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Hype or help? Journalists' perceptions of mispriced stocks

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ABSTRACT

The business press is a key information intermediary in stock markets, but little is known about how journalists themselves process information. To test competing hypotheses, I combine composite mispricing scores constructed from about 200 cross-sectional anomalies with the content of about two million firm-specific newspaper articles. I find that journalists tend to write positively (negatively) about stocks likely to be undervalued (overvalued). The effect is strongest for national newspapers and overvalued stocks. These and further findings collectively lend more, though not unambiguous, support to the bright side of financial journalism. In most cases, journalists act as "watchdogs", not as "cheerleaders".

1. Introduction

The business press is among the most influential information intermediaries in financial markets.[2] There is compelling evidence that media coverage can affect economic aggregates (e.g., Blankespoor et al., 2018; Dougal et al., 2012; García, 2013; Liu et al., 2014; Peress, 2014; Tetlock, 2007; Wisniewski and Lambe, 2013). In contrast, still little is known about how the business press itself creates, collects, selects, evaluates, repackages, and disseminates news, thereby shaping a firm's information environment.

In this paper, I aim to take a step in this direction by exploiting both a comprehensive newspaper article database and a large cross-sectional anomaly data set. This combination allows me to shed some light on the following questions: given their complex internal and external incentives, do financial journalists primarily act as "watchdogs" or as a "cheerleaders" with respect to mispricing in the cross-section of stocks? What factors influence media coverage and writing style?

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[1] This study was partly conducted while I worked at the University of Mannheim. I am particularly grateful to Alexander Hillert for providing me with the media data set as well as 8-K filings used in this study. I thank two anonymous referees, an associate editor, David Florysiak, Alexander Hillert, Sebastian Müller, Harm Schütt, and seminar participants at the 2016 Berlin meeting of the DFG Scientific Network on "Textual Analysis in Economics and Finance" for valuable comments.

[2] For instance, Fang and Peress (2009, p. 2023) highlight that "every weekday, some 55 million newspaper copies are sold to individual readers in the United States [...]. If we consider online subscriptions and multiple readers per copy, the actual readership of the printed press is even larger, and certainly far broader than other sources of corporate information such as analyst reports."

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Based on about 200 individual anomalies, I first compute two composite mispricing metrics following the ideas in Stambaugh et al. (2015) and Engelberg et al. (2018). They show that such mispricing proxies quantify price distortions caused by biased beliefs in combination with market frictions. I combine these mispricing scores with the content of more than two million firm-level articles published in leading national or local U.S. newspapers between 1989 and 2010, as relied on in Hillert et al. (2014). An advantage of this data set is that it covers the full CRSP/Compustat stock universe and firm-level articles published in the New York Times, the Wall Street Journal, the Washington Post, the USA Today as well as 41 local outlets. As discussed in Miller and Skinner (2015), the existing literature often concentrates on a comparatively narrow set of stocks, articles, and outlets, thereby raising questions about the generalizability of the findings.

To quantify news content, I rely on a transparent dictionary approach. Article tone during the month in which mispricing arises is computed as the fraction of negative words, as suggested by Loughran and McDonald (2011). This procedure allows me to test how article content differs for firms that belong to either the long long or the short leg of composite mispricing portfolios.

My main result is that journalists tend to write positively (negatively) about stocks likely to be underpriced (overpriced). While the exact mechanism is unobservable, two channels are likely to contribute to this finding. First, the financial press appears to collect and transmit fundamentally relevant public information, such as earnings surprises, in an objective way. Second, journalists also appear to uncover new information as well as to express their personal opinions, expectations, and beliefs.

My findings are disproportionately driven by firms in the short leg of mispricing portfolios, both with respect to the strength and the frequency of media signals. This result suggests that journalists actively target firms that seem to be overvalued. In general, my findings tend to be stronger for national than for local newspapers. This pattern contributes to the evolving literature on the impact of journalist experience and newspaper reputation (e.g., Ahern and Sosyura, 2015; Gurun and Butler, 2012; Li, 2018).

The market reaction to articles suggests that investors tend to be surprised by the content. In line with Engelberg et al. (2018), firms likely to be overvalued (undervalued) generate substantial negative (positive) abnormal announcement returns. This pattern can also be identified for firms without other public news in the pre-event period and on the announcement day. The magnitude of abnormal returns and also of abnormal trading volume depends on article tone, which is consistent with the conjecture that at least some investors partly update their beliefs in the light of unexpected media signals. This analysis complements work that studies stock returns around news stories (e.g., Blankespoor et al., 2018; Chan, 2003; Engelberg et al., 2018). In contrast to this stream of the literature, the focus of my study is on exploring the output of journalistic work instead of taking this output as given and studying the market response.

Analyzing more specific forms of overpricing likely to be related to positive skewness preference and/or overconfidence, I find that the press also reports negatively about stocks characterized by high betas, large differences of opinion, financial distress, or lottery-type features. This is notable as these stocks have been shown to be particularly appealing to many individual investors (and thus customers). Nevertheless, this monitoring role does not seem to apply to all facets of mispricing. The press tends to write less favorably about stocks contained in the long leg of anomalies related to capital investment and growth, innovation, and accruals. These findings possibly suggest that the press may sometimes misvalue discretionary corporate actions.

As pointed out by Dougal et al. (2012, p. 639), "the media is often modeled as a faceless institution, but its main product – news content – is generated by people". Relating journalists' word choice to different forms of cross-sectional undervaluation and overvaluation may thus help to enhance our understanding of the business press in financial markets. How journalists react to mispricing is an open empirical question, as the following discussion of competing hypotheses shows.

Several findings in the literature give rise to the conjecture that journalists write negatively (positively) about firms likely to be overvalued (undervalued).

Early clinical studies show that media coverage can help to speed up information diffusion (Huberman and Regev, 2001; Klibanoff et al., 1998). By disseminating value-relevant information to a broad audience, the media has been argued to reduce information asymmetries (e.g., Bushee et al., 2010). Media coverage can reduce the post-earnings-announcement drift (e.g., Peress, 2008), increase the speed of price adjustment after insider trading news (e.g., Rogers et al., 2016) or analyst recommendation revisions (e.g., Ahn et al., 2019), and help to mitigate cash flow mispricing (e.g., Drake et al., 2014). More broadly, media tone can help to predict firms' fundamentals (Tetlock et al., 2008). By detecting management malfeasance and by bringing corporate governance issues to the attention of market participants, the business press is also often considered to be an effective monitor (e.g., Dai et al., 2015; Dyck et al., 2008; Dyck et al., 2010; Miller, 2006; You et al., 2018b). Indeed, in a recent survey (Call et al., 2020), more than 80% of financial journalists state that monitoring companies to hold them accountable and providing in-depth, timely, and accurate articles are their most important objectives.

However, there are also good reasons to assume that financial journalists either do not distinguish between under- and overvalued stocks at all, or that they even hype (write off) overvalued (undervalued) stocks. In other words, media coverage may also have a "dark side" in that the content of newspaper articles could be biased.

On the one hand, this bias could be driven by the supply side and reflect journalists' cognitive constraints or expectational errors about firms with certain characteristics. If biased beliefs are widespread among investors (e.g., Barber and Odean, 2013; Daniel and Hirshleifer, 2015), then journalists may on average show a similar behavior.

On the other hand, media bias could also stem from the demand side and mainly reflect the media's profit-maximizing choice to appeal to the preferences (and potentially prejudices or judgment biases) of their readers. On the theoretical side, Mullainathan and Shleifer (2005) develop a model of the market for news in which competition leads to media slant if readers share common beliefs which they would like to see confirmed.[3] Similarly, Shiller (2000, p. xiv) states: "Driven as their authors are by competition for readers, listeners, and viewers, media accounts tend to be superficial and thus to encourage basic misconceptions about the market." More than two thirds of the surveyed financial journalists in Call et al. (2020) state that competition for readers has indeed increased during their career, and almost one third believes that entertaining readers is very important.

The cross-sectional studies of Engelberg et al. (2012), Hillert et al. (2014), and You et al. (2018a) show that media coverage can indeed lead to price distortions. Moreover, Solomon (2012) shows that journalists may be susceptible to corporate influence. Some journalists take the view that writing negative articles about a firm may result in loss of access to the company's management, which at the same time is an important source of information (Call et al., 2020). Furthermore, Gurun and Butler (2012) and Reuter and Zitzewitz (2006) find that the financial media partly suffers from advertising bias.

Overall, my analysis adds to the emerging work exploring the behavior of key information intermediaries in the context of price distortions. On the one hand, Engelberg et al. (2020) and Guo et al. (2020) find that the price targets and recommendations of financial analysts tend to be on the wrong side of anomaly signals. On the other hand, Brockman et al. (2015) conclude that financial analysts at least partly anticipated the financial crisis 2007/2008. Based on news stories about 458 internet IPOs during 1996 to 2000 and control firms, Bhattacharya et al. (2009) provide evidence for media hype, which they nevertheless find unable to explain the internet bubble. My broader analysis lends more, though not unambiguous, support to the "bright side" of journalistic activities.

Collectively, my findings show that financial journalists' behavior depends on the specific anomalies and settings under consideration. This insight helps to reconcile the contrasting views on the role of the media discussed above. Nevertheless, it is important to emphasize limitations of my "big picture" analysis of how journalists select and present information as well. The approach may be able to generate fresh insights, to provide several new stylized facts, and to cautiously suggest broad mechanisms. It is, however, not able to document exactly how information flows through the news media or to precisely identify the complex drivers of journalistic activities. Methodological constraints and the fact that large parts of the journalistic work process are unobservable imply that I am not able to draw causal inferences. In this respect, my work may represent a starting point for future research with a narrower focus.

The remainder of the paper is organized as follows. In Section 2, I describe my empirical design and explore how the national press writes about firms likely to be mispriced. Section 3 analyzes local newspapers and studies determinants of abnormal media coverage. Section 4 documents the market reaction to the publication of newspaper articles. In Section 5, I analyze media tone and media coverage with respect to ten more specific anomaly groups. Section 6 discusses potential economic drivers behind the findings and suggests areas for future research. Section 7 concludes.

2. Empirical approach and baseline findings

2.1. Quantifying mispricing

Empirically, one of the challenges for my analysis is to identify cross-sectional price distortions. I start with the simple and intuitive bottom-up method proposed in Stambaugh et al. (2015). The authors synthesize the information from eleven individual anomalies in an attempt to optimize the signal-to-noise ratio. I follow their statistical approach, but condense the information contained in 204 individual anomalies to further minimize noise. The online appendix provides an overview of these cross-sectional return phenomena. In each month and for each individual anomaly separately, I rank stocks so that the presumably most overpriced (underpriced) stock receives the lowest (highest) rank. I divide the ranks by the number of eligible stocks. For each stock month, I then compute the average of all available relative ranks. In each month, the resulting aggregate mispricing score is again standardized to uniformly range from from zero to one. Stocks with a value below 0.1 (above 0.9) are considered to be overpriced (underpriced) and form the short (long) leg of the aggregate mispricing portfolio.

Engelberg et al. (2018) propose an alternative methodology which concentrates on the tails of the anomaly rankings. Separately for each firm month, they count how often a stock enters the long or short leg of individual anomalies. The difference between the number of times a stock is considered to be underpriced (and thus in the long leg) and the number of times a stock is considered to be overpriced (and thus in the short leg) is used as a proxy for aggregate mispricing. I implement this approach again based on the extended set of 204 anomalies. I standardize the resulting composite mispricing variable and focus on firms in the top and bottom decile.

I implement both mispricing proxies for common stocks with a lagged market capitalization above ten million USD. To be consistent with the media-based tests, the sample period runs from January 1989 to December 2010. Table 1 shows that both approaches are powerful. In Panel A, I regress the pooled excess stock returns in month t on the uniformly distributed mispricing measure computed in month $t-1$. In Panel B of Table 1, I compute average monthly excess returns and Fama and French (1993) three-factor alphas for value-weighted decile portfolios. The weighting scheme gives the largest weight to the economically most important stocks. As the next section shows, larger stocks also have a much higher likelihood of being

[3] Gentzkow and Shapiro (2006) develop a model in which media bias can arise even when readers care only about learning the truth. Baron (2006) provides further theoretical rationale for media slant. The idea that the mass media produces mainly entertainment is already expressed in Jensen (1979). Bosman et al. (2017) provide an experimental study on how journalists' writing style affects the readers' perception of news.

Table 1
Aggregate mispricing scores and the cross-section of stock returns.
This table explores the relation between two proxies for cross-sectional mispricing and monthly excess returns as well as monthly Fama and French (1993) alphas. Excess returns and alphas are expressed in %. The sample period covers January 1989 to December 2010. Panel A shows the results obtained from regressions of pooled stock-level excess returns on the composite mispricing score, which is uniformly distributed between zero and one in each month. Standard errors are double-clustered by firm and month. To compute the estimates shown in Panel B, I construct value-weighted decile portfolios sorted on the composite mispricing score. The table shows the average excess return and the Fama and French (1993) alpha obtained from the monthly time-series of these portfolios. Decile 1 (10) contains firms deemed to be overvalued (undervalued). In both panels, statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Panel A: Mispricing score (0,1]								
Firm universe	Mispricing approach: Engelberg et al. (2018)				Mispricing approach: Stambaugh et al. (2015)			
All	N	Score (0,1]	t-stat		N	Score (0,1]	t-stat	
	1,351,273	2.485***	(5.23)		1,329,838	2.695***	(5.40)	
Panel B: Value-weighted monthly alphas (N=264)								
Firm universe	Mispricing approach: Engelberg et al. (2018)				Mispricing approach: Stambaugh et al. (2015)			
	Excess returns		Three-factor alphas		Excess returns		Three-factor alphas	
Decile 1	−0.551	(−1.05)	−1.482***	(−5.59)	−0.825	(−1.51)	−1.746***	(−6.55)
Decile 2	0.051	(0.12)	−0.793***	(−4.54)	−0.077	(−0.17)	−0.938***	(−5.06)
Decile 3	0.222	(0.65)	−0.464***	(−4.02)	0.389	(1.10)	−0.278**	(−2.09)
Decile 4	0.453	(1.43)	−0.168*	(−1.70)	0.444	(1.37)	−0.224**	(−2.38)
Decile 5	0.671**	(2.24)	0.059	(0.60)	0.605**	(2.08)	0.019	(0.21)
Decile 6	0.519*	(1.90)	−0.028	(−0.27)	0.609**	(2.32)	0.066	(0.81)
Decile 7	0.747***	(3.03)	0.245***	(2.90)	0.718***	(2.87)	0.238**	(2.50)
Decile 8	0.805***	(3.28)	0.322***	(3.73)	0.918***	(3.79)	0.456***	(4.56)
Decile 9	0.736***	(3.00)	0.307***	(2.70)	0.827***	(3.21)	0.396***	(2.70)
Decile 10	1.038***	(3.76)	0.597***	(3.76)	1.132***	(4.03)	0.647***	(4.03)
Diff: 10–1	1.590***	(3.57)	2.079***	(5.45)	1.956***	(4.32)	2.393***	(6.44)

covered by the media and are thus particularly relevant for my purpose. Table 1 shows that monthly return differences between the top and bottom decile exceed 150 basis points in each test. The online appendix shows that the long/short approaches also generate large and significant alphas relative to the recently proposed asset pricing models of Fama and French (2015) and Hou et al. (2015). There is also no long-term return reversal, suggesting that firms in the short (long) leg are indeed overvalued (undervalued). The composite mispricing scores therefore provide a useful benchmark against which I can evaluate journalists' writing style.

2.2. Quantifying media coverage and article content

As in Hillert et al. (2014), the baseline media data set covers articles about NYSE/Amex/Nasdaq stocks that appear on both CRSP and Compustat at some point during 1989 and 2010. The data comprises firm-specific articles published in four leading national newspapers (New York Times, Wall Street Journal, Washington Post, and USA Today) as well as in 41 local newspapers, which partly have a shorter sample period as described in detail in the online appendix. In total, there are about 600,000 (1.75 million) eligible news stories in national (local) newspapers. Table 2 provides descriptive statistics about media coverage (in Panels A and B) as well as article tone (in Panels C and D).

As shown in Panel A as well as in Fang and Peress (2009), firm size has an overwhelming impact on newspaper coverage. For instance, stocks in the smallest (largest) NYSE size quintile have on average 0.06 (4.27) articles per month in national newspapers and 0.13 (13.30) articles in local newspapers.

As proposed in Loughran and McDonald (2011), article tone is defined as the fraction of negative words. Loughran and McDonald (2011) show that their method outperforms standard dictionary approaches, which are often misspecified in a stock market setting.[4] Their approach is widely used in the related literature, including García (2013), Gurun and Butler (2012), or Hillert et al. (2014).

Throughout the paper, and separately for national and local newspapers, article tone is measured at the level of a firm month. If firm i has several articles in month t, I use the average tone of these articles. As shown in Panel C of Table 2, there is large cross-sectional variation in article tone, which I exploit in my analysis. For instance, the mean fraction of negative words used in a national newspaper article is 1.79%, but the standard deviation is 2.28%. There is also considerable time-series variation. Using raw tone without controls for these general time patterns does not change my insights. Nevertheless, to isolate cross-sectional effects and to make the construction of the media variables comparable to the construction of the mispricing variables, I standardize tone. For each month t as well as for national and local newspaper separately, I subtract the average tone and normalize the resulting *standardized abnormal article tone* to have a standard deviation of one:

$$\textit{Standardized abnormal article tone}_{i,t} = (\textit{Article tone}_{i,t} - \textit{Average tone}_t)/(\textit{SD tone}_t) \quad (1)$$

[4] Following previous work, I focus on negative words because using the fraction of positive words or net tone is problematic, for instance due to frequent negations. Loughran and McDonald (2016) provide a detailed discussion of this issue.

Table 2
Descriptive statistics of media coverage and article tone.
The *National media* comprise the New York Times, the Wall Street Journal, the Washington Post, and the USA Today. The *local media* comprise 41 newspapers in total (see Hillert et al., 2014 and the online appendix for details). Panel A illustrates the distribution of firm-specific articles. *Mean* (*SD*) refers to the average number (standard deviation) of firm-specific articles. *P*1/*P*50/*P*99 denote percentiles. *NYSE size quintile* 1 (5) refers to small (large) firms. Panel B reports time-series characteristics of the average number of firm-level articles per month. Panel C reports descriptive statistics of pooled article tone averaged for each firm month. Article tone is computed as the fraction of negative words based on the word list of Loughran and McDonald (2011). Panel D reports time-series characteristics of the average firm-level tone per month.

Firm Universe	Mean	SD	P1	P50	P99	Mean	SD	P1	P50	P99
	Panel A: Media coverage, pooled sample									
	National media (N=600,469)					Local media (N=1,749,288)				
All	0.41	2.94	0.00	0.00	8.00	1.21	9.82	0.00	0.00	23.00
NYSE size quintile 1	0.06	0.42	0.00	0.00	1.00	0.13	1.03	0.00	0.00	2.00
NYSE size quintile 2	0.17	0.94	0.00	0.00	3.00	0.41	2.69	0.00	0.00	6.00
NYSE size quintile 3	0.33	1.43	0.00	0.00	5.00	0.88	4.10	0.00	0.00	13.00
NYSE size quintile 4	0.75	2.71	0.00	0.00	10.00	1.99	8.86	0.00	0.00	25.00
NYSE size quintile 5	4.27	10.30	0.00	1.00	53.00	13.30	35.10	0.00	2.00	180.00
	Panel B: Media coverage, monthly time series									
	National media (N=264)					Local media (N=264)				
All	0.41	0.06	0.28	0.41	0.54	1.22	0.50	0.21	1.35	2.00
	Panel C: Article tone, pooled sample									
	National media (N=159,471)					Local media (N= 238,401)				
All	1.79	2.28	0.00	1.12	10.37	1.67	1.29	0.00	1.46	6.12
	Panel D: Article tone, monthly time series									
	National media (N=264)					Local media (N=264)				
All	1.84	0.26	1.33	1.80	2.63	1.70	0.17	1.43	1.69	2.10

As a consequence, a value of zero for firm i in month t means that the fraction of negative words contained in the article(s) written about a given firm in a given month equals the fraction of negative words contained in the articles written about the average firm in the same month. A positive (negative) value implies that the press' perception of this stock is negative (positive) relative to other stocks that appear in the media in this month.

Prior research suggests that media content could be influenced by lagged returns (e.g., Tetlock, 2007), and that the impact of negative and positive performance may be asymmetric (García, 2018). Past returns are also correlated with the inclusion in the mispricing portfolios. For instance, with respect to the previous six-month return, the average firm contained in the long (short) leg of the Stambaugh et al. (2015) measure is at the 67th (26th percentile) of the distribution. In an attempt to control for the direction and magnitude of past returns, I compute an alternative version of abnormal tone. More specifically, I rely on the residual $\varepsilon_{i,t}$ from monthly cross-sectional regressions of raw article tone on a variable that equals the cumulative x-month return if positive and zero otherwise as well as on a variable which is equal to the cumulative x-month return if negative and zero otherwise:

$$Article\ tone_{i,t} = \alpha_t + \beta_{1,t} \cdot Positive\ return\ control_{i,t-x} + \beta_{2,t} \cdot Negative\ return\ control_{i,t-x} + \varepsilon_{i,t} \qquad (2)$$

I vary the cumulative x-month return from one to 36 months.[5] In the following tables, I refer to the resulting $\varepsilon_{i,t}$, normalized each month to have a standard deviation of one, as *standardized abnormal article tone with controls for past returns*.

As the online appendix shows in more detail, negative previous stock-level returns tend to go along with negative tone, while positive returns have little influence on article content. The sources of this pattern are not unambiguously clear. For instance, article content may to some extent reflect the past instead of beliefs about the future and, in addition, investors may "want the journalists to color the financial news emphasizing the negative domain" (García, 2018, p. 19). Alternatively, journalists may have extrapolative expectations, in particular with respect to past loser firms. This behavior could, in general, be both biased and rational. On the one hand, journalists may suffer from the representativeness heuristic or other judgment biases resulting in erroneous expectations. On the other hand, journalists may correctly believe in slow information diffusion, i.e. assume that the fundamentally relevant information partly contained in (primarily negative) past performance is not fully reflected in current prices yet. Indeed, the analysis in Section 2.1 suggests that such a belief appears to be justified in my setting.

In the first two cases sketched above, controlling for the impact of past returns on article content arguably results in a better proxy for the true unobservable effect I am interested in, while in the third case relying on raw tone may be justified. Empirically, I am unable to distinguish between these competing hypotheses. However, it seems reasonable to assume that

[5] Conceptually, a similar residual-based method has been used in Hong et al. (2000) to quantify abnormal analyst coverage or in Hillert et al. (2014) to quantify abnormal media coverage. My way to distinguish between the impact of positive and negative returns follows, for instance, Chordia et al. (2007). The online appendix shows that inferences are unchanged if I use alternative approaches to control for past performance.

Table 3
Mispriced stocks and article tone in national newspapers.
This table tests whether measures of abnormal tone of firm-specific articles published in national newspapers are systematically related to composite mispricing scores. Article tone is averaged for each firm month and measured in the month at the end of which mispricing scores are formed. In Panel A, *standardized abnormal article tone* is defined as the difference between the average fraction of negative words contained in the articles covering the firm month under consideration and the average fraction of negative words contained in all firm-level observations in this month. In Panel B, *standardized abnormal article tone with controls for past returns* is defined as the residual obtained from monthly cross-sectional regressions of raw article tone on a variable which equals the previous cumulative x-month return if positive and zero otherwise as well as on a variable which equals the previous cumulative x-month return if negative and zero otherwise. The x-month return is winsorized at the 1% and 99% levels. In both panels, abnormal tone is normalized to have a standard deviation of one. The third column reports the coefficient obtained from regressing the abnormal tone of the pooled eligible firm months (N) on a composite mispricing score that is uniformly distributed between zero and one (*Score (0,1]*). In addition, standardized abnormal article tone (with or without return controls) for firm months contained in either the top decile or bottom decile of the mispricing measure is reported in columns four and five (*Long leg*/*Short leg*). Column six tests whether journalists' writing style for firms contained in the long leg differs systematically from the writing style for firms contained in the short leg. The sample period ranges from January 1989 to December 2010. In all specifications, t-statistics (in parentheses) are based on standard errors that are double-clustered by firm and month. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Mispricing approach	Return controls	Score (0,1]	Long leg	Short leg	Long-short
Panel A: Standardized abnormal article tone					
Engelberg et al. (2018)	No return controls	−0.345***	−0.123***	0.273***	−0.395***
	t-stat	(−21.34)	(−9.48)	(21.11)	(−22.20)
	N	156,880	12,911	16,704	29,615
Stambaugh et al. (2015)	No return controls	−0.355***	−0.151***	0.236***	−0.387***
	t-stat	(−20.65)	(−10.37)	(17.27)	(−19.49)
	N	156,292	8130	15,233	23,363
Panel B: Standardized abnormal article tone with controls for past returns					
Engelberg et al. (2018)	One-month return	−0.234***	−0.086***	0.186***	−0.272***
	t-stat	(−14.80)	(−6.63)	(15.04)	(−15.63)
	N	155,090	12,911	16,697	29,608
Stambaugh et al. (2015)	One-month return	−0.237***	−0.115***	0.148***	−0.263***
	t-stat	(−14.18)	(−7.77)	(11.44)	(−13.58)
	N	154,504	8,119	14,957	23,076
Engelberg et al. (2018)	Three-month return	−0.167***	−0.064***	0.129***	−0.193***
	t-stat	(−11.00)	(−4.92)	(10.98)	(−11.60)
	N	153,878	12,909	16,689	29,598
Stambaugh et al. (2015)	Three-month return	−0.167***	−0.092***	0.092***	−0.184***
	t-stat	(−10.34)	(−6.23)	(7.38)	(−9.75)
	N	153,293	8105	14,742	22,847
Engelberg et al. (2018)	Six-month return	−0.108***	−0.046***	0.075***	−0.121***
	t-stat	(−7.46)	(−3.56)	(6.64)	(−7.52)
	N	151,954	12,902	16,685	29,587
Stambaugh et al. (2015)	Six-month return	−0.109***	−0.075***	0.043***	−0.118***
	t-stat	(−6.97)	(−5.13)	(3.63)	(−6.55)
	N	151,371	8083	14,481	22,564
Engelberg et al. (2018)	Twelve-month return	−0.091***	−0.038***	0.067***	−0.105***
	t-stat	(−6.29)	(−2.98)	(5.97)	(−6.59)
	N	148,029	12,889	16,526	29,415
Stambaugh et al. (2015)	Twelve-month return	−0.099***	−0.065***	0.046***	−0.111***
	t-stat	(−6.25)	(−4.38)	(3.74)	(−5.92)
	N	147,454	7960	13,671	21,631
Engelberg et al. (2018)	24-month return	−0.155***	−0.060***	0.121***	−0.182***
	t-stat	(−10.11)	(−4.60)	(9.90)	(−10.44)
	N	139,801	12,751	15,531	28,282
Stambaugh et al. (2015)	24-month return	−0.174***	−0.085***	0.118***	−0.203***
	t-stat	(−10.22)	(−5.47)	(8.52)	(−9.89)
	N	139,247	7649	11,934	19,583
Engelberg et al. (2018)	36-month return	−0.198***	−0.080***	0.152***	−0.232***
	t-stat	(−12.32)	(−5.92)	(11.78)	(−12.70)
	N	132,054	12,514	13,883	26,397
Stambaugh et al. (2015)	36-month return	−0.223***	−0.104***	0.152***	−0.256***
	t-stat	(−12.44)	(−6.41)	(10.31)	(−11.83)
	N	131,550	7447	10,248	17,695

my findings with (without) controls for past returns represent a lower (upper) bound of the confidence interval quantifying journalists' perceptions of mispriced stocks. I therefore report both measures in all remaining tests of this paper.

2.3. Baseline results

Separately for each firm month included in the mispricing tests, I quantify the writing style of articles published during the month at the end of which long/short anomaly portfolios are formed. Following standard asset pricing logic, this is the month during which mispricing arises, is not sufficiently corrected, or even intensifies. I use this timing throughout the paper, but the qualitative nature of my findings does not change if I rely on articles published one month earlier or later instead.

In the baseline analysis, I analyze the tone of articles published in national newspapers. The final sample consists of close to 157,000 pooled firm months. The average (median) observation has the following properties. The firm has a market capitalization of about 10.1 billion USD (1.45 billion USD) and 11.5 (10) analysts provide estimates for the firm's fiscal year 1 earnings. About 40% of the firm months are attributable to S&P 500 firms. In sum, the analysis focuses on large and economically relevant firms.

Table 3 shows my main findings with respect to journalists' writing style. The dependent variable in Panel A of Table 3 is the standardized abnormal article tone without controls for past returns. I regress the pooled observations on the mispricing score which is uniformly distributed between zero and one in each month. Alternatively, I test whether the average abnormal tone for firm months contained in the long leg or in the short leg of the mispricing portfolios is significantly different from zero. In all regressions, standard errors are clustered by both firm and month.[6]

The main finding is that articles written about firms classified as overvalued (undervalued) contain significantly more (less) negative words than articles written about other firms in this month. This result is both statistically significant and economically meaningful. For instance, with respect to Stambaugh et al. (2015) mispricing, the content of articles written about firms entering the long leg of the portfolio at the end of the month is about 0.15 standard deviation less negative than on average. For firms entering the short leg, the content is about 0.23 standard deviations more negative than the average content. In both cases, the results are also highly statistically significant. The findings for the approach of Engelberg et al. (2018) are similar.

In Panel B of Table 3, I report findings from analogous tests that additionally control for past returns. Panel B provides two insights. First, and as expected, point estimates decrease in magnitude. Second, the results remain economically meaningful and statistically significant at the one percent level. For instance, again with respect to Stambaugh et al. (2015) mispricing, the implied tone difference between overvalued and undervalued firms is estimated to range roughly between roughly 0.1 and 0.25 standard deviations. My findings tend to be weakest when controlling for the past six-month or twelve-month return. For the sake of brevity and to provide conservative estimates, I thus rely on the past-six month return in the following.

In sum, journalists' writing style tends to be rather positive (negative) for stocks likely to be undervalued (overvalued). These findings are consistent with the notion that the press tends to act as a monitor. The results are inconsistent with the idea of media slant according to which the press reports (un)favorably about already overvalued (undervalued) firms.

3. Further insights related to the baseline analysis

3.1. Local newspapers

I hypothesize that rerunning the baseline analysis with journalists working for local newspapers should generate weaker findings. The national business press may have more and better resources to create or evaluate information through journalistic activities or to conduct investigative reporting (e.g., Ahern and Sosyura, 2015; Bushee et al., 2010). Survey results indicate that journalists at top outlets target their articles at more sophisticated audiences (Call et al., 2020). Moreover, there is some evidence that local outlets may sometimes act as "cheerleaders" (e.g., Gurun and Butler, 2012).

The findings, which are shown in Panels A (no return controls) and D (with return controls) of Table 4, confirm the predictions. While the overall picture is comparable to the one obtained for the national media, the effect size is about 10% to 20% smaller. These differences partly further increase in Panels B and C as well as E and F, in which I condition on those firms that are covered by both national and local newspapers in the same month.

3.2. Extent of media coverage

While article tone may be regarded as the strength of the signal generated by the media, the number of articles may represent the frequency of the signal. To test whether journalists disproportionately cover stocks in the long leg or short

[6] Inferences remain unchanged if I run monthly Fama and MacBeth (1973) regressions of abnormal tone on mispricing scores or if I run the analysis at the level of an article instead of a firm month.

Table 4
Mispriced stocks and article tone in local newspapers.
This table tests whether measures of abnormal tone of firm-specific articles published in local (and partly national) newspapers are systematically related to composite mispricing scores. The approach in Panels A to C (D to F) corresponds to the approach used in Panel A (Panel B) of Table 3, which provides more details. In Panels B, C, E, and F, I condition on firm months with coverage in both national and local newspapers. *t*-Statistics (in parentheses) are based on standard errors that are double-clustered by firm and month. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Mispricing approach	Score (0,1]	Long leg	Short leg	Long-short
Panel A: Standardized abnormal article tone in local newspapers				
Engelberg et al. (2018) approach	−0.294***	−0.108***	0.235***	−0.343***
t-stat	(−18.45)	(−8.74)	(18.25)	(−19.60)
N	234,905	20,924	21,989	42,913
Stambaugh et al. (2015) approach	−0.296***	−0.138***	0.202***	−0.340***
t-stat	(−17.59)	(−10.46)	(15.82)	(−18.49)
N	234,132	15,128	20,415	35,543
Panel B: Local newspaper tone conditioning on national media coverage				
Engelberg et al. (2018) approach	−0.259***	0.038**	0.338***	−0.300***
t-stat	(−10.96)	(2.06)	(17.13)	(−11.60)
N	94,975	7582	9058	16,640
Stambaugh et al. (2015) approach	−0.260***	0.017	0.312***	−0.294***
t-stat	(−10.14)	(0.75)	(16.02)	(−10.10)
N	94,822	4361	8050	12,411
Panel C: National newspaper tone conditioning on local media coverage				
Engelberg et al. (2018) approach	−0.329***	−0.060***	0.320***	−0.380***
t-stat	(−16.07)	(−3.59)	(18.24)	(−15.89)
N	94,975	7582	9058	16,640
Stambaugh et al. (2015) approach	−0.338***	−0.083***	0.291***	−0.374***
t-stat	(−15.23)	(−4.10)	(15.83)	(−13.66)
N	94,822	4361	8050	12,411
Panel D: Stand. abnormal article tone in local newspapers with controls for six-month return				
Engelberg et al. (2018) approach	−0.094***	−0.047***	0.058***	−0.104***
t-stat	(−6.24)	(−3.78)	(4.76)	(−6.20)
N	227,616	20,914	21,962	42,876
Stambaugh et al. (2015) approach	−0.094***	−0.076***	0.033***	−0.109***
t-stat	(−5.80)	(−5.69)	(2.66)	(−6.07)
N	226,847	15,002	19,458	34,460
Panel E: Local newspaper tone with controls for six-month return, cond. on national media coverage				
Engelberg et al. (2018) approach	−0.069***	0.102***	0.168***	−0.067***
t-stat	(−3.07)	(5.48)	(9.02)	(−2.68)
N	92,667	7581	9050	16,631
Stambaugh et al. (2015) approach	−0.063**	0.081***	0.155***	−0.074***
t-stat	(−2.52)	(3.48)	(8.19)	(−2.60)
N	92,515	4351	7620	11,971
Panel F: National newspaper tone with controls for six-month return, cond. on local media coverage				
Engelberg et al. (2018) approach	−0.112***	0.018	0.135***	−0.117***
t-stat	(−6.04)	(1.06)	(8.87)	(−5.41)
N	92,667	7581	9050	16,631
Stambaugh et al. (2015) approach	−0.109***	−0.005	0.114***	−0.119***
t-stat	(−5.32)	(−0.26)	(6.89)	(−4.63)
N	92,515	4351	7620	11,971

leg, I draw on Hillert et al. (2014) by focusing on the residual obtained from running monthly cross-sectional regressions as follows:

$$ln(1 + no.\ articles) = \alpha + \beta_1 \cdot ln(size) + \beta_2 \cdot S\&P\ 500 + \beta_3 \cdot NASDAQ + \beta_4 \cdot ln(1 + analyst) + \varepsilon_{media} \quad (3)$$

In other words, I construct a measure of unexpected coverage, which controls for analyst coverage, index membership, and firm size, which is the predominant determinant of raw media coverage (see Table 2). As an alternative specification, I augment the approach with the two controls for the previous six-month return. Table 5 shows the main results.

Firms contained in the long leg do not receive abnormal coverage. In contrast, the national and, to a lesser extent, the local press has a tendency to write about overvalued firms. All else equal, the stocks entering the short leg of composite mispricing receive positive abnormal national coverage that is equal to about 5% to 10% of one standard deviation of residual coverage. These findings are consistent with the survey results in Call et al. (2020). About 60% of journalists acknowledge that they are more likely to write about controversial firms.

Table 5
Mispriced stocks and residual media coverage.
This table explores the relation between composite cross-sectional mispricing scores and average residual national media coverage (Panels A and B) or residual local media coverage (Panels C and D). In all panels, residual coverage is measured in the month at the end of which anomaly portfolios are formed. Following Hillert et al. (2014), *residual media coverage* in Panels A and C is the residual obtained from monthly cross-sectional regressions of ln(1+number of articles) on logarithmized lagged firm size, logarithmized analyst coverage, and dummy variables for S&P 500 and Nasdaq membership. In Panels B and D, controls additionally include a variable that equals the previous cumulative six-month return if positive and zero otherwise as well as on a variable that equals the previous cumulative six-month return if negative and zero otherwise. These returns are winsorized at the 1% and 99% levels, respectively. The third column reports the coefficient obtained from regressing the pooled *residual media coverage* of all eligible firm months (*N*) on a uniformly distributed composite mispricing score (*Score (0,1]*). In addition, residual media coverage (with or without return controls) for firm months contained in either the top decile or bottom decile of the mispricing measure is reported in columns four and five (*Long leg*/*Short leg*). Column six tests whether residual media coverage of firms contained in the long leg is systematically different from coverage of firms contained in the short leg. In all tests, residual coverage is normalized to have a mean of zero and a standard deviation of one. *T*-statistics (in parentheses) are based on standard errors that are double-clustered by firm and month. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Mispricing approach	*N*	Score (0,1]	Long leg	Short leg	Long-short
Panel A: Residual national media coverage, controls as in Hillert et al. (2014)					
Engelberg et al. (2018) approach	1,286,393	−0.175***	−0.021	0.126***	−0.147***
		(−10.35)	(−1.63)	(11.24)	(−9.19)
Stambaugh et al. (2015) approach	1,284,552	−0.162***	−0.013	0.115***	−0.128***
		(−10.04)	(−1.59)	(10.73)	(−9.82)
Panel B: Residual national media coverage, additional controls for six-month return					
Engelberg et al. (2018) approach	1,232,152	−0.097***	−0.005	0.0518***	−0.0571***
		(−5.85)	(−0.41)	(4.74)	(−3.62)
Stambaugh et al. (2015) approach	1,230,330	−0.084***	0.007	0.0406***	−0.0337***
		(−5.21)	(0.81)	(3.87)	(−2.59)
Panel C: Residual local media coverage, controls as in Hillert et al., 2014					
Engelberg et al. (2018) approach	1,286,393	−0.119***	−0.010	0.0850***	−0.0951***
		(−6.90)	(−0.78)	(7.11)	(−5.89)
Stambaugh et al. (2015) approach	1,284,552	−0.102***	−0.001	0.0713***	−0.0725***
		(−6.13)	(−0.14)	(6.36)	(−5.28)
Panel D: Residual local media coverage, additional controls for six-month return					
Engelberg et al. (2018) approach	1,232,152	−0.065***	0.001	0.0310***	−0.0303*
		(−3.82)	(0.05)	(2.68)	(−1.92)
Stambaugh et al. (2015) approach	1,230,330	−0.048***	0.013	0.0171	−0.0041
		(−2.88)	(1.48)	(1.59)	(−0.31)

4. Market reaction to newspaper articles

Quantifying the market reaction to article publication represents a conceptually different way to validate competing hypotheses about article content. If media slant reconfirms or amplifies biased investor beliefs underlying mispricing, then positive (negative) abnormal returns for firms likely to be overvalued (undervalued) are to be expected. If journalists' writing style contradicts investor expectations, then the opposite pattern may be observed.

Empirically, I compute abnormal event-time returns as the difference between the return on the announcement day (t=0) and the return implied by a Fama and French (1993) model. Panel A of Table 6 shows that stocks likely to be overvalued (undervalued) have a negative (positive) abnormal announcement return. The return difference is highly statistically significant and economically meaningful. These findings are consistent with Engelberg et al. (2018) who show that anomalies are several times stronger on days with earnings announcements or other news. The result suggests that unexpected article content forces some investors to partly update their biased beliefs.

This finding is also the main insight of Panel B, in which I attempt to separate the impact of newspaper article content from the impact of other public news. More specifically, I condition on firms without an earnings announcement, dividend announcement, 8-K filing, or 10-K filing during the event days $t= -5$ to t=0.[7]

In an attempt to further isolate the role of article content, I regress the abnormal return on abnormal tone, defined as the difference between the average tone of articles written about the firm under consideration on day t=0 and the average tone for all firms. Panel C, which mirrors Panel A, shows that the market reaction is strongly related to tone, in particular with respect to firms likely to be overvalued. Panel D shows that inferences again do not change if I condition on firms without other public news in the event period.

[7] www.sec.gov/answers/form8k.htm defines an 8-K filing as a "'current report' companies must file with the SEC to announce major events that shareholders should know about". 8-K (10-K) filings are available from 1995 (1994) onwards. My baseline findings hold in the 1995–2010 subsample.

Table 6
Market reaction to firm-specific articles in national newspapers.
Separately for different portfolios, this table reports average abnormal returns on the publication date of firm-specific articles in national newspapers. Abnormal returns are defined as the announcement day return (t=0) minus the expected buy-and-hold return as implied by a Fama and French (1993) three-factor model. Factor loadings are estimates from rolling regressions over the previous twelve months. Panels A and C contain all observations. Panels B and D condition on observations without an earnings or dividend announcement as well as without an 8-K or 10-K filing during calendar days t=-5 to t=0. In Panels B and D, I regress abnormal returns on abnormal tone, defined as the difference between the raw tone of all articles written about the firm under consideration on day t=0 and the average firm-level tone on day t=0. Abnormal tone is standardized to have unit variance. In all panels, t-statistics (in parentheses) are based on standard errors that are double-clustered by firm and day. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Mispricing approach		Long leg	Short leg	Long-short
Panel A: Market reaction to press articles (unconditional)				
	Abnormal return	0.191***	−0.181***	0.372***
Engelberg et al. (2018)	t-stat	(11.23)	(−5.20)	(9.51)
	N	32,018	36,814	68,832
Stambaugh et al. (2015)	Abnormal return	0.214***	−0.191***	0.405***
	t-stat	(9.35)	(−4.76)	(8.75)
	N	17,267	30,648	47,915
Panel B: Market reaction to press articles (conditional on firms without news in event period)				
Engelberg et al. (2018)	Abnormal return	0.165***	−0.144***	0.309***
	t-stat	(8.79)	(−3.95)	(7.58)
	N	24,660	27,606	52,266
Stambaugh et al. (2015)	Abnormal return	0.170***	−0.146***	0.316***
	t-stat	(6.84)	(−3.46)	(6.48)
	N	13,189	22,734	35,923
Panel C: Market reaction to article tone (unconditional)				
Engelberg et al. (2018)	Coeff. abnormal tone	−0.110***	−0.344***	0.233***
	t-stat	(−6.72)	(−11.68)	(6.94)
	Constant	0.185***	−0.105***	
	t-stat	(11.23)	(−3.11)	
	N	32,018	36,814	68,832
Stambaugh et al. (2015)	Coeff. abnormal tone	−0.129***	−0.388***	0.258***
	t-stat	(−5.67)	(−11.66)	(6.43)
	Constant	0.205***	−0.109***	
	t-stat	(9.28)	(−2.76)	
	N	17,267	30,648	47,915
Panel D: Market reaction to article tone (conditional on firms without news in event period)				
Engelberg et al., 2018	Coeff. abnormal tone	−0.118***	−0.290***	0.172***
	t-stat	(−6.73)	(−9.00)	(4.72)
	Constant	0.160***	−0.084**	
	t-stat	(8.76)	(−2.34)	
	N	24,660	27,606	52,266
Stambaugh et al., 2015	Coeff. abnormal tone	−0.135***	−0.331***	0.196***
	t-stat	(−5.38)	(−8.75)	(4.32)
	Constant	0.161***	−0.081*	
	t-stat	(6.68)	(−1.93)	
	N	13,189	22,734	35,923

The results above suggest that the publication of articles may help to correct mispricing. This raises the question of whether stocks covered by journalists are less mispriced on average than stocks not covered by journalists. I describe the corresponding tests and results in the online appendix. In short, the market reaction is limited to the day on which the article is published. I do not find clear evidence that stocks with higher media coverage are less mispriced than stocks with lower media coverage. One possible explanation for the lack of significant difference is the lack of a clean counterfactual. The optimal test would compare mispricing among firms that, for exogenous reasons, have high media coverage to that among firms that, for exogenous reasons, have low media coverage. Since media coverage is never exogenous, I cannot conduct such analysis. Another possible explanation for the lack of significant difference is that media coverage, and, thus, the cross-sectional dispersion in media coverage, tends to be moderate, which lowers the power of my analysis.

In the online appendix, I rerun the analysis shown in Table 6 for local newspapers. As expected, findings are qualitatively unchanged, but quantitatively weaker, in particular with respect to the impact of tone. Given the arguably higher reputation and larger audience of national newspapers such as the Wall Street Journal or the New York Times, this pattern further strengthens the interpretation proposed above. The online appendix also provides further support for the idea that unexpected press articles lead investors to update their priors. Trading activity, as measured by abnormal daily firm-level turnover, is significantly higher on days with media coverage, including observations without other observable public news in the event window. The effect size is positively related to strength of the signal, as measured by absolute abnormal tone, and to the credibility of the signal, as measured by national versus local coverage. In sum, the findings are in line with the insights of the baseline analysis in Section 2.3.

5. Journalists and specific return predictors

In the following, I study ten more specific return phenomena. While I highlight behavioral explanations of these return patterns, it should be stressed that rational explanations have also been proposed in the literature. In this respect, the firm characteristics studied in this subsection represent a weaker proxy for actual mispricing than the composite scores analyzed so far. However, studying a set of conceptually diverse and more specific return phenomena may help to gain a more nuanced understanding of journalists' coverage decision and writing styles. The ten return patterns can be classified in three broad categories as follows:

Mispricing driven by slow information diffusion: The common theme behind the following anomalies is limited investor attention towards fundamentally relevant news.

- Post-earnings announcement drift: Stocks tend to drift in the same direction as their most recent earnings surprise (e.g., Bernard and Thomas, 1989). Fama (1998, p. 286) refers to the PEAD as the "granddaddy of underreaction events".
- Dividend-based anomalies: Cognitively constrained investors also appear to underreact to the signals contained in dividend events such as dividend initiations or resumptions (e.g., Michaely et al., 1995).
- Lead-lag effects: There is systematic cross-stock return predictability among economically related firms (e.g., Cohen and Frazzini, 2008).

Mispricing driven by non-standard preferences and/or overconfidence The common theme is overvaluation due to positive skewness preference of (mainly retail) investors and/or due to excessive belief in one's own skill.

- Anomalies related to lottery-like pay-offs: Kumar (2009), Bali et al. (2011), and other work shows that stocks with lottery-type features tend to underperform stocks without these features.
- Volatility anomalies: Stocks with high beta or high total volatility tend to underperform. Behavioral explanations have recently been proposed in Bali et al. (2017), Hong and Sraer (2016), and other work.
- Financial distress anomalies: Financially distressed firms underperform financially healthy firms (e.g., Campbell et al., 2008). Recent evidence in An et al. (2020) or Conrad et al. (2014) points to the importance of the lottery-type features of distressed firms.
- Differences of opinion: Due to overconfidence coupled with short-selling constraints, stocks for which there is strong dispersion in beliefs about future prospects tend to underperform (e.g., Ang et al., 2006; Diether et al., 2002).

Mispricing driven by misreaction to corporate actions: The common theme is that investors misvalue discretionary corporate actions, leading to expectational errors about future cash-flows.

- Capital investment: Firm growth and investment negatively predict performance (e.g., Cooper et al., 2008). There may be managerial overinvestment and cognitively constrained investors may overvalue firms with "bloated" balance sheets.
- Innovation: Proxies for (changes in) innovation activities tend to positively predict abnormal returns (e.g., Eberhardt et al., 2004).
- Accruals: Investors may not adequately distinguish between cash flows from operations and accruals and thus have too optimistic (pessimistic) expectations for high (low) accrual firms (e.g., Sloan, 1996).

For each of the ten anomaly groups sketched above, I compute a composite mispricing measure using the framework of Stambaugh et al. (2015). The online appendix provides more information. With these proxies for different faces of mispricing, I rerun my analysis of abnormal article tone as well as of abnormal media coverage in national newspapers. Tables 7 and 8 show the main findings.

With respect to the PEAD, there is compelling evidence that the article tone goes in the same direction as the most recent earnings surprise, which is consistent with the existing literature (e.g., Peress, 2008). For the two other underreaction-driven anomalies, findings are considerably weaker. With respect to all anomalies likely to be driven by non-standard preferences and/or overconfidence, journalists write unfavorably about stocks likely to be overvalued. The coefficients for the anomalies possibly caused by misreaction to discretionary corporate actions are notable as they stand in contrast to the results presented so far. I discuss potential drivers behind these results as well as my baseline findings in the next section.

6. Potential economic mechanisms

Why do journalists tend to compose more positive (negative) articles for firms that reside in the long (short) leg of anomalies? My findings suggest two broad channels.

First, the results are consistent with the idea that the media disseminates already existing, public, hard information to a broader audience (e.g., Drake et al., 2014; Engelberg and Parsons, 2011; Peress, 2014). On average, fundamentally relevant news tends to be positive (negative) for undervalued (overvalued) firms (e.g., Bernard and Thomas, 1989; La Porta et al., 1997; Engelberg et al., 2018). Reporting this news in an unbiased way will all else equal therefore likely go along

Table 7
Anomaly groups and article tone in national newspapers.
This table tests whether measures of abnormal tone of firm-specific articles published in national newspapers are systematically related to specific anomaly groups. The approach in Panel A (B) corresponds to the approach used in Panel A (the first specification of Panel B) of Table 3, which provides more details. *T*-statistics (in parentheses) are based on standard errors that are double-clustered by firm and month. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Meta anomaly group	*N*	Score (0,1]		Long leg		Short leg		Long-short	
Panel A: Standardized abnormal article tone									
Anomalies related to the PEAD	143,858	−0.441***	(−28.09)	−0.137***	(−12.65)	0.353***	(23.82)	−0.490***	(−25.98)
Anomalies related to dividend events	160,431	−0.0528***	(−3.10)	−0.0543***	(−4.62)	−0.0075	(−0.44)	−0.0468**	(−2.31)
Anomalies related to lead-lag effects	18,512	−0.0266	(−0.86)	−0.0070	(−0.31)	0.0080	(0.22)	−0.0151	(−0.34)
Anomalies related to lottery-like pay-offs	135,835	−0.223***	(−10.90)	−0.0313***	(−2.93)	0.215***	(10.42)	−0.247***	(−10.19)
Low volatility anomalies	153,183	−0.246***	(−11.99)	−0.0737***	(−5.27)	0.206***	(10.55)	−0.280***	(−11.15)
Financial distress anomalies	148,360	−0.390***	(−18.23)	−0.0869***	(−6.71)	0.324***	(14.71)	−0.411***	(−15.84)
Anomalies related to differences of opinion	154,946	−0.404***	(−18.20)	−0.0952***	(−7.17)	0.295***	(13.43)	−0.390***	(−15.05)
Anomalies related to capital investment and growth	139,922	0.0948***	(5.60)	0.0902***	(5.57)	0.0059	(0.42)	0.0843***	(3.92)
Anomalies related to innovation	125,745	0.127***	(6.43)	0.131***	(6.49)	−0.0147	(−1.29)	0.146***	(6.23)
Anomalies related to accruals	122,246	0.0812***	(4.69)	0.115***	(7.00)	0.0262*	(1.65)	0.0890***	(4.08)
Panel B: Standardized abnormal article tone with controls for past returns									
Anomalies related to the PEAD	142,338	−0.294***	(−19.27)	−0.0960***	(−8.71)	0.230***	(15.48)	−0.326***	(−17.46)
Anomalies related to dividend events	155,417	−0.0074	(−0.44)	−0.0203	(−1.63)	0.0001	(0.00)	−0.0204	(−1.01)
Anomalies related to lead-lag effects	18,424	−0.0049	(−0.15)	0.0248	(1.09)	0.0089	(0.24)	0.0159	(0.35)
Anomalies related to lottery-like pay-offs	135,399	−0.0175	(−0.94)	0.0185*	(1.75)	0.0262	(1.40)	−0.00767	(−0.36)
Low volatility anomalies	152,914	−0.0826***	(−4.21)	−0.0247*	(−1.77)	0.0879***	(4.86)	−0.113***	(−4.74)
Financial distress anomalies	148,085	−0.160***	(−7.90)	−0.0300**	(−2.33)	0.124***	(5.89)	−0.154***	(−6.17)
Anomalies related to differences of opinion	153,687	−0.180***	(−8.76)	−0.0420***	(−3.16)	0.112***	(5.57)	−0.154***	(−6.45)
Anomalies related to capital investment and growth	139,619	0.119***	(7.48)	0.0751***	(4.72)	−0.0325**	(−2.48)	0.108***	(5.21)
Anomalies related to innovation	125,497	0.116***	(5.92)	0.118***	(6.03)	−0.00411	(−0.36)	0.122***	(5.35)
Anomalies related to accruals	121,978	0.0960***	(5.75)	0.0886***	(5.49)	−0.0138	(−0.92)	0.102***	(4.90)

Table 8
Anomaly groups and and residual media coverage.
This table explores the relation between specific anomaly groups and average residual national media coverage.The approach in Panel A (B) corresponds to the approach used in Panel A (B) of Table 5, which provides more details. *t*-Statistics (in parentheses) are based on standard errors that are double-clustered by firm and month. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Meta anomaly group	*N*	Score (0,1]		Long leg		Short leg		Long-short	
Panel A: Residual national media coverage, controls as in Hillert et al. (2014)									
Anomalies related to the PEAD	1,088,897	−0.0408***	(−8.05)	−0.0065	(−1.58)	0.0393***	(11.53)	−0.0458***	(−11.35)
Anomalies related to dividend events	1,302,151	−0.0139	(−1.28)	−0.0388***	(−4.15)	−0.0034	(−0.33)	−0.0354***	(−2.75)
Anomalies related to lead-lag effects	77,890	0.0485**	(2.43)	0.0120	(0.43)	−0.0554***	(−4.65)	0.0673**	(2.24)
Anomalies related to lottery-like pay-offs	1,034,640	−0.139***	(−9.93)	−0.0668***	(−5.16)	0.0752***	(31.07)	−0.142***	(−10.89)
Low volatility anomalies	1,214,396	−0.0844***	(−8.47)	−0.0445***	(−5.17)	0.0366***	(10.39)	−0.0811***	(−8.73)
Financial distress anomalies	1,131,173	−0.0863***	(−5.70)	−0.0007	(−0.04)	0.0654***	(32.87)	−0.0661***	(−3.65)
Anomalies related to differences of opinion	1,224,586	−0.140***	(−11.23)	−0.0531***	(−4.26)	0.0775***	(27.48)	−0.131***	(−10.24)
Anomalies related to capital investment and growth	1,059,065	0.0239***	(4.02)	0.0177***	(4.16)	−0.0026	(−0.57)	0.0203***	(3.59)
Anomalies related to innovation	873,951	0.0237	(1.51)	0.0045	(0.52)	−0.0095	(−0.94)	0.0140	(1.05)
Anomalies related to accruals	869,762	0.0411***	(6.59)	0.0385***	(7.46)	−0.0071*	(−1.79)	0.0456***	(8.79)
Panel B: Residual national media coverage, additional controls for past returns									
Anomalies related to the PEAD	1,073,806	−0.0267***	(−5.30)	−0.0039	(−0.95)	0.0259***	(7.62)	−0.0298***	(−7.38)
Anomalies related to dividend events	1,247,403	−0.0119	(−1.05)	−0.0360***	(−3.60)	−0.0021	(−0.20)	−0.0338**	(−2.56)
Anomalies related to lead-lag effects	77,348	0.0497**	(2.50)	0.0127	(0.45)	−0.0562***	(−4.73)	0.0688**	(2.29)
Anomalies related to lottery-like pay-offs	1,028,332	−0.120***	(−8.58)	−0.0618***	(−4.79)	0.0578***	(25.39)	−0.120***	(−9.25)
Low volatility anomalies	1,212,517	−0.0583***	(−5.90)	−0.0348***	(−4.05)	0.0198***	(5.65)	−0.0546***	(−5.89)
Financial distress anomalies	1,129,963	−0.0706***	(−4.71)	0.0019	(0.11)	0.0491***	(24.00)	−0.0472***	(−2.62)
Anomalies related to differences of opinion	1,216,809	−0.113***	(−9.10)	−0.0455***	(−3.67)	0.0576***	(21.79)	−0.103***	(−8.16)
Anomalies related to capital investment and growth	1,056,028	0.0257***	(4.35)	0.0148***	(3.48)	−0.0069	(−1.54)	0.0217***	(3.88)
Anomalies related to innovation	871,442	0.0161	(1.03)	−0.0015	(−0.17)	−0.00762	(−0.76)	0.0062	(0.46)
Anomalies related to accruals	867,139	0.0408***	(6.56)	0.0338***	(6.53)	−0.0107***	(−2.72)	0.0445***	(8.62)

with a more positive (negative) tone for firms in the long (short) leg. Support for this conjecture stems from my findings being particularly strong for composite (and therefore relatively unambiguous) mispricing as well as for the post-earnings-announcement drift. Moreover, the results tend to be stronger for observations in which press articles co-exist with other public news. The survey findings in Call et al. (2020) also show that journalists often use publicly available information such as press releases, 8-K reports, or industry reports when developing an article.

Second, my results indicate that the media may also actively generate, process, and communicate new information or at least express personal views with respect to existing news. This second channel is also in line with the survey results in Call et al. (2020). They show that journalists often rely on non-public sources, such as private phone calls with the company's management as well as input from analysts or institutional and activist investors. In addition, more than 80% of journalists state that it is very important "to provide insight or analysis on corporate news" (p. 29). Similarly, Strauß (2019) reports that financial journalists consider themselves both "as informants and educators" (p. 280).

Several findings support the second channel. The qualitative nature of the market reaction to press articles is unchanged when conditioning on observations without other observable public news. Moreover, both the return and volume reaction depend strongly on article tone. In addition, both the strength and frequency of media-based signals are more pronounced for firms in the short leg of mispricing portfolios. This asymmetry suggests that the media not only reports standard public information such as earnings announcements, but actively shapes a firm's information environment.

Further support for the second channel stems from the observation that my results on both the writing style and the market reaction are stronger for national than for local media. This pattern suggests that journalists working for leading national newspapers may be more likely to identify price distortions than authors writing for local outlets. National newspapers have larger budgets and in general more capacity to create information through journalistic activities (e.g., Bushee et al., 2010), to conduct investigative reporting, and to publish articles in a timely manner. Consistent with this conjecture, Call et al. (2020) show that in particular prominent and experienced journalists ask questions in earnings conferences calls or evaluate relatively unstructured, complex documents such as court documents and government disclosures. Expressions published in leading national outlets are also considered to be more credible, influential, and reputable (e.g., Dyck and Zingales, 2003). Moreover, journalists working for respected national media are generally more likely to act as "watchdogs" (e.g., Miller, 2006, Dyck et al., 2008; Gurun and Butler, 2012; Strauß, 2019).

With regard to their incentives, the fact that journalists tend to write often and negatively about stocks popular among retail investors suggests that providing objective analysis is more important than catering to the preferences of (at least some) readers. This monitoring role corroborates the self-perception of journalists indicated in the surveys of Call et al. (2020) and Strauß (2019).[8]

Nevertheless, and to the extent that the specific anomalies discussed in section 5 are indeed the result of mispricing, my findings also suggest that journalists are not able to identify all forms of inefficiencies. Journalists write less negative articles about firms with high accruals than about firms with low accruals. This pattern might indicate that journalists do not adequately distinguish between earnings components and neglect managers' incentive to manage earnings (e.g., Hirshleifer, 2015). The media also reports more favorably about firms with higher capital investment, possibly suggesting that journalists might overreact to past firm growth rates or incorrectly assess managers' empire building tendencies (e.g., Titman et al., 2004). Finally, the results on anomalies related to innovation support the results in Dai et al. (2020). They show that media coverage can impede firm innovation, in part because the press imposes short-term market pressures on managers.

Future research may take a narrower or conceptually different approach in an attempt to provide a fuller understanding of the financial media and its rich relations to other market participants in the context of mispricing. Studying journalists' individual characteristics, as in Dougal et al. (2012) or Ahern and Sosyura (2015), appears to be a fruitful avenue for further work. For instance, the role of education, reputation, and experience may be explored. Surveys or in-depth interviews (e.g., Call et al., 2020; Strauß, 2019; Usher, 2012; Willnat et al., 2017) and perhaps also experimental approaches (e.g., Weitzel et al., 2020) may also shed new light on financial journalists' complex incentive structures and behavioral patterns. Finally, and as discussed in the literature review of Miller and Skinner (2015), there is a lack of models formalizing the determinants and consequences of journalistic work in financial markets.

7. Conclusion

While the business press is as a key information intermediary in financial markets, little is known about how journalists react to presumably mispriced stocks. To empirically discriminate between competing hypotheses, I combine composite mispricing scores that synthesize the information from more than 200 individual cross-sectional anomalies with the linguistic content of more than two million newspaper articles. Collectively, my findings are consistent with the idea that the business press acts primarily, but not always, as a corporate "watchdog" instead of as a "cheerleader".

[8] Biased investors may still have an incentive to pay for newspapers. For instance, and as modeled in Daniel et al. (1998), overconfidence in combination with self-attribution bias may lead investors to overweight (underweight) signals that confirm (contradict) their priors. Empirical support for this type of confirmation bias is provided in Park et al. (2013).

Declaration of Competing Interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2020.07.029.

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