series test results for the portfolio. We classify firms into 27 portfolios based on the 33rd and 67th percentile breakpoints of *SIZE*, *APRESS*, and *EP*. *APRESS* = abnormal press coverage as the residual value from the annual regressions of press coverage on firm size and industry dummies. A firm is also included in the most overpriced (underpriced) group if its *EP* is classified in the top (bottom), where *EP* is the measure of excess price based on Berger and Ofek (1995), which is computed in equation (2). *CMA* (conservative minus aggressive) = the monthly return difference between the portfolios of high and low accruals (*ACCRUAL*) developed by Hirshleifer, Hou, and Teoh (2012), where *ACCRUAL* = operating accruals that are calculated using the indirect balance sheet method: $ACCRUAL_t = [(\Delta Current\ assets_t - \Delta Cash_t) - (\Delta Current\ liabilities_t - \Delta Short\text{-}term\ Debt_t - \Delta Taxes\ payable_t) - Depreciation\ and\ amortization\ expense_t]/Total\ assets_{t-1}$. *APC* (abnormal press coverage) = the monthly return difference between the portfolios with high and low abnormal press coverage. In Panel B, we estimate factor loadings with monthly returns over the previous 60 months (24 months minimum) using a five-factor model ($R_m^M - R_m^F$, *SMB*, *HML*, *CMA*, *APC*). We then estimate Fama–MacBeth (1973) regressions of monthly returns in the model that includes characteristics, such as size, B/M, previous returns, *ACCRUAL*, and *APRESS*, along with the factor loadings. Refer to the Appendix for detailed variable descriptions. The numbers in parentheses are *t*-statistic values.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

ACCRUAL is significant and negative but the *CMA* loading is not significant. This finding indicates that investors misprice the accrual characteristic and cast doubt on the rational risk explanation for the accruals anomaly. For abnormal press coverage, we find that both the *APRESS* characteristic and the *APC* loading are significantly and positively related to stock returns, although the relation of *APRESS* is stronger in a statistical sense. In contrast, we find that both effects disappear for underpriced firms as reported in column (2). This evidence of an asymmetric press coverage effect is confirmed in our subsequent tests as well. In sum, because the *APC* loadings can capture only part of the ability of the abnormal press coverage characteristic to predict returns, we can conclude that the relation between return performance and abnormal press coverage cannot be fully explained by a rational asset pricing factor explanation.

V. Regression Analysis

Regression of Mispricing on Abnormal Press Coverage

The differences in mispricing across *APRESS* groups revealed in the previous section could be driven by factors that were not controlled in the univariate framework. Thus, we proceed to the multivariate tests and report results in Table 6. Columns (1) through (4) display the models where the dependent variables are mispricing (*MP*) and mispricing dummy (*MPD*), and columns (5) through (10) show models where the dependent variable is abnormal future returns (*AR*s). The results show a significant positive relation between abnormal press coverage and mispricing, suggesting that higher abnormal press coverage is strongly associated with higher levels of mispricing. *AR* regressions show that the effect of abnormal press coverage on absolute abnormal future returns decreases with the return horizon, consistent with the notion that over time markets tend to correct mispricing. In particular, for the models that include the complete set of control variables, the coefficient on *APRESS* is 0.0012 in the 3-month average abnormal return model, 0.0011 in the 6-month average abnormal return model, and 0.0007 in the 12-month average abnormal return model.

The remaining (control) variables have, for the most part, coefficients with the expected signs. For example, the results show that mispricing decreases with firm size, supporting the view that smaller firms display greater informational uncertainty (Zhang 2006). In addition mispricing is lower for dividend-paying firms and diversified firms. Mispricing is negatively related to excess analyst coverage (*EAF*). Consistent with univariate test results, the multivariate evidence in Table 6 provides support for the biased media and the media sentiment hypotheses.

Information Risk and Mispricing

Our results thus far are in sharp contrast to the predictions of the information intermediary and corporate governance hypotheses. To provide more convincing evidence that would allow us to dismiss these two hypotheses from the rest of our analysis, we need to evaluate the relation between mispricing and information risk. Information risk arises when some investors have more and better information than others about a firm's prospects. Aslan et al. (2008) document that the size of such risk depends on a variety of factors such as the

TABLE 6. Abnormal Press Coverage and Mispricing.

	Dependent Variables									
	MP		*MPD*		*AR3*		*AR6*		*AR12*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
APRESS	0.0530***	0.0482***	0.0868***	0.0878***	0.0017***	0.0012*	0.0015***	0.0011**	0.0009***	0.0007**
	(10.72)	(9.87)	(6.09)	(6.02)	(2.58)	(1.81)	(3.31)	(2.39)	(2.65)	(2.11)
EAF		0.0040		−0.0769***		−0.0031***		−0.0023***		−0.0021***
		(0.70)		(−4.56)		(−4.02)		(−4.50)		(−5.51)
SIZE		−0.0208***		−0.0587***		−0.0034***		−0.0023***		−0.0017***
		(−8.62)		(−8.20)		(−10.44)		(−10.55)		(−10.76)
B/M		−0.1770***		−0.2210***		−0.0106***		−0.0087***		−0.0029***
		(−15.59)		(−6.58)		(−6.83)		(−8.38)		(−3.87)
EVOL		−0.0209***		−0.0355***		0.0014***		0.0009***		0.0006***
		(−7.74)		(−4.44)		(3.97)		(3.76)		(3.41)
Ln(1 + *NSEG*)		−0.0847***		−0.1739***		−0.0047**		−0.0020		−0.0002
		(−6.03)		(−4.17)		(−2.48)		(−1.63)		(−0.27)
DIV		−0.0573***		−0.1952***		−0.0135***		−0.0099***		−0.0078***
		(−6.03)		(−6.93)		(−10.58)		(−11.68)		(−12.58)
Intercept	0.4607***	1.0770***	−0.0387	1.4744***	0.0314***	0.1141***	0.0219***	0.0780***	0.0167***	0.0550***
	(36.70)	(23.25)	(−1.07)	(10.69)	(18.75)	(18.08)	(19.68)	(18.58)	(20.61)	(18.05)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,736	12,736	12,732	12,732	11,909	11,909	11,909	11,909	11,909	11,909
Adj. R^2 (or pseudo R^2)	1.48%	5.95%	0.30%	2.05%	2.67%	7.01%	1.96%	6.72%	1.60%	6.43%

Note: This table reports the coefficient estimates of regression of mispricing on abnormal press coverage and other variables. Refer to the Appendix for detailed variable descriptions. The numbers in parentheses are *t*-statistic values.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

quality of a firm's accounting information, the availability of public information sources about the firm, the frequency of new information events, and the fraction of investors who have better information. In this subsection we control for several information risk measures. These measures include measures of earnings quality, captured by the absolute size of abnormal accruals; measures of the quality of security analysts' forecasts; and a measure of stock return volatility.

Abnormal accruals (i.e., accruals larger or smaller than expected) reflect poor earnings quality as well as difficulty that investors face in assessing firms' future prospects. Based on Francis et al. (2005), the first measure of earnings quality (*EQ1*) is defined as the absolute value of firm-specific residuals from an industry regression of total accruals on the reciprocal of total assets, sales growth, and fixed assets. Following Dechow and Dichev (2002), we also create an alternative earnings quality (*EQ2*) measure that is the absolute value of firm-specific residuals from the regression of total accruals on lagged, contemporaneous, and leading cash flows from operations. The third measure of earnings quality (*EQ3*) combines the Francis et al. model and Dechow and Dichev model. It is measured as the absolute value of firm-specific residuals from an annual industry regression of total accruals on lagged, contemporaneous, leading cash flows from operations, sales growth, and fixed assets.

We also use two variables constructed from nonstale security analyst one-fiscal-year-ahead forecasts, issued every June and extracted from IBES Detail History Database. These are the absolute value of the analyst forecast error (*AFE*) and the dispersion of analyst forecasts (*AFD*). The absolute forecast error captures forecasting ability of security analysts covering the firm and has been used by several studies as a proxy of information risk (e.g., see Atiase and Bamber 1994; Christie 1987). If there is less information risk, a considerable amount of information about future earnings is available to market participants, and so analysts should be in a better position to make accurate earnings forecasts. Barron et al. (1998) show that analyst forecast dispersion reflects both diversity of analyst beliefs and the uncertainty (lack of precision) in analyst forecasts. Prior studies use the dispersion of analyst forecasts as an information uncertainty proxy (e.g., see Zhang 2006), as well as an information asymmetry proxy (e.g., see Krishnaswami and Subramaniam 1999).

Finally, because investors may have greater information risk when the stock returns are more volatile, we also use return volatility (*RVOL*), measured as the standard deviation of daily stock returns in the calendar year.

We include the six information risk measures in the cross-sectional model of mispricing. In Table 7, we continue to find an incremental effect of news on mispricing after controlling for the different information risk measures. The estimated coefficient on *APRESS* is statistically significant at the 1% level in all models. We also find that the information risk variables are positively associated with mispricing.[15]

[15] We also directly test the link between abnormal press coverage and several information risk measures. We find support for the biased media and the media sentiment hypotheses. All six information risk proxies are positively related to abnormal press coverage.

TABLE 7. Abnormal Press Coverage and Information Risk.

	Dependent Variable = *MP*						Dependent Variable = *MPD*					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
APRESS	0.0540***	0.0536***	0.0541***	0.0434***	0.0399***	0.0433***	0.0377***	0.0379***	0.0381***	0.0288***	0.0234***	0.0296***
	(10.69)	(10.20)	(10.29)	(8.05)	(7.54)	(8.85)	(6.42)	(6.18)	(6.23)	(4.54)	(3.74)	(5.22)
EQ1	0.0538***						0.0411***					
	(7.77)						(5.10)					
EQ2		0.1342***						0.0989***				
		(6.91)						(4.36)				
EQ3			0.1030***						0.0902***			
			(6.20)						(4.66)			
AFE				0.0041***						0.0033**		
				(3.61)						(2.43)		
AFD					0.0093						0.0143*	
					(1.32)						(1.72)	
RVOL						2.3857***						2.2154***
						(9.79)						(7.86)
EAF	0.0159***	0.0167***	0.0175***	0.0610***	0.0937***	0.0054	−0.0236***	−0.0254***	−0.0246***	0.0030	0.0276**	−0.0288***
	(2.71)	(2.69)	(2.82)	(6.43)	(8.79)	(0.96)	(−3.46)	(−3.52)	(−3.41)	(0.27)	(2.19)	(−4.38)
SIZE	−0.0232***	−0.0228***	−0.0230***	−0.0123***	−0.0031	−0.0111***	−0.0227***	−0.0221***	−0.0221***	−0.0134***	−0.0074*	−0.0140***
	(−9.07)	(−8.52)	(−8.61)	(−3.97)	(−0.93)	(−4.31)	(−7.65)	(−7.10)	(−7.09)	(−3.70)	(−1.86)	(−4.69)
B/M	−0.1722***	−0.1889***	−0.1944***	−0.3728***	−0.4514***	−0.1838***	−0.0770***	−0.0865***	−0.0895***	−0.2572***	−0.3656***	−0.0927***
	(−14.68)	(−15.37)	(−15.92)	(−24.91)	(−28.30)	(−16.22)	(−5.64)	(−6.04)	(−6.29)	(−14.61)	(−19.35)	(−7.07)
EVOL	−0.0213***	−0.0222***	−0.0222***	−0.0243***	−0.0253***	−0.0242***	−0.0153***	−0.0156***	−0.0157***	−0.0159***	−0.0171***	−0.0169***
	(−7.65)	(−7.63)	(−7.64)	(−7.74)	(−8.03)	(−8.94)	(−4.71)	(−4.60)	(−4.63)	(−4.30)	(−4.58)	(−5.39)
Ln(1 + *NSEG*)	−0.0970***	−0.0932***	−0.0942***	−0.0801***	−0.0808***	−0.0796***	−0.0820***	−0.0829***	−0.0842***	−0.0716***	−0.0645***	−0.0628***
	(−6.58)	(−6.24)	(−6.30)	(−4.92)	(−4.78)	(−5.69)	(−4.78)	(−4.76)	(−4.83)	(−3.74)	(−3.22)	(−3.87)
DIV	−0.0573***	−0.0636***	−0.0655***	−0.0427***	−0.0367***	−0.0301***	−0.0786***	−0.0810***	−0.0817***	−0.0669***	−0.0553***	−0.0510***
	(−5.81)	(−6.20)	(−6.39)	(−3.88)	(−3.32)	(−3.05)	(−6.85)	(−6.78)	(−6.85)	(−5.17)	(−4.21)	(−4.46)
Intercept	1.1014***	1.0996***	1.1135***	0.9862***	0.8197***	0.8060***	1.0592***	1.0521***	1.0553***	0.9723***	0.8841***	0.8248***
	(22.26)	(21.17)	(21.51)	(16.48)	(12.36)	(15.01)	(18.40)	(17.38)	(17.50)	(13.82)	(11.25)	(13.27)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,772	10,696	10,696	8,341	7,708	12,734	11,772	10,696	10,696	8,341	7,708	12,734
Adjusted R^2	7.56%	8.10%	8.02%	13.86%	17.71%	6.63%	3.06%	3.11%	3.13%	4.97%	7.72%	3.13%

Note: This table reports the coefficient estimates of regression of mispricing on abnormal press coverage, information risk, and other variables. The dependent variable, *MISPRICING*, is alternatively *MP* or *MPD*. Refer to the Appendix for detailed variable descriptions. The numbers in parentheses are *t*-statistic values.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

VI. Interpreting the Relation between Abnormal Press Coverage and Mispricing

Regression results in Tables 6 and 7 suggest that abnormal press coverage can be associated with media bias and/or investor sentiment. To gain further insight into the relative validity of the two hypotheses, we retest the mispricing regression models separately for overpriced and underpriced firms.[16] We consider a firm to be overpriced (underpriced) if its current value is higher (lower) than its fundamental value (i.e., the imputed capital in equation (2)), in which case the measure of excess price (*EP*) will be positive (negative). On one hand, the biased media hypothesis suggests that media tend to report information biased in favor of companies. If this is true, the effect of media coverage on stock prices should be positive no matter whether prices are above or below fundamental value. Therefore, we should find abnormal press coverage is positively (negatively) associated with mispricing for overpriced (underpriced) firms. On the other hand, the media sentiment hypothesis suggests a positive relation between abnormal press coverage and mispricing for both under- and overpriced firms. Thus, although both hypotheses predict that overpriced firms are getting more overpriced when there is abnormal press coverage, they make opposite predictions about underpriced firms.

We separately retest the mispricing models for the overpriced and underpriced groups, and present the results in Table 8. In line with the evidence in Table 4, we find that abnormal press coverage has a significant effect on mispricing only in the regressions of overpriced firms. The magnitude of the *APRESS* coefficient in the overpriced firms regression is 9.1 times greater (9.5 times in *MPD* regression) than in the underpriced firms regression. If we are allowed to label excessive coverage of underpriced (overpriced) firms as bad (good) news coverage, we can then interpret these results as consistent with the notion that the market overreacts more to good news than to bad news.

Excess analyst coverage shows asymmetric effects on mispricing, as well. We find that excess analyst coverage is generally associated with a positive effect on valuation by exaggerating overvaluation (columns (1) and (3)) but alleviating undervaluation (columns (2) and (4)). This finding is consistent with the evidence of Doukas, Kim, and Pantzalis (2005) who document that excessively high analyst coverage can cause overvaluation and low future returns.

Based on the results in Table 8, we cannot completely reject either the biased media hypothesis or the media sentiment hypothesis. In fact, there are at least two possible explanations for the findings in Table 8. First, these results could be indicative of a combined effect of media bias and media-induced sentiment. This view is supported by the significant positive relation for overpriced firms and reduced effect for underpriced firms (i.e., in the case of bad news coverage, investor sentiment is weakened by media bias). Alternatively, these results are also consistent with a combination of media-induced investor sentiment and short-selling constraints. In both of these environments, abnormal news coverage will have a stronger (weaker) effect on prices in the case of good (bad) news.

[16] Note that mispricing is measured as the absolute value of excess firm value.

TABLE 8. Overpriced versus Underpriced Firms.

	Dependent Variable = *MP*		Dependent Variable = *MPD*	
	Overpriced Firms	Underpriced Firms	Overpriced Firms	Underpriced Firms
	(1)	(2)	(3)	(4)
APRESS	0.0654***	0.0072	0.1183***	0.0125
	(10.13)	(1.23)	(5.49)	(0.54)
EAF	0.0897***	−0.1129***	0.2004***	−0.3726***
	(11.08)	(−17.33)	(7.48)	(−14.37)
SIZE	−0.0172***	−0.0191***	−0.0347***	−0.0760***
	(−5.03)	(−7.20)	(−3.04)	(−7.26)
B/M	−0.8115***	0.3118***	−2.5816***	1.0469***
	(−40.10)	(23.72)	(−34.17)	(18.47)
EVOL	−0.0302***	0.0061*	−0.0708***	0.0281**
	(−8.42)	(1.92)	(−6.02)	(2.22)
Ln(1 + *NSEG*)	−0.0820***	−0.0022	−0.1199*	−0.0138
	(−4.09)	(−0.15)	(−1.83)	(−0.23)
DIV	0.0021	−0.0757***	0.0183	−0.2865***
	(0.16)	(−6.88)	(0.43)	(−6.59)
Intercept	1.2635***	0.5270***	1.7901***	0.6424***
	(19.41)	(10.18)	(8.25)	(3.15)
Year dummies	Yes	Yes	Yes	Yes
N	6,257	6,313	6,257	6,313
Adj. R^2 (or pseudo R^2)	29.07%	17.71%	20.58%	10.56%

Note: This table reports the coefficient estimates of regression of mispricing on abnormal press coverage and other variables. We test the models separately for overpriced firms and underpriced firms. A firm is classified into overpriced (underpriced) group if its price is higher (lower) than the imputed price in equation (2). Refer to the Appendix for detailed variable descriptions. The numbers in parentheses are *t*-statistic values.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

Are Results Driven by a Combination of Media-Induced Sentiment and Short-Selling Constraints?

To see whether short-selling constraints are a necessary condition for a significant effect of abnormal press coverage on mispricing, we introduce an interaction term between abnormal press coverage and short-selling constraints in our main model. We construct two proxies for the degree of short-selling constraints. First, based on Pontiff (2006) who points out that arbitrageurs are averse to trading when firms are idiosyncratic, we use the stock's idiosyncratic volatility. To measure the stock's idiosyncratic volatility, we first estimate R^2 for each stock for each calendar year using weekly data to regress stock returns on market index returns. Logistic relative idiosyncratic volatility ($\psi_{i,t}$) measures the ratio of unexplained variance to explained variance, and high levels in idiosyncratic volatility represent greater constraints of short selling.

As a second proxy for short-selling constraints, we use institutional ownership. D'Avolio (2002) shows that institutional ownership is a major determinant of the quantity of shares supplied to the market. Therefore, the cost of short selling should be less (more) expensive for stocks with high (low) institutional ownership. Gompers and Metrick (2001) report a strong relation between institutional ownership and liquidity. This suggests that the cost of trading large quantities of shares for stocks with high institutional ownership should be low. The search and bargaining cost for stocks with high institutional ownership is also expected to be low. Indeed, if several institutional investors are lending many shares, it should be less costly to locate them and competition should lower the cost of direct borrowing. Finally, derivative instruments, and in particular put options, an alternative method of creating short positions, are likely to be more often available for stocks with high levels of institutional shareholdings.[17] Therefore, stocks with low institutional ownership are subject to a higher short-selling cost.

We create two indicator variables for firms subject to high levels of short-selling constraints (*SC*) based on the two variables described previously. In each year, if a firm's idiosyncratic volatility is greater than the median of the sample, the first short-selling constraints indicator (i.e., high idiosyncratic volatility, *IV*) equals 1, and 0 otherwise. Equivalently, if a firm's percentage of shares owned by institutions is lower than the median value, the second short-selling constraints indicator (i.e., low institutional ownership, *INSTP*) equals 1, and 0 otherwise. We introduce interactions of *APRESS* with *IV*, or alternatively, with *INSTP* in the regression model. We expect a significant coefficient on the interaction term if the effect of *APRESS* on mispricing is determined by short-selling constraints. The results in the left half of Table 9 show that although the *APRESS* coefficient remains significant as in our prior tests, the interactions of *APRESS* with *IV* or *INSTP* have insignificant coefficients. From this evidence, we conclude that the relation between *APRESS* and mispricing does not rely on the short-selling constraints investors might face.

There is an alternative mechanism through which short-selling constraints can cause the patterns of results we produced in our previous tables, that is, the asymmetric effect of *APRESS* on mispricing. Assuming abnormal news coverage can adequately proxy for firm-specific information, *APRESS* could increase idiosyncratic volatility, which in turn should impede short selling (Pontiff 2006). Because high levels of press coverage are also associated with greater volume,[18] a proxy for differences of opinion among investors, this effect would induce an increase in price, regardless of the content of news (Miller 1977). This mechanism should reduce both underpricing and the subsequent positive excess returns.

We test for the importance of the mechanism described previously by conducting a dynamic test using changes as opposed to levels. Specifically, we examine the relation of changes in mispricing as a function of changes in *APRESS*, changes in short-selling constraints (ΔSC), as well as their interactions. *SC* is proxied by *IV* and *INSTP*, as before. The dependent variable is the absolute value of the excess price change between year t–1 and t, $Abs(\Delta EP)$. We regress $Abs(\Delta EP)$ on shocks to abnormal news coverage ($\Delta APRESS$), changes in short selling constraints (ΔSC), their interactions, and other

[17] Ofek, Richardson, and Whitelaw (2004) show that the violation of the put–call parity is strongly related to lending fees. Lending fees, however, are related to institutional ownership.

[18] This is discussed in the next section and shown in the results of Table 10.

TABLE 9. Abnormal Press Coverage and Mispricing under Short-Selling Constraints.

	Dependent Variable = *MP*		Dependent Variable = *MPD*		Dependent Variable = $Abs(\Delta EP)$					
	All		All		All		$\Delta EP > 0$		$\Delta EP \leq 0$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
APRESS	0.0541***	0.0483***	0.1072***	0.0955***						
	(8.84)	(7.29)	(5.85)	(4.57)						
IV	−0.0285***		−0.0519**							
	(−3.42)		(−2.10)							
*APRESS***IV*	−0.0135		−0.0481							
	(−1.33)		(−1.59)							
INSTP		0.0125		0.0010						
		(1.26)		(0.03)						
*APRESS***INSTP*		0.0120		0.0228						
		(1.13)		(0.68)						
$\Delta APRESS$					0.0096	0.0139*	0.0172*	0.0171*	0.0036	0.0071
					(1.42)	(1.82)	(1.94)	(1.73)	(0.36)	(0.64)
ΔIV					0.0031		0.0016		0.0019	
					(0.54)		(0.21)		(0.22)	
$\Delta APRESS^{*}\Delta IV$					0.0004		0.0031		−0.0058	
					(0.05)		(0.25)		(−0.42)	
$\Delta INSTP$						0.0064		−0.0017		0.0148
						(0.90)		(−0.18)		(1.47)
$\Delta APRESS^{*}\Delta INSTP$						−0.0085		−0.0177		0.0012
						(−0.78)		(−1.22)		(0.08)
EAF	0.0019	0.0219***	−0.0811***	−0.0393*	0.0159***	0.0041	−0.0045	−0.0166**	0.0261***	0.0148*
	(0.33)	(3.19)	(−4.77)	(−1.82)	(3.66)	(0.76)	(−0.76)	(−2.21)	(4.22)	(1.95)
SIZE	−0.0239***	−0.0172***	−0.0650***	−0.0550***	−0.0231***	−0.0231***	−0.0317***	−0.0271***	−0.0138***	−0.0176***
	(−9.29)	(−5.52)	(−8.49)	(−5.61)	(−12.51)	(−9.55)	(−12.94)	(−8.44)	(−5.12)	(−5.07)
B/M	−0.1712***	−0.3102***	−0.2121***	−0.5375***	−0.0888***	−0.0727***	−0.2601***	−0.2757***	0.0264**	0.0463***
	(−14.95)	(−22.91)	(−6.26)	(−12.72)	(−10.33)	(−6.38)	(−21.06)	(−16.68)	(2.20)	(2.95)
EVOL	−0.0210***	−0.0251***	−0.0362***	−0.0439***	0.0108***	0.0157***	0.0163***	0.0196***	0.0064**	0.0123***
	(−7.79)	(−8.41)	(−4.53)	(−4.69)	(5.23)	(6.51)	(5.96)	(6.13)	(2.16)	(3.55)

(Continued)

Table 9. Continued.

	Dependent Variable = *MP*		Dependent Variable = *MPD*		Dependent Variable = $Abs(\Delta EP)$					
	All		All		All		$\Delta EP > 0$		$\Delta EP \leq 0$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln(1 + *NSEG*)	−0.0848***	−0.0898***	−0.1742***	−0.2090***	−0.0021	0.0007	0.0264*	0.0337*	−0.0256*	−0.0242
	(−6.04)	(−5.61)	(−4.17)	(−4.16)	(−0.20)	(0.05)	(1.87)	(1.95)	(−1.67)	(−1.31)
DIV	−0.0562***	−0.05000	−0.1931***	−0.1864***	−0.0865***	−0.0910***	−0.0575***	−0.0555***	−0.1040***	−0.1145***
	(−5.91)	(−4.72)	(−6.85)	(−5.63)	(−11.93)	(−10.59)	(−5.95)	(−4.82)	(−9.90)	(−9.40)
Intercept	1.1469***	1.0632***	1.6150***	1.5892***	0.7971***	0.8716***	1.0202***	0.9387***	0.6130***	0.7529***
	(22.70)	(16.78)	(10.72)	(7.97)	(21.44)	(17.72)	(20.82)	(15.21)	(11.34)	(10.59)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,704	9,035	12,700	9,031	10,742	6,631	5,180	3,069	5,562	3,562
Adj. R^2 (or pseudo R^2)	6.01%	11.58%	2.09%	3.63%	8.20%	9.03%	16.68%	17.57%	6.16%	5.51%

Note: This table reports the coefficient estimates of regression of mispricing on abnormal news coverage and other variables under short-selling constraints. Refer to the Appendix for detailed variable descriptions. The numbers in parentheses are *t*-statistic values.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

control variables. We also split the sample into two subsamples based on the sign of the change of excess price (ΔEP) and retest the model for these subsamples. The results, shown in the right half of Table 9, indicate that shocks (with regard to previous years) to abnormal news coverage are positively related to changes in excess prices. However, this pattern is only shown for firms that become overpriced from the previous year. Overall, we find similar results with consistent patterns from Table 8. Overpriced firms show a significant association with the change in abnormal press coverage, while underpriced firms do not present such significant relation. Moreover, the interactions of $\Delta APRESS$ with ΔIV or $\Delta INSTP$ have insignificant coefficients, which imply that short-selling constraints are not significant drivers of the relation between abnormal press coverage and mispricing.

Are Media-Induced Sentiment and Media Bias Coexisting Effects?

To answer this question, we proceed in two steps. First, we develop a test to confirm that there is a media sentiment effect. As discussed in Hong and Stein (2007), mispricing can evolve along disagreement (high volume) in the market when there is abnormal news coverage. Consequently, we test whether liquidity measures display a positive relation with abnormal news coverage.

We construct four alternative measures of liquidity. The first two measures are based on trading volume. The first variable, trading volume (*VOLUME*), is the average over the year of the daily trading volume in dollars. The second measure, scaled trading volume (*SVOLUME*), is the average over the year of the daily trading volume scaled by the number of outstanding shares. The second pair of measures is based on the one developed by Amihud (2002). This measure, which is described in detail later, uses the ratio of stock return to trading volume (order flow) to capture illiquidity. The development of the Amihud illiquidity measure relies on Kyle's (1985) argument that the order flow of informed traders cannot be differentiated from that of liquidity (i.e., noise) traders. Market makers regard excess demand as informed trading, which is positively related to price change, and such a positive relation is commonly called the price impact. Our third measure, Amihud's illiquidity (*ILLIQ*), is the average over the year of the daily ratio of stock's absolute return to its trading volume in dollars. Our last measure, scaled Amihud's illiquidity (*SILLIQ*), is the average over the year of the daily ratio of stock's absolute return to its trading volume scaled by the number of outstanding shares.

We present the results from the liquidity regressions in Table 10. As documented in other papers, stock liquidity is highly correlated with size and B/M. The *APRESS* coefficients are significant and positive in the volume measure regressions, whereas they are significant and negative in the illiquidity measure regressions. In line with Hong and Stein (2007), these results provide strong support for the media sentiment hypothesis.

Next, we design a test that will allow us to confirm whether there is a media bias effect as well. To do this we need to identify groups of firms where media bias would be more or less likely. Given the nature of our data, that is, the total count of articles by four national U.S. newspapers, it is hard to clearly identify cases where media bias is definitely present. However, Gurun and Butler (2012) find that coverage of firms by local press

TABLE 10. Abnormal Press Coverage and Liquidity.

	Dependent Variables			
	VOLUME	*SVOLUME*	*ILLIQ*	*SILLIQ*
	(1)	(2)	(3)	(4)
APRESS	0.1085***	0.0533***	−0.0682***	−0.0134
	(7.41)	(4.97)	(−4.55)	(−1.24)
EAF	0.8285***	0.5971***	−0.8426***	−0.6115***
	(48.85)	(48.10)	(−48.50)	(−48.87)
SIZE	1.1449***	0.2203***	−1.2646***	−0.3407***
	(158.98)	(41.75)	(−171.38)	(−64.06)
B/M	−2.1977***	−0.6188***	2.3685***	0.7880***
	(−64.87)	(−24.95)	(68.24)	(31.53)
EVOL	0.0078	0.0568***	0.0299***	−0.0185***
	(0.96)	(9.65)	(3.63)	(−3.11)
Ln(1 + *NSEG*)	−0.2921***	−0.1598***	0.2178***	0.0854***
	(−6.96)	(−5.20)	(5.07)	(2.76)
DIV	−0.5278***	−0.6187***	0.1928***	0.2822***
	(−18.56)	(−29.72)	(6.62)	(13.45)
Intercept	−7.3669***	−9.8131***	5.7520***	8.2184***
	(−53.16)	(−96.68)	(40.51)	(80.32)
Year dummies	Yes	Yes	Yes	Yes
N	12,789	12,784	12,788	12,783
Adjusted R^2	77.59%	37.23%	80.63%	48.00%

Note: This table reports the coefficient estimates of regression of liquidity on abnormal press coverage and other variables. Refer to the Appendix for detailed variable descriptions. The numbers in parentheses are *t*-statistic values.
***Significant at the 1% level.

tends to have a positive slant, and an important element in terms of the extent of media bias is geographic distance between the firm headquarters and the location of the newspaper offices. We therefore use LexisNexis to collect the number of local newspaper articles for 2002–2007 for the subsample of S&P 500 firms. We then use the local press coverage count to construct a measure of abnormal local press coverage and use it in conjunction with our (national) abnormal press coverage in our main regression model to examine whether their effects on mispricing are different.[19]

Table 11 documents that nonlocal abnormal news coverage has a strong positive and significant effect on mispricing, while local abnormal news coverage does not have a significant effect on mispricing. We then test the model separately for subsamples classified on relative valuation (overpriced vs. underpriced). Regressions show that the positive effect of abnormal press coverage is largest for overpriced firms receiving nonlocal (national) coverage. As in our previous tests, national coverage is also positively

[19] Data availability constraints for the 2002–2007 period allow us to include only three national papers (*New York Times, Wall Street Journal*, and *Washington Post*) in the new subsample.

TABLE 11. Local versus Nonlocal Abnormal Press Coverage.

	Dependent Variable = *MP*			Dependent Variable = *MPD*		
	All Firms	Overpriced Firms	Underpriced Firms	All Firms	Overpriced Firms	Underpriced Firms
	(1)	(2)	(3)	(4)	(5)	(6)
APRESS (Local)	−0.0005	0.0093	−0.0168**	−0.0272	−0.0059	−0.0718*
	(−0.08)	(1.18)	(−2.36)	(−1.12)	(−0.16)	(−1.95)
APRESS (Nonlocal)	0.0364***	0.0387***	0.0158	0.1351***	0.1437***	0.0906*
	(4.63)	(3.76)	(1.62)	(4.21)	(3.02)	(1.79)
EAF	−0.0011	0.1399***	−0.0902***	0.0378	0.5661***	−0.2688***
	(−0.07)	(5.71)	(−5.74)	(0.62)	(5.12)	(−3.13)
SIZE	−0.0440***	−0.0607***	−0.0133	−0.1019***	−0.1563***	−0.0223
	(−6.30)	(−6.25)	(−1.62)	(−3.57)	(−3.50)	(−0.53)
B/M	0.0010*	−0.0017	0.0011**	0.0063**	−0.0115	0.0069**
	(1.88)	(−0.79)	(2.40)	(2.21)	(−1.31)	(2.22)
EVOL	0.0398	−0.9876***	0.3435***	0.5056***	−3.3631***	1.9761***
	(1.32)	(−12.74)	(11.41)	(3.75)	(−8.83)	(9.75)
Ln(1 + *NSEG*)	−0.0515***	−0.0145	−0.0173	−0.1573**	−0.1428	0.0181
	(−3.17)	(−0.67)	(−0.87)	(−2.37)	(−1.46)	(0.17)
DIV	−0.0807***	−0.0537**	−0.0522**	−0.2866***	−0.1371	−0.2869***
	(−4.51)	(−2.25)	(−2.45)	(−3.94)	(−1.26)	(−2.59)
Intercept	1.4984***	2.1581***	0.4159**	2.5225***	4.8820***	−0.7928
	(9.91)	(10.38)	(2.28)	(4.09)	(5.05)	(−0.84)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
APRESS (Local) – *APRESS* (Nonlocal) = 0	−0.0368***	−0.0294**	−0.0327**	−0.1624***	−0.1496**	−0.1623**
	[0.0007]	[0.0420]	[0.0116]	[0.0002]	[0.0250]	[0.0153]
N	1,737	872	865	1,737	872	865
Adj. R^2 (or pseudo R^2)	7.65%	27.35%	22.46%	4.21%	14.21%	15.71%

Note: This table reports the coefficient estimates of regression of mispricing on abnormal news coverage and other variables. We test models separately for all firms, overpriced firms, and underpriced firms. A firm is classified into the overpriced (underpriced) group if its price is higher (lower) than the imputed price in equation (2). Refer to the Appendix for detailed variable descriptions. The numbers in parentheses are *t*-statistic values.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

associated with underpricing, consistent with the notion that excessive national press coverage can induce sentiment. More important, the coefficient of local abnormal press coverage becomes negative and significant for underpriced firms. Assuming that press coverage of local firms is more positively slanted (Gurun and Butler 2012), these results are consistent with the notion that in the case of bad news (i.e., when there is underpricing) the sentiment generated by national press is countered by the favorably biased coverage provided by the local press.

Overall, the results in Table 11 indicate that abnormal news coverage leads to mispricing mainly caused by the sentiment it generates among investors. However, the observed effect of press coverage on relative valuation can also be attributed to media bias. Specifically, the sentiment effect is exaggerated (attenuated) by biased local press coverage when firms have good (bad) news.

VII. Robustness

Controlling for Endogeneity

One important concern when assessing the relation between press coverage and relative valuation is that there is the potential for endogeneity. For example, press coverage could be higher for firms that have experienced extreme price movements, that is, a shift of investor sentiment toward a particular firm that causes mispricing, could lead to greater attention from the media, that is, abnormal press coverage. We use two-stage least squares (2SLS) models to control for problems associated with endogeneity.

In the first stage, we estimate *APRESS* by using a model that includes firm characteristics and exchange dummies as independent variables. In addition, an instrument is needed that is suitable in both an economic and an econometric sense. Such an instrument would be a strong explanatory variable of the first stage dependent variable (*APRESS*) as well as uncorrelated with the error term of the second-stage regression. We construct a valid set of instruments. We use information on congressional bills by recognizing that there is a close relation between legislative activity and business news but not necessarily a clear, strong relation between legislative activity and mispricing. The Congressional Bills Project data set (http://www.congressionalbills.org/download.html) provides comprehensive information on bills introduced in the U.S. House and Senate including the topics and descriptions of bills, information on sponsors and committees, and passing records of bills. We first excluded bills related to civil rights, labor market, crime, and so on, that are not directly relevant to any particular industry. This instrument is a firm-level variable that counts the number of bills generated (sponsored or cosponsored) by the congressman from the district where the firm's headquarters is located and the senators from the firm's home state. However, it is possible that the instrumental variable increases legal risk and, as a result, mispricing. This would induce a positive correlation between the instrumental variable and mispricing. Therefore, we include state-fixed effects in our regressions to tackle this issue. We add information risk variables (*EQ1*, *AFD*, and *RVOL*), which are substantially correlated with abnormal news coverage. We also control for metropolitan effects

TABLE 12. Controlling for Reverse Causality and Endoegeneity.

	First Stage	Second Stage			
		Dependent Variable			
	APRESS	*MP*	*MPD*	*MP*	*MPD*
	(1)	(2)	(3)	(4)	(5)
APRESS		0.0986***	0.0735***	0.3924***	0.3468***
		(4.27)	(2.60)	(4.95)	(3.92)
EAF	−0.0022	0.1331***	0.0532***	0.1212***	0.0428**
	(−0.07)	(9.68)	(3.17)	(6.41)	(2.02)
SIZE		0.0019	0.0007	−0.0494***	−0.0461***
		(0.46)	(0.14)	(−3.91)	(−3.26)
B/M	−0.2806***	−0.5663***	−0.4885***	−0.4532***	−0.3728***
	(−5.50)	(−25.73)	(−18.15)	(−13.53)	(−9.96)
EVOL	0.0278***	−0.0303***	−0.0216***	−0.0410***	−0.0323***
	(2.89)	(−7.53)	(−4.40)	(−6.85)	(−4.83)
Ln(1 + *NSEG*)	0.3067***	−0.1010***	−0.0753***	−0.1437***	−0.1222***
	(6.30)	(−4.68)	(−2.85)	(−4.65)	(−3.54)
DIV	0.0598*	−0.0663***	−0.0799***	−0.0220	−0.0359*
	(1.68)	(−5.03)	(−4.96)	(−1.15)	(−1.67)
Ln(1 + *BILL*)	0.0001				
	(0.00)				
EQ1	−0.0098				
	(−0.35)				
AFD	0.0093				
	(0.44)				
RVOL	5.7678***				
	(3.95)				
METRO	0.0366				
	(0.72)				
NASDAQ	−0.2165***				
	(−6.11)				
AMEX	−0.0154				
	(−0.13)				
Intercept	−0.8994*	0.7595***	0.7910***	2.0366***	2.1225***
	(−1.85)	(9.05)	(7.71)	(5.17)	(4.82)
Year dummies	Yes	Yes	Yes	Yes	Yes
State dummies	Yes	No	No	Yes	Yes
N	4,479	4,479	4,479	4,479	4,479
F-stat.	7.26	102.44	41.27	18.19	9.70
F-stat. on the excluded instrument	40.66				

Note: This table reports the coefficient estimates of the two-stage least squares (2SLS) regressions. Refer to the Appendix for detailed variable descriptions. The numbers in parentheses are *t*-statistic values.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

(*METRO*) and exchange effects (*NASDAQ* and *AMEX*) as well as other firm characteristics.

Table 12 provides the results of the two-stage models. In the first stage, abnormal media coverage for a firm from state *j* is not significantly associated with the number of bills introduced by the legislators. We interpret this finding as consistent with the notion that the effects generated by the bills are subsumed by the controlled state-fixed effects. From other variables, we find that diversified growth firms with volatile earnings and stock returns and located in large metropolitan areas tend to receive greater press coverage. Also, as expected, firms listed on *NASDAQ* and *AMEX* tend to receive less press coverage than those listed on the *NYSE*. In the second stage, we test the models with and without the state dummies and find that the results remain qualitatively similar. We show a strong, positive effect of *APRESS* on mispricing. Thus, our main finding remains unchanged after controlling for the endogenous nature of the relation between abnormal press coverage and mispricing.

Other Robustness Checks

We conduct additional robustness tests by using alternative mispricing measures. First, following Berger and Ofek (1995), we construct alternative measures of mispricing by using other accounting items-based multipliers, such as sales and *EBIT* (named *MP2* and *MP3*, respectively), in lieu of total asset. Second, we use two-digit SIC codes for industry classification. Note that in our previous model, we assign sample firms into industries based on the Fama–French 49-industry classification.

According to Petersen (2009), the most common econometric models used for similar investigations in recently published finance papers are the Fama–MacBeth (1973) procedure, fixed-effect regressions, and cluster-correcting models. He shows that the chosen methods can be incorrect and yield different results in many cases. Therefore, we also examine whether our evidence holds when we use different econometric methods. The first alternative estimation methodology is a fixed-effect model that solves the problem that arises with cross-sectional ordinary least squares (OLS) models when differences between firms are regarded as parametric shifts of the regression function. Second, we use a random-effects model that accounts for the possibility that constant terms are randomly distributed across cross-sectional units. Third, we estimate OLS regressions with standard errors adjusted for clustering at the firm level and for heteroskedasticity using White's (1980) method. Fourth, we estimate the model using Newey–West standard errors. Fifth, we estimate a model using only the last-year observation of each firm. One may argue that the level of press coverage for each firm can be stable over the period. In this case, the standard error on the estimated coefficient of *APRESS* will be small and the regression model provides a problematic high *t*-statistic value. Therefore, the check with the last-year data only allows us to see whether previous results are not driven by similar multiple observations on the same firms. Finally, we report results controlling for other firm characteristics (*SIZE*, *B/M*, *AGE*, *LEV*, *EVOL*, *NSEG*, *RVOL*, *METRO*, and *EXCH*) in the construction of abnormal press coverage.[20]

[20] We also use various models by combining these variables differently and confirm that the results hold.

We find that all regressions show a consistent pattern of coefficients on abnormal press coverage. Therefore, our results are robust to alternative measures and econometric specifications. The results are left out of the current article for the sake of brevity but are available upon request.

VIII. Summary and Conclusions

Is press coverage important for stock prices, and will investors price stocks more or less efficiently when press coverage becomes intense? Does the press play the role of an information intermediary, does it improve corporate governance, or does it trigger investor sentiment and provide biased coverage? The answers to these questions are an empirical issue, for which there is little direct evidence. We address these issues by examining the relation between the extent of abnormal press coverage and measures of stock prices' deviation from fundamental values.

Our empirical tests provide evidence against the information intermediary and corporate governance hypotheses. In particular, we find that (1) mispricing significantly rises with abnormal press coverage and (2) information risk measures are significantly positively related to abnormal news coverage. These two pieces of evidence, combined with the fact that abnormal news coverage is associated with greater trading volume, are consistent with the predictions of both the biased media and the media-induced sentiment hypotheses.

We conduct additional tests to determine the relative importance of the biased media and media-induced sentiment hypotheses. First we investigate the impact of abnormal press coverage separately for undervalued and overvalued firms, that is, for firms that likely have been recently experiencing bad news and good news, respectively. In line with the media sentiment hypothesis, we find that abnormal press coverage increases the magnitude of mispricing only for overvalued (good news) firms. This finding of an asymmetric response to negative and positive news coverage could be interpreted as consistent with a combination of the media-induced sentiment and binding short-selling constraints. On the other hand, this finding is also in line with the concurrent existence of both a media-induced sentiment and a media bias effect. In both of the above environments (i.e., the media-induced sentiment with binding short-selling constraints and the media-induced sentiment with biased media) abnormal news coverage will have a stronger (weaker) effect on prices in the case of good (bad) news.

In the final part of our analysis we investigate whether a media bias effect exists, by examining the effects of both national and local press coverage on firms' mispricing. We find that there is an asymmetric response to good and bad news coverage firms receive from local press outlets, which is indicative of a biased media effect.

Overall, our results indicate that abnormal news coverage leads to mispricing that is rooted primarily in the fact that press coverage creates sentiment among investors. However, mispricing can also be attributed to the tendency of the local press to provide biased coverage for nearby-located firms.

Appendix: Variable Definitions

Variables	Definitions
	Press Coverage
PRESS	The number of news articles related to the firm from the ProQuest search engine. We use LexisNexis to collect the number of local newspaper articles for the subsample of S&P 500 firms.
APRESS	Abnormal press coverage that is measured as the residual value from the regression of press coverage on firm size, industry dummies, and year dummies: $\text{Ln}(1 + PRESS_{i,t}) = \beta_0 + \beta_1\, SIZE_{i,t} + \Sigma\beta_S\, IND_{i,t} + e_{i,t}$, where *PRESS* is the raw number of newspaper articles related to the firm i and reported in major four newspapers in a calendar year. Because *PRESS* is highly skewed, we use a log-transformed measure as a dependent variable. *SIZE* is the log of total assets and *IND* is a vector of 49 industry dummy variables.
	Mispricing
MP	Mispricing measure based on Berger and Ofek (1995). It is the absolute term of $EP_{i,t}$. The excess price ($EP_{i,t}$) is computed by $\text{Ln}[CAPITAL_{i,t}\,/Imputed(CAPITAL_{i,t})]$, where i indexes firms and t is a yearly time index. $CAPITAL_{i,t}$ is the market value of common equity plus book value of debt, and $Imputed(CAPITAL_{i,t})$ is computed as the product of the firm's total assets and the firm's primary industry-median ratio of total capital to total assets. We assign firms into industries based on the Fama–French 49-industry classification.
MPD	Mispricing dummy, which equals 1 if the *EP* value of firm i is in the top quartile (high positive) or in the bottom quartile (high negative values) after sorting all firms based on *EP* in year t, and 0 otherwise.
AR3, *AR6*, *AR12*	Absolute values of average excess monthly future return over 3, 6, and 12 months, respectively. *AR3* (*AR6*, *AR12*) is measured as the difference between the average monthly return of firm i from January to March (June, December) in year t+1 and the median monthly return of a matching firms' benchmark portfolio that consists of all sample firms that belong to the same industry and in the same size and book-to-market ratio quintiles as firm i.
	Analyst Coverage
AF	The number of security analysts' forecasts.
EAF	Excess analyst coverage. The residual value from the regression of analyst coverage on firm size, industry dummies, and year dummies, measured as in Hong, Lim, and Stein (2000).
	Factor
APC	Monthly return difference between the portfolios of high and low abnormal press coverage (*APRESS*). We classify the firm into the high (low) *APRESS* portfolio if its *APRESS* is included in the top (bottom) tercile.
CMA	Monthly return difference between the portfolios of high and low accruals (*ACCRUAL*), developed by Hirshleifer, Hou, and Teoh (2012). We classify the firm into the high (low) *ACCRUAL* portfolio if its *ACCRUAL* is included in the top (bottom) tercile.
SMB	Monthly return difference between small and big firms. The factor is extracted from Kenneth R. French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).
HML	Monthly return difference between high book-to-market and low book-to-market firms. The factor is extracted from Kenneth R. French's website.

(Continued)

Appendix. Continued.

Variables	Definitions
UMD	Monthly return difference between winners and losers. The factor is extracted from Kenneth R. French's website.
	Information Risk
EQ1	Earnings quality 1: $\frac{TACCR_{i,t}}{TA_{i,t-1}} = k_1 \frac{1}{TA_{i,t-1}} + k_2 \frac{\Delta SALES_i}{TA_{i,t-1}} + k_3 \frac{PPE_{i,t}}{TA_{i,t-1}} + e_{i,t}$, where $TACCR_{i,t} = (\Delta CA_{i,t} - \Delta CL_{i,t} - \Delta CASH_{i,t} + \Delta STDEBT_{i,t} - DEPN_{i,t})$ = firm i's total accruals in year t; $\Delta CA_{i,t}$ = change in current assets between year t–1 and year t; $\Delta CL_{i,t}$ = change in current liabilities between year t–1 and year t; $\Delta CASH_{i,t}$ = change in cash between year t–1 and year t; $\Delta STDEBT_{i,t}$ = change in debt in current liabilities between year t–1 and t; $DEPN_{i,t}$ = depreciation and amortization expense in year t; $\Delta SALES_i$ = change in sales between year t–1 and t; $PPE_{i,t}$ = property, plant, and equipment in year t; and $TA_{i,t-1}$ = total assets in year t–1.
EQ2	Earnings quality 2: $\frac{TACCR_{i,t}}{TA_i} = k_0 + k_1 \frac{CFO_{i,t-1}}{TA_i} + k_2 \frac{CFO_{i,t}}{TA_i} + k_3 \frac{CFO_{i,t+1}}{TA_i} + e_{i,t}$, where $CFO_{i,t}$ is firm i's cash flow from operations in year t and computed as net income before extraordinary items minus total accruals.
EQ3	Earnings quality 3: $\frac{TACCR_{i,t}}{TA_i} = k_0 + k_1 \frac{CFO_{i,t-1}}{TA_i} + k_2 \frac{CFO_{i,t}}{TA_i} + k_3 \frac{CFO_{i,t+1}}{TA_i} + k_4 \frac{\Delta SALES_i}{TA_i} + k_5 \frac{PPE_{i,t}}{TA_i} + e_{i,t}$.
AFE	Analyst forecast error, computed by $\lvert Median(AF)_{i,t} - EPS_{i,t+1}/ / \lvert Median(AF)_{i,t}\rvert$, where forecast error, $\lvert Median(AF)_{i,t} - EPS_{i,t+1}/$, is the absolute value of the difference between the median analyst forecast ($Median(AF)_{i,t}$) and the actual earnings per share ($EPS_{i,t+1}$).
AFD	Analyst forecast dispersion. computed by $StdDev(AF)_{i,t}\ /\lvert Median(AF)_{i,t}\rvert$, where $StdDev(AF)_{i,t}$ is standard deviation of one-year-ahead analyst forecasts.
RVOL	Stock return volatility, measured as the standard deviation of daily stock returns in the calendar year.
	Liquidity
VOLUME	The average over the year of the daily trading volume in dollars. $VOLUME = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} VOL_{i,d,t}$, where $D_{i,t}$ is the number of days for which data are available for stock i at year t. $VOL_{i,d,t}$, is daily volume in dollars on day d at year t.
SVOLUME	The average over the year of the daily trading volume scaled by the number of outstanding shares. $SVOLUME = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \left[\frac{VOL_{i,d,t}}{S_{i,d,t}}\right]$, where $S_{i,d,t}$ is the market value of common shares on day d at year t.
ILLIQ	The average over the year of the daily ratio of stock's absolute return to its trading volume in dollars. $ILLIQ = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \left[\frac{R_{i,d,t}}{VOL_{i,d,t}}\right]$, where $R_{i,d,t}$ is firm i's return on day d at year t.
SILLIQ	The average over the year of the daily ratio of stock's absolute return to its trading volume scaled by the number of outstanding shares: $SILLIQ = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \left[\frac{R_{i,d,t}}{\left(VOL_{i,d,t}/S_{i,d,t}\right)}\right]$. Liquidity measures are transformed after taking the natural log.
	Other Firm Characteristics
SIZE	Log of total assets.
B/M	The ratio of firm's book value to market value.
EVOL	Earnings volatility, which is the log of the standard deviation of changes in earnings per share over the past five years.
NSEG	The number of business segments reported.
DIV	A dummy that equals 1 if the firm pays dividends, and 0 otherwise.
METRO	A dummy that equals 1 if the firm is located in a metropolitan area, and 0 otherwise.
NASDAQ	A dummy that equals 1 if the firm's listing exchange is NASDAQ, and 0 otherwise.

(Continued)

Appendix. Continued.

Variables	Definitions
AMEX	A dummy that equals 1 if the firm's listing exchange is AMEX, and 0 otherwise.
BILLS	The number of bills introduced by the congressman from the district where the firm's headquarter is located and the senators from the firm's home state.
PRET(–1,–1)	The previous month's return.
PRET(–12,–2)	The cumulative return from month –12 to month –2.
PRET(–36,–13)	The cumulative return from month –36 to month –13.
ACCRUAL	Operating accruals are calculated using the indirect balance sheet method: $ACCRUAL_t = [(\Delta Current\ assets_t - \Delta Cash_t) - (\Delta Current\ liabilities_t - \Delta Short\text{-}term\ Debt_t - \Delta Taxes\ payable_t) - Depreciation\ and\ amortization\ expense_t]/Total\ assets_{t-1}$
IV	A dummy that equals 1 if the firm's idiosyncratic volatility is greater than the median of the sample, and 0 otherwise. ΔIV is a dummy that equals 1 if the change in the firm's idiosyncratic volatility is greater than the median of the sample, and 0 otherwise. To measure the stock's idiosyncratic volatility, we first estimate R^2 for each stock for each calendar year using weekly data to regress stock returns on market index returns. The regression model estimated for each stock *i* in year *t* is as follows: $r_{i,w,t} = \alpha_{i,t} + \beta_{i,t} r_{m,w,t} + e_{i,w,t}$, where $r_{i,w,t}$ is the excess return for stock *i* in week *w* in year *t*, and $r_{m,w,t}$ is the value-weighted excess market index return in week *w* in year *t*. From this regression equation, the idiosyncratic variance is defined as $\sigma^2_{ie,t} = \sigma^2_{i,t} - (\sigma^2_{im,t}/\sigma^2_{m,t})$, where $\sigma^2_{i,t} = \mathrm{Var}(r_{i,w,t})$, $\sigma^2_{m,t} = \mathrm{Var}(r_{m,w,t})$, and $\sigma_{im,t} = \mathrm{Cov}(r_{i,w,t}, r_{m,w,t})$. We compute each stock's relative idiosyncratic volatility (i.e., the ratio of idiosyncratic volatility to total volatility), $\sigma^2_{ie,t}/\sigma^2_{i,t}$ or equivalently $1–R^2_{i,t}$, for each year *t*. The relative idiosyncratic volatility is transformed to a logistic version as follows: $\psi_{i,t} = \ln\left(\frac{1-R^2_{i,t}}{R^2_{i,t}}\right) = \ln\left(\frac{\sigma^2_{ie,t}}{\sigma^2_{i,t}-\sigma^2_{ie,t}}\right)$.
INSTP	A dummy that equals 1 if the firm's percentage of shares owned by institutions is lower than the median of the sample, and 0 otherwise. $\Delta INSTP$ is a dummy that equals 1 if the change in the firm's institutional ownership is smaller than the median of the sample, and 0 otherwise.

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