Large Idiosyncratic Information Shocks and the Informativeness of Journalists' Stories

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October 2024

Abstract

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Keywords: *media; transparency; information shocks, earnings announcements*

Data Availability: *All data are publicly available from the sources identified in the text.*

*Corresponding author: sbb151@psu.edu. This study has benefited from the useful comments and suggestions of workshop participants at Purdue University, Paul Richardson, Shuoyang Xie, David Yu, and Mina Zarrin, and the excellent research assistance of Sheiva Ansary and Sarah Marriott. Muller acknowledges financial support from the Poole Faculty Fellowship.

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Abstract

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1. Introduction

This study examines whether large firm-specific information shocks result in more informative journalist stories. Such stories by journalists are those that better add to, clarify, or interpret the idiosyncratic information shocks. Journalists face incentives to provide more informative stories as large idiosyncratic shocks lead to greater uncertainty for investors and, accordingly, greater investor demand for information. Specifically, as Veldkamp (2006) demonstrates, greater investor demand for information occurs when there are large idiosyncratic information shocks because shocks to future firm payoffs are multiplicative and thus lead to more pronounced changes in the variance of expected future firm payoffs. If journalists respond to the increased investor demand for information, then they will invest more heavily in creating and releasing more informative articles. Investments in creating more informative stories could include tasks such as interviewing managers, analysts, or industry specialists or conducting more detailed analyses to interpret the announced information. Although prior media research (e.g., Blankespoor et al., 2018) has examined how media coverage contributes to firm-specific information shocks (i.e., the average effect of the informativeness of journalist stories), our study goes beyond this evidence by examining whether, when, and how the informativeness of journalists' stories varies with idiosyncratic shocks.

To investigate these issues, we examine whether the marginal effect of the market reaction to the release of journalist stories increases with the magnitude of idiosyncratic information shocks.[1] We focus on earnings announcements as journalist stories overwhelmingly are released on these dates (e.g., Tetlock et al. 2008). In addition, we assess the magnitude of firm-specific information shocks at earnings announcements using two typically used market-based measures of earnings announcement information content (e.g., Landsman et al., 2012; Beaver et al., 2020)—abnormal return volatility and abnormal trading volume. Announcement period abnormal return volatility captures the average change in investors' beliefs, while abnormal trading volume captures investors' idiosyncratic interpretation of the information announced; thus, increases in either measure reflects greater information content.[2] The key difference, however, in the measures is that price changes reflect the

[1] The marginal effect, similar to a coefficient estimate, in our quantile regression tests (discussed below) indicates how much one journalist story affects the outcome variable. Accordingly, a higher marginal effect when there are larger idiosyncratic information shocks relative to smaller shocks suggests that journalist stories are relatively more informative.

[2] Larger idiosyncratic information shocks can instead increase investor consensus and, accordingly, lower abnormal

market's average overall assessment of the information released at the earnings announcement, while trading volume reflects diversity of opinions across individual investors arising from information released at the earnings announcement. Accordingly, the two measures capture distinct aspects of how firm-specific information shocks affect market prices and trading (Kim and Verrecchia 1991a,b, 1997).[3]

Because the idiosyncratic information shocks are dependent variables in our tests, we cannot investigate different levels of idiosyncratic information shocks by simply forming sub-samples based on the magnitude of the outcome variables. We overcome this issue by using quantile regression (Koenker and Bassett Jr, 1978), which allows us to examine the marginal effect of the market reaction to the release of journalist stories across different quantiles of abnormal price reactions and abnormal trading volume. The marginal effect captures the average effect of a journalist story on the earnings announcement period market reaction. To test whether the average journalist story is relatively more informative when there is a large idiosyncratic shock we compare the marginal effect for the top quantile with that for the bottom quantile. In contrast to our research question, concurrent research by Allen and Schmidt (2020) and Sun (2023) provide evidence that media coverage is higher on average for earnings announcements with greater market reactions. More journalists covering large firm-specific shocks increases competition making it more difficult for individual journalists to create new information and thereby more informative stories.[4] Beyond the challenges created by greater competition, large firm-specific shocks should also make it more difficult for individual journalists to generate more informative stories because the shocks create or reflect greater uncertainty about expected future firm payoffs.

If journalists produce more informative stories in response to information shocks, we also expect the release of full articles during large information shocks to be more responsible for the higher marginal effects on abnormal price reactions and abnormal trading volume. Full articles typically contain journalist-created news content, which can come from journalists' background knowledge about the firm or the industry that leads to insights based on the information in the earnings

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trading volume. Prior media research, however, finds that greater coverage leads to higher abnormal volume (e.g., Blankespoor et al. 2018), consistent with greater investor informedness being more important than increased investor consensus.

[3]Prior media research has used other market-based measures—e.g., fraud detection, bid-ask spreads, depths, mispricing of cash flows and accruals, earnings response coefficients, intraperiod timeliness, and intraperiod efficiency. We do not investigate these measures, as they do not relate the magnitude of idiosyncratic information shocks.

[4]As we discuss later in greater detail, we use an instrumental variables approach to mitigate such reverse causality.

announcement, from interviews with managers, analysts, or industry experts, or from information the journalist acquires in response to the earnings announcement, for example, by looking through the financial reporting footnotes. In contrast, news flash articles only provide brief summaries of public announcements and, thus, are less likely to contain new journalist-created content (Drake et al., 2014). Given these differences in journalist-provided content, we use news flash articles as a benchmark for assessing the changing importance of the information content of journalist stories in full articles given the magnitude of idiosyncratic information shocks. Accordingly, for larger information shocks we expect that the increase in the marginal effect of journalists' full articles will be larger than the increase in the marginal effect of news flash stories.

In addition, we more closely examine whether the informativeness of journalist stories is responsible for our findings related to full articles using two additional tests. First, we examine heterogeneity in the abnormal trading behavior of institutional and retail investors in response to journalist articles released at earnings announcements. We expect that institutional investors, which tend to engage more in information-based trading than retail investors (Blankespoor et al., 2018), will have a relatively higher marginal response to the release of full articles if these full articles are more informative. This expectation is based on the Veldkamp (2006) theory that the informativeness of journalists' stories, not just stories that disseminate information, will grow with investor demand for news. Furthermore, previous research provides evidence that sophisticated investors are informed by news (Engelberg et al., 2012). In contrast, retail investors appear to respond to news slowly or overreact to non-news or attention-grabbing events (Chan, 2003; Barber and Odean, 2008; Tetlock, 2011; Barber et al., 2022). Second, we explore whether more informative articles that are produced by *Wall Street Journal* (*WSJ*) journalists affect the abnormal trading behavior of institutional investors to a greater extent than that for retail investors relative to articles released by journalists at other outlets. We expect a higher marginal response of institutional investor trading to *WSJ* articles as *WSJ* articles are typically of higher quality (i.e., they contain more detailed and greater original content) relative to articles from other news outlets (Bonsall et al., 2018; Guest, 2021) and as institutional investors are more likely to trade for information-based reasons.

A potential issue in our analyses is that the media generate a higher number of articles when idiosyncratic shocks are higher at earnings announcements. Evidence of such behavior exists in concurrent research. Specifically, Allen and Schmidt (2020) and Sun (2023) show that the media coverage of firms increases with earnings announcement market reactions.[5] This reverse causality is expected, given the cost-benefit trade-off faced by the media when deciding to generate news stories. Journalists along with their editors face time constraints and must make choices about which events to cover that will lead to the greatest circulation (e.g., Hamilton, 2004). Even though higher media coverage when idiosyncratic shocks are larger should bias against finding larger marginal effects of individual stories at such times (i.e., greater competition should reduce journalists' ability to obtain unique information), we address this potential issue using an instrumental variable (IV) quantile regression approach (Kaplan, 2022). Following prior media research (Soltes, 2011; Drake et al., 2014; Bonsall et al., 2018; Guest, 2021), we use two IVs that capture how busy the media is on the earnings announcement day. The first IV measures the abnormal proportion of stories appearing in the *WSJ* that relate to non-business news during a firm's earnings announcement window relative to the average during the fiscal year, scaled by the average during the fiscal year. The second IV measures the abnormal number of press releases issued by firms outside the three-digit SIC code of a firm during the earnings announcement period relative to average number during the fiscal quarter, scaled by the average number during the fiscal quarter. If these instruments are reliable, our estimates and inferences will be attributable to the exogenous variation in the firm's media coverage related to how busy the media is with the arrival of other exogenous news (e.g., macroeconomic events, currencies, weather, etc.) and not to the endogenous variation in media coverage related to the size of the idiosyncratic information shock at the firm's earnings announcement.[6]

Using a sample of earnings announcements from 2007–2022 and IV quantile regression, we provide evidence that the marginal effect of abnormal price volatility and abnormal trading volume to a journalist's story is higher for earnings announcements with larger idiosyncratic information shocks, consistent with journalists producing more informative articles during such times. In addition, the differences we find across the deciles of shocks are quite large. For abnormal price volatility, the marginal effect of a shock at the 90th percentile is almost three times higher than a shock at the 50th percentile. For abnormal trading volume, the marginal effect of a shock at the 90th percentile is over three times higher than a shock at the 50th percentile. Further, we find that larger idiosyn-

[5] Similar to Allen and Schmidt (2020) and Sun (2023), in untabulated descriptive tests (discussed later in greater detail), we find for our sample a small or moderate increase in overall media coverage based on the size of the information shock.

[6] As discussed later, our inferences, with one exception, are unchanged if we alternatively use standard quantile regression without instruments, which suggests that any possible endogeneity is relatively limited.

cratic shocks also lead to markedly higher abnormal trading by institutional and retail traders to a journalist's story, due to more informative stories and more attention-grabbing stories.

When we separately examine full articles and news flash articles, we find higher marginal effects to full articles for larger idiosyncratic shocks. This evidence is consistent with our findings being attributable to journalist-created information rather than greater dissemination. For institutional trades, we find a much larger marginal effect for full articles relative to news flashes, consistent with the larger marginal effects for greater idiosyncratic shocks being attributable to more informative journalist stories. In contrast, for retail investors, we find that the marginal effects for full articles and news flashes are similar for most quantiles, consistent with retail trade being attributable to the dissemination of news. At the highest quantiles of retail investor trading volume, the marginal effect for full articles becomes larger than that for news flashes, consistent with retail investors reacting more to full articles to a greater extent when there are large attention-grabbing events.

For *WSJ* articles versus non-*WSJ* articles, for institutional trade, we find significantly higher marginal effects for larger shocks for *WSJ* journalist stories relative to other news outlet articles, again suggesting that the higher marginal effect for large idiosyncratic shocks is related to greater information-based trade. In sharp contrast, for retail trade, we find higher marginal effects for non-*WSJ* news outlet articles for larger shocks and that the higher marginal effects are greater than for *WSJ* articles, consistent with greater attention-based trade. Following Guest (2021), we provide more direct evidence that *WSJ* journalists produce stories with a higher level of new textual information content during times of larger information shocks.[7] This evidence supports our interpretation that the information content of *WSJ* articles is responsible for our findings, as opposed to institutional investors reacting to some other aspect of the stories—e.g., the greater attention created by articles reporting larger idiosyncratic shocks.

Our findings offer several contributions. First, relative to prior media research (e.g., Bushee et al., 2010; Drake et al., 2014; Blankespoor et al., 2018; Bonsall et al., 2020; Guest, 2021), we provide evidence that journalists release more informative stories when large idiosyncratic shocks occur at earnings announcements, despite the shocks creating increased competition among journalists and a potentially more uncertain environment. In closely related research, Bonsall et al. (2020) provide

[7]The findings are based on random samples of 1,000 firms with low information shocks and 1,000 firms with high information shocks and two textual analysis variables that compare the differences in words and tone for each *WSJ* story with those of the related earnings announcement press release.

evidence that higher macroeconomic uncertainty leads journalists to increasingly produce news flash stories that disseminate key earnings information to the broad market, which can help investors quickly understand shocks to macroeconomic uncertainty. In addition, Bonsall et al. (2020) find that, due to the increase in news flashes and the lack of investor demand for idiosyncratic information, journalists move away from issuing full stories during times of high macroeconomic uncertainty. In contrast, our study provides evidence that when larger idiosyncratic shocks occur, journalists release more informative stories, consistent with journalists responding to greater investor demand for more firm-specific full news stories. Our additional tests provide further evidence that journalists' stories are more informative during such times.

Second, we extend the literature that investigates the equity market reaction to earnings releases by showing that the magnitude of the reaction can create a complementary relationship with an important information intermediary—business press journalists. This complementary relationship can lead to larger changes to abnormal return volatility and abnormal trading volume than otherwise would occur because of more informative journalist stories being released. Accordingly, the complementary relationship has implications for studies investigating why there is variation in earnings announcement reactions over time and across firms (e.g., Beaver et al., 2020) and for studies focused on the determinants of large market reactions to earnings releases (e.g., Skinner and Sloan, 2002).

Finally, we extend the literature on intermediaries—in our case, journalists—by showing that they are not static in their response to idiosyncratic information shocks. We provide evidence that larger shocks create demand for the release of more information by intermediaries. Our findings are consistent with journalists increasing story content to meet the increased demand. Other information intermediaries, such as financial analysts and credit analysts, may or may not face similar incentives and similar constraints. That is, the higher uncertainty from a large information shock could limit their ability to generate new information or, alternatively, access to private information could make their forecasts or ratings more relevant. We believe it would be interesting to explore how other information intermediaries respond to large idiosyncratic shocks.[8]

[8] Our paper provides a starting point for examining how financial analysts behave when there is a large firm-specific information shock, as we find in Table 2 that the number of financial analysts, $LFollow$, has a larger marginal effect when the size of the information shock is larger in magnitude. However, in other analyses where the results for $LFollow$ are not shown for brevity, this relationship does not hold. In particular, for analyses examining retail investor trading volume, we find that the marginal effect for $LFollow$ has a lower marginal effect with the size of the

2. Background and hypothesis development

2.1. Background

The primary objective of the media is to generate the greatest readership and advertising revenue conditional on the costs of producing stories (e.g., Veldkamp, 2006). Given this objective and the importance of earnings announcements, business media coverage tends to concentrate on the days surrounding earnings releases (Thompson et al., 1987; Tetlock et al., 2008; Drake et al., 2014). In addition, firms with higher demand for information receive higher abnormal press coverage at earnings announcements. For instance, Bushee et al. (2010) provide evidence of higher coverage for firms with a larger number of employees and Bonsall et al. (2020) provide evidence of higher coverage for firms with greater analyst coverage and institutional ownership. Also, firms that are more visible (e.g., larger firms) receive higher abnormal press coverage at earnings announcements (Soltes, 2011).

Shifts in the demand for information by market participants and in the supply of information available to the media at earnings announcements can change the information provided and dissemination of stories by journalists and, accordingly, change the information efficiency of financial markets and the capital market reactions to earnings releases. Regarding information asymmetry in financial markets, in early research, Bushee et al. (2010) and Soltes (2011) provide evidence that greater media coverage at earnings announcements reduces bid-ask spreads and increases depth. Later research provides further support for these findings (e.g., Blankespoor et al., 2018; Guest, 2021). In addition, prior research shows that greater media coverage of earnings announcements mitigates the mispricing of earnings announcements. Drake et al. (2014), for instance, find that the mispricing of cash flow information is reduced for firms that receive greater media coverage of their earnings releases. In addition, previous research provides evidence that greater media coverage decreases the amount of time required for financial markets to impound earnings information. Twedt (2015) finds that management earnings guidance is priced more quickly for firms with greater coverage. Bonsall et al. (2020) find similar evidence for the speed of incorporation of disclosed earnings surrounding earnings announcements.

information shock. There are likely potential reasons why this would occur; however, investigating them are beyond the scope of this paper and can be explored in future research.

Media coverage can also contribute to the magnitude of the capital market response to earnings announcements. Prior research by Bonsall et al. (2020) finds that the return volatility at earnings announcements grows with media coverage. Consistent with a causal link between media coverage and price volatility, relying on natural experiments in several countries, Peress (2014) finds that when media coverage drops due to national newspaper strikes, the dispersion of stock prices declines. In addition, other research (e.g., Soltes, 2011; Engelberg and Parsons, 2011; Blankespoor et al., 2018; Bonsall et al., 2020; Bushee et al., 2020) finds that trading volume at earnings announcements increases with media coverage and that trading volume generally increases for both institutional and retail traders. Together, the evidence on the effects of earnings announcement media coverage suggests that media coverage leads to greater investor informedness and attention-based trading.

2.2. Hypothesis development

Within the framework proposed by Veldkamp (2006), when the variance of firms' expected future payoffs grows, significant shifts in the demand for firm-specific information should follow. As modeled by Veldkamp (2006), because shocks to payoffs are assumed to be multiplicative and time varying, there is a changing demand for information from investors. Specifically, the payoff for the risky asset, u_{t+1}, is (firm-specific notation omitted for simplicity):

$$u_{t+1} = \theta_{t+1} + \varepsilon_{t+1}$$

where $\varepsilon_{t+1} \sim N\left(0, \sigma_{\varepsilon}^2\right)$. The persistent component of a firm's payoff $\theta_{t+1} = (1-\rho)\mu + \rho\theta_t(1+\eta_{t+1})$ follows an AR(1) process with mean μ and increasing and decreasing shocks $\eta_{t+1} \sim N\left(0, \sigma_{\eta}^2\right)$. The multiplicative nature of shocks to payoffs leads to changes in the variance of expected payoff innovations ($\sigma_{\theta t}$) that vary over time. When $\sigma_{\theta t}$ increases, the demand for firm-specific information increases as information about future payoffs becomes more valuable. The increased demand from investors provides journalists with incentives to produce detailed stories that contain more information content.[9]

[9] We rely on various strategies to infer that information shocks lead to journalists creating more informative stories that have a resulting larger impact on investor reactions. These empirical strategies described below include comparing full articles to news flash stories, comparing institutional and retail investor reactions to the stories, and comparing *WSJ* to non-*WSJ* stories.

The prediction that journalists produce more informative stories when large firm-specific shocks occur is in sharp contrast to how journalists are predicted to behave in the case of other shocks (e.g., macroeconomic shocks). Prior findings indicate that due to the common component in changes in the variance of expected payoffs for firms when macroeconomic uncertainty grows, the demand for news stories increases the most for articles that provide information that resolves macroeconomic uncertainty. As Bonsall et al. (2020) discuss, journalists indicate in interviews that higher macroeconomic uncertainty creates an increased demand for the dissemination of quick and simple stories that re-iterate key metrics in firms' earnings announcements. Consistent with this, Bonsall et al. (2020) predict and find that when macroeconomic uncertainty increases, the media move away from issuing full stories and toward releasing news flashes that quickly disseminate firms' earnings information to investors. In addition, Bonsall et al. (2020) find that macroeconomic uncertainty creates a greater demand for coverage of bellwether firms, whose earnings reveal more information about macroeconomic uncertainty.

Earnings announcements are a natural event to study information shocks. Prior research finds significant variation in investor reactions to earnings announcements and connects these reactions to information released at the announcement. For example, as Holthausen and Verrecchia (1990) demonstrate, larger abnormal price reactions arise due to improved investor informedness (i.e., the amount of information gained by investors through the release of information) and consensus (i.e., whether investors agree to a greater extent after the release of information). In addition, larger abnormal trading volume reactions can arise if there is greater investor disagreement.

Larger idiosyncratic information shocks at earnings announcements as opposed to smaller shocks at earnings announcements increase the variance of expected payoff innovations (i.e., $\sigma_{\theta t}$). The increase in the variance of expected payoff innovations leads to demand for news. The increase in investors' demand for information and journalists' response during idiosyncratic shocks is intuitive and matches anecdotal evidence of investor and journalist behavior. During a larger information shock, more investors read related news stories to understand the nature and implications of the shock. Consequently, journalists' observe investors' interest by anticipating investor response, by directly observing their reading behavior, or inferring interest from their trading activity. In response to the increased attention to news stories, journalists invest more time and resources in writing relevant stories during the shock. Journalists can respond to heightened demand by acquiring more costly information or meeting with managers, analysts, or firm experts and incorporating the information into a full article. Consequently, a journalist's story that further clarifies or expands on the information released during the earnings announcement will generate a greater market reaction. If full stories during such times lead to greater investor informedness (i.e., the amount of information gained by investors through the release of a story) and consensus (i.e., whether investors agree to a greater extent following the release of a story), then we predict that each journalist's story will have an even greater effect on abnormal price and abnormal volume reactions.[10]

Importantly, our prediction that journalists increase their production of information in their stories for larger firm-specific information shocks is distinct from the prediction that overall journalist coverage of larger information shocks leads to higher overall abnormal return volatility and abnormal trading volume. A larger number of stories may increase the total amount of information and dissemination conveyed by the media. However, our prediction is about the incremental information content of an additional news story.

In contrast to our prediction that journalists increase information production in response to investor demand, other changes in response to large idiosyncratic shocks may limit journalists from increasing information production for several reasons. First, if journalists write more news stories when there are larger information shocks, competition for providing informative stories should limit journalists' ability to create on a per story basis stories that are incrementally informative. Second, if the information shock creates uncertainty about a firm's future performance, the uncertainty may limit journalists' ability to find and generate useful information that may reduce such uncertainty. Third, the available supply of information other than that released during the earnings announcement by the firm or generated by journalists can change in response to the information shock. An increase in other information during an earnings announcement can crowd out opportunities for the production of information by journalists. Given these possibilities, journalists' stories can be less informative to market participants when there is a large idiosyncratic shock. Because of this, we may fail to find that journalists provide more informative stories at earnings announcements with larger idiosyncratic shocks or we may find opposite results.

Our primary hypothesis is about the incremental information produced by journalists during

[10] See Drake et al. (2014) for greater discussion of the distinction between full articles and less detailed news flash articles.

information shocks. Alternatively, the dissemination role of journalist stories can also systematically differ depending on the magnitude of information shocks at earnings announcements. Because larger market reactions discussed in journalist stories are greater attention-grabbing events, the reaction by investors, particularly retail investors, can lead journalist stories to have a greater impact on abnormal return volatility and abnormal trading volume at earnings announcements because more widely disseminated news may grab the attention of a larger set of retail investors. Accordingly, if the dissemination of the earnings release through a full article or news flash article leads to limited-attention investors (e.g., Hirshleifer et al., 2009) increasing their trading activities, particularly those buying shares in response to good news (e.g., Barber and Odean, 2008), the marginal effect of retail trading in response to a media story can increase with the magnitude of the information shock at the earnings announcement. Alternatively, if the media increase their dissemination of larger market reactions to earnings announcements by providing more stories that are followed by retail investors, then the marginal effect of retail trading volume in response to an individual journalist story will be muted.

An additional approach to testing whether journalists' stories are incrementally informative during information shocks because they produce more informative stories is by comparing changes in how different types of investors respond to the stories. Institutional investors are more likely to fully respond to information released at earnings announcements (e.g., Bartov et al., 2000; Bushee et al., 2020). In contrast, retail traders do not fully respond to information (e.g., Bartov et al., 2000; Bushee et al., 2020) or trade due to media dissemination (e.g., Blankespoor et al., 2018; Bonsall et al., 2020; Bushee et al., 2020). If retail traders respond more during information shocks, it could be because of increased information or because stories written during information shocks are more likely to grab their attention leading to greater abnormal trading volume even if the stories do not contain more information. Because of this, we expect that the marginal effect of abnormal trading volume in response to individual news stories when abnormal trading volume is higher will be greater for institutional investors when the stories are full articles. However, we may fail to find such evidence and could find opposing results as the possibility exists that the supply of information available to journalists is reduced and opportunities to create follow-up articles are more limited when there are large idiosyncratic shocks at earnings announcements.

If journalists at outlets that specialize in more detailed and in-depth coverage, such as the *WSJ*, respond to greater investor demand, then we predict that each story from such outlets will have an even greater effect on abnormal price and abnormal volume reactions. Other outlets, such as the *Yahoo Finance*, tend to add limited amounts of information (e.g., analyst forecasts) beyond reported earnings (see Guest, 2021, for a greater discussion) and, accordingly, are expected to have a relatively lower effect on abnormal price and abnormal volume reactions. Furthermore, since institutional investors are more likely to engage in information-based trades relative to retail investors, we expect that the greater effect on abnormal price and abnormal volume reactions for stories written by journalists at the *WSJ* will be more pronounced for institutional investors.

3. Sample and identification approach

3.1. Sample

Our sample selection process begins with all quarterly earnings announcements in Compustat for the 2007–2022 period, yielding 514,384 unique firm-quarter observations. After requiring the existence of a CRSP PERMNO at the time of an earnings announcement, our initial sample declines to 320,781 firm-quarter observations. We use media articles from the RavenPack Analytics Full Edition with a relevance score of 90 or higher as the basis for measuring media coverage over the trading days [0,+1] relative to an earnings announcement. Requiring non-missing measurements of our four dependent variables of interest reduces our sample by 19,716 firm-quarters. Requiring non-missing measurements for our control variables further reduces our sample by 171,896 observations. Of this reduction in usable observations, 141,218 firm-year observations relate to missing data for the number of employees and coverage by the Compustat Snapshot database for the measurement of non-missing financial statement items (Beaver et al., 2020). Our final sample for our quantile regression analyses is comprised of 129,169 firm-quarter observations covering 2007 through 2022 earnings announcements.

Table 1 provides summary statistics for the dependent variables, variables of interest, and controls. For the dependent variables, mean abnormal institutional trading volume is approximately two times higher than retail trading volume (i.e., $AbnLargeVol = 0.139$ and $AbnRetailVol = 0.076$). For the coverage variables, mean full article coverage is nearly two times higher than that for news flash articles (i.e., $LCoverage_{Full} = 72.057$ and $LCoverage_{Flash} = 36.971$). In addition, mean non-

WSJ coverage dramatically exceeds that for *WSJ* stories (i.e., $LCoverage_{NonWSJ} = 108.584$ and $LCoverage_{WSJ} = 0.521$). The control variable distributions are similar to those observed in prior research (e.g., Fang and Peress, 2009; Bushee et al., 2010; Drake et al., 2014; Hillert et al., 2014; Blankespoor et al., 2018; Drake et al., 2017; Bonsall et al., 2018; Beaver et al., 2020; Bonsall et al., 2020).

3.2. Identification approach

We investigate if journalists' production of information in stories increases with the magnitude of firm-specific shocks at earnings announcements using quantile regression (Koenker and Bassett Jr, 1978). As an illustration of the approach, consider the effects of a new drug for arthritis on patients. Individuals suffering the most may benefit the most from the new drug. Alternatively, individuals suffering the most may benefit the least, as the condition is too severe to respond to treatment. Quantile regression allows for the investigation of heterogeneous effects based on the level of the outcome variable: in this case, improvement in the patient.[11] Because quantile regression only changes the weights given to positive and negative residuals depending on the quantile or percentile examined, the approach does not lead to issues of non-random sample selection.

The possibility exists that the magnitude of market responses to earnings announcements leads to greater media coverage (i.e., reverse causality could occur). Consistent with this possibility, Allen and Schmidt (2020) and Sun (2023) show that the stock market reaction to events influences the media's decision to cover the event. Consistent with this, for our sample firms with abnormal return volatility or trading volume in the 90th percentile, news story counts average 102.07 and 159.70, respectively. For the same firms, when they are not in the 90th percentile, news story counts average 102.06 and 106.07, respectively. These univariate analyses provide some evidence that higher abnormal return volatility and trading volume leads to higher media coverage. Again, higher coverage for large firm-specific shocks should bias against finding that journalist stories are

[11] In an interesting application of quantile regression, Armstrong et al. (2015) examine heterogeneity in the relation between firms' tax avoidance and corporate governance and managers' equity incentives. The study finds that more sophisticated and independent boards have a negative relationship with tax avoidance for firms with the highest levels of tax avoidance but a positive relation for firms with the lowest levels of tax avoidance. This evidence is indicative of stronger boards playing an important role in limiting agency problems associated with tax aggressiveness. Other studies have used quantile regression in a variety of settings to investigate such issues as heterogeneity in union wage premiums (Chamberlain, 1994), the returns to education (Arias et al., 2002), determinants of house prices (Zietz et al., 2008), and Value-at-Risk estimates (Gaglianone et al., 2011).

more informative during large shocks, as journalists likely face greater constraints producing novel information when more journalists provide coverage.

Due to differences in coverage across the levels of market responses, we provide results using IV quantile regressions to mitigate the influence of reverse causality on our results.[12,13] The intent of the IV quantile regression analysis is to capture only firm variation in coverage that is exogenous to the magnitude of a firm's information shock and, thus, is unaffected by endogenous coverage changes attributable to a firm's information shock. Under this approach, similar to prior related research (e.g., Soltes, 2011; Drake et al., 2014; Bonsall et al., 2018; Guest, 2021), we use two instrumental variables (IVs): $AbnNBWSJ$ and $AbnIndPR$. We define $AbnNBWSJ$ as the abnormal proportion of stories appearing in *The Wall Street Journal* (*WSJ*) that relate to non-business news during a firm's earnings announcement window relative to the average during the fiscal year, scaled by the average during the fiscal year. The percentage of non-business news in *The Wall Street Journal* are RavenPack articles that are not about specific firms but instead cover other news such as macroeconomic events, currencies, or the weather. We define $AbnIndPR$ as the abnormal number of press releases issued by firms outside the three-digit SIC code of a firm during the earnings announcement period relative to average number during the fiscal quarter, scaled by the average number during the fiscal quarter.

We expect the two IVs to be relevant as on days when a higher quantity of other news is included in the *WSJ* or when firms issue more press releases it is more likely that coverage of a firm's earnings release will be crowded out. In addition, we expect the two IVs to be reliable instruments as the return volatility or abnormal trading volume for a particular firm should not be affected by how busy the media is with other news on particular trading days. We estimate the first stage of the IV analysis for $LCoverage$, our primary media coverage variable, using the instruments $AbnNBWSJ$ and $AbnIndPR$ and the other explanatory variables determining return volatility and trading volume. For later analyses that disaggregate $LCoverage$ into full stories ($LCoverage_{Full}$) and news flashes ($LCoverage_{Flash}$) and into *WSJ* stories ($LCoverage_{WSJ}$) and non-*WSJ* stories

[12]See Heckman and Vytlacil (2007) and Morgan and Winship (2015) for a discussion of how average causal effects, identified by local instrumental variables, are weighted average estimates of marginal treatment effects.

[13]The impact of potential endogeneity on our inferences is rather limited. In untabulated tests, when we alternatively use standard quantile regression without instruments, our inferences are unchanged, with the exception of the abnormal trading volume findings for news flash articles. In that analysis, we find significantly negative coefficients for $LCoverage_{Flash}$ in the 50th and 90th percentiles, which is likely attributable to failing to control for endogeneity.

($LCoverage_{NonWSJ}$), we separately instrument for each variable using $AbnNBWSJ$ and $AbnIndPR$ and the other explanatory variables. We estimate these models using the smoothed IV quantile regression approach of Kaplan (2022), which allows for multiple IVs.

Appendix B provides the results from the first stage of our IV approach. In the estimations for each of the coverage variables, the instruments $AbnNBWSJ$ and $AbnIndPR$ are both significantly negative, consistent with busy media days crowding out coverage of firms' earnings announcements. The results also suggest that the two instruments are strong instruments for the coverage variables (e.g., the weak instrument test for $LCoverage$ has an F-statistic of 36.47). For $LCoverage$, media coverage is significantly negatively related to $LOwn$ and $InstHold$, and significantly positively related to $AbsEarnSurp$, $NegSurp$, $LEmployee$, $LMktCap$, $LFollow$, $IVol$, $SP500Member$, $NasdaqTraded$, $Turnover$, $MomStrength$ $Guidance$, AF, and FS. These findings parallel those documented in other studies (e.g., Soltes, 2011; Drake et al., 2014; Bonsall et al., 2018; Guest, 2021). For $SP500Member$, the marginal effects are higher (in absolute value) for $LCoverage_{Full}$ than $LCoverage_{Flash}$ and for $LCoverage_{WSJ}$ than $LCoverage_{NonWSJ}$, suggesting that the demand effects for coverage of full stories and *WSJ* stories are relatively higher for firms that are more visible. In addition, firms with higher $Turnover$ face higher demand for full stories and for *WSJ* stories. In contrast, firms with more analyst coverage, institutional investor holdings, and more frequent management guidance face a higher demand for news flashes, and those with higher absolute earnings surprises, negative surprises, more employees, fewer owners, larger market capitalization, higher idiosyncratic volatility, more momentum, and more frequent releases of management guidance, analyst forecasts and financial statement items face a lower demand for *WSJ* stories than for non-*WSJ* stories. Similarly, firms with higher absolute earnings surprises, negative surprises, more employees, larger market capitalization, more analyst following, higher idiosyncratic volatility, NASDAQ traded shares, more momentum, and more frequent releases of management guidance, analyst forecasts, and financial statement items face a higher demand for full stories than for news flash stories.

4. Empirical design and findings

4.1. Journalist heterogeneity in information production: Evidence from return volatility and abnormal trading volume

Our first analysis investigates heterogeneity in journalists' production of information in stories depending on the magnitude of firm-specific information shocks using the absolute value of returns ($|AbnReturn|$) and abnormal trading volume ($AbnVol$) at earnings announcements as proxies for shocks and estimating the following IV quantile regression model:

$$\begin{array}{c} |AbnReturn_{it}| \\ or \\ AbnVol_{it} \end{array} = \alpha_0 + \alpha_1 LCoverage_{it} + \alpha_2 Controls + \varepsilon_{it} \tag{1}$$

Following Bonsall et al. (2020), we define $|AbnReturn|$ as the absolute value of the raw return minus the CRSP value-weighted index return during the earnings announcement period $[0, +1]$ and $AbnVol$ as the share turnover during the earnings announcement period $[0, +1]$ less the median two-day share turnover of consecutive two-day periods during the non-announcement period, which is comprised of all dates between five trading days subsequent to the release date of quarter $t-1$ earnings and five trading days prior to the release of quarter t earnings. $LCoverage$ is the natural logarithm of one plus the number of news articles with relevance scores greater than or equal to 90 captured by RavenPack on days $[0, +1]$ relative to the quarterly earnings announcement. We predict that journalists' production of information in stories will increase, as higher magnitude firm-specific shocks should increase investor demand for information that resolves uncertainty about the shock. Larger information shocks will have a greater effect on the market reaction at earnings announcements if journalists invest in stories with greater original content or if the coverage generates greater attention and trade by investors. On the other hand, if journalists are constrained by the limited supply of other information during larger information shocks at earnings releases or greater coverage by media and non-media sources occurs, we predict a lower marginal effect for a journalist's story during large market reactions. Our control variables include important determinants of return volatility and trading volume, as well as variables that could confound our inferences of the effect of the media on return volatility and trading volume, and follow those used in related research (e.g., Fang and Peress, 2009; Bushee et al., 2010; Drake et al., 2014; Hillert et al., 2014; Blankespoor et al., 2018; Drake et al., 2017; Bonsall et al., 2018; Beaver et al., 2020; Bonsall et al., 2020). These variables include (see Appendix A for complete descriptions) $AbsEarnSurp$, $NegSurp$, $LEmployee$, $LOwn$, BM, $LMktCap$, $LFollow$, $InstHold$, $IVol$, Ret, $SP500Member$, $NasdaqTraded$, $Turnover$, $MomStrength$, $Guidance$, AF, and FS.

Panel A of Table 2 graphs the IV quantile regression marginal effects from the return volatility analysis. The marginal effects are presented from the 10th percentile through the 90th percentile. The figure provides evidence that the market reaction to a journalist's story at earnings announcements is the lowest when $|AbnReturn|$ is at the lowest decile. At the 10th percentile, the quantile regression marginal effect is 0.000674. The figure also provides evidence that the market reaction to a journalist's story grows with the magnitude of abnormal returns at earnings announcements. Consistent with this, at the 90th percentile, the quantile regression marginal effect grows to 0.00958. These marginal effects imply that the market reaction to a journalist's story at earnings releases with the largest return volatility is more than 14 times larger than during earnings announcement periods with the smallest return volatility. In addition, the figure indicates the marginal effect of return volatility to a journalist's story becomes much larger in magnitude for return volatility over the 70th percentile.

The first three columns of Panel B of Table 2 present the full results from the IV quantile regressions examining the marginal effect of return volatility, $|AbnReturn|$, to a journalist's story for the 10th, 50th, and 90th percentiles. The marginal effects for the 10th, 50th, and 90th percentiles are 0.000674, 0.00354, and 0.00958. The estimates imply that an interquartile range increase in journalist articles results in a 2.28 percent, 11.95 percent, and 32.34 percent increase in return volatility, respectively.[14] Panel C of Table 2 provides formal tests of the differences in the IV quantile regression marginal effects. The marginal effect for the 50th percentile is statistically larger than that for the 10th percentile. In addition, the marginal effect for the 90th percentile is statistically larger than those for the 50th and 10th percentiles. Other important determinants of $|AbnReturn|$ include $AbsEarnSurp$, $NegSurp$, $LEmployee$, $LOwn$, BM, $LMktCap$, $LFollow$, $InstHold$, $IVol$, Ret, $SP500Member$, $NasdaqTraded$, $Turnover$, $MomStrength$, $Guidance$, AF, and FS.

[14]For the 25th percentile, the calculation of the increase is $[(0.000674 \times (ln(1 + ((1 + 120)/(1 + 36)))) /0.043]$.

We also investigate the marginal effect of abnormal trading volume, $AbnVol$, in response to a journalist's story at different quantiles of abnormal trading volume to earnings announcements. We plot the IV quantile regression marginal effects from the abnormal trading volume analysis in Panel A of Table 2. The marginal effects are positive, consistent with journalist stories increasing investor informedness—a finding similar to those of prior related research (e.g., Bonsall et al., 2020). Similar to the analysis for return volatility, the figure provides evidence that the marginal effect of abnormal trading volume in response to a journalist's story is larger when the information shock at earnings announcements is greatest. The quantile regression marginal effect at the 10th percentile is 0.000105, while at the 90th percentile it is 0.0159. The marginal effect at the 90th percentile is again dramatically larger: in this case, approximately 151 times larger. Also, the figure indicates the marginal effect of abnormal trading volume to a journalist's story similarly becomes much larger for abnormal trading volume when over the 60th percentile.

The last three columns in Panel B of Table 2 provide the full estimation results for the IV quantile regression marginal effects for the marginal effect of abnormal trading volume, $AbnVol$, to journalist stories. Panel A presents the marginal effects for the 10th, 50th, and 90th percentiles for the IV quantile regression estimations. The marginal effects using IV quantile regression approach are similar: 0.000105, 0.00499, and 0.0159, respectively. The estimates imply that an interquartile range increase in journalist articles results in a 0.54 percent, 25.87 percent, and 82.43 percent increase in abnormal trading volume, respectively. Panel C provides the results of formal tests of the differences in marginal effects. The 50th percentile marginal effect is significantly larger than the 10th percentile marginal effect. Also, the 90th percentile marginal effect is significantly larger than the 50th and 10th percentile marginal effects. Similar to the determinants of $|AbnReturn|$, variation in $AbsEarnSurp$, $NegSurp$, $LEmployee$, $LOwn$, BM, $LMktCap$, $LFollow$, $InstHold$, $IVol$, Ret, $SP500Member$, $NasdaqTraded$, $Turnover$, $MomStrength$, $Guidance$, AF, and FS. Further, significant directional differences exist across the 10th, 50th, and 90th percentiles for the IV quantile marginal effects for a large number of our control variables. However, the direction of the marginal effect differences across quantiles are not always the same across the $|AbnReturn|$ and $AbnVol$ IV quantile regressions—i.e., the direction differs for $AbsEarnSurp$, $NegSurp$, $LOwn$, $InstHold$, $IVol$, Ret, $Guidance$, and AF. That the conditional distribution of the response distributions is not constant for many of the control variables is not surprisingly, as the typical OLS regression assumption of a constant mean and variance for the response distribution is rarely met in practice (see Koenker and Hallock, 2001). Consistent with this, finding increasing or decreasing marginal effect differences across the 10th, 50th, and 90th percentiles for a large number of control variables is common in quantile regression estimations in other studies (e.g., Abadie, Angrist, and Imbens, 2002; Koenker and Hallock, 2001; Wooldridge, 2007). Further, as seen in the estimates, the smoothed instrumental variable quantile regression of Kaplan (2022) used in the paper, as well as other quantile regression approaches, (correctly) does not permit crossing of the quantile functions.

4.2. Are traders more sensitive to journalists' full stories at earnings announcements with larger information shocks?

We next conduct a more detailed examination into how the type of news story affects the marginal effect of the market reactions during earnings announcements to a journalist's story by separately investigating news flashes and full stories. Specifically, in place of $LCoverage$, we include $LCoverage_{Full}$ defined as the natural logarithm of one plus the number of full news stories with relevance scores greater than or equal to 90 captured by RavenPack on days $[0, +1]$ relative to the quarterly earnings announcement, and $LCoverage_{Flash}$, defined as the natural logarithm of one plus the number of news flashes with relevance scores greater than or equal to 90 captured by RavenPack on days $[0, +1]$ relative to the quarterly earnings announcement. If journalists respond to heightened investor demand resulting from larger information shocks, then full news stories should contain more price-relevant information. This will lead to an even larger marginal effect in response to journalist stories at earnings announcements with larger shocks—i.e., the marginal effect for $LCoverage_{Full}$ will be even higher at higher quantiles of information shocks. In addition, if journalist stories lead to greater attention-based trade when information shocks are larger, the marginal effect of the market reaction to journalist stories during earnings announcements will be higher for higher shocks, leading to the marginal effect for $LCoverage_{Flash}$ being larger at higher quantiles of abnormal return volatility and abnormal trading volume.

Panel A of Table 3 graphically shows the IV marginal effects for return volatility and abnormal return volume by type of story for each decile of the market reaction at the earnings announcement. As shown in the figure, while the marginal effect of return variability to both full and news flash stories is increasing with the quantile of return variability, the increase is much more pronounced for full news stories. The increase becomes dramatically more pronounced around the 70th percentile. For full stories, the marginal effect is 0.000730 at the 10th percentile and grows to 0.00869 at the 90th percentile. In contrast, for news flash stories, the marginal effect is 0.00161 and insignificant at the 10th percentile but grows only to 0.00368 at the 90th percentile. Consequently, at the highest levels of return variability, the marginal effect to full stories is over two times greater than that for news flashes. The results in Panel B confirm the evidence in the related figure that the marginal effect of return variability to full stories, $LCoverage_{Full}$, is larger at higher percentiles of $|AbnReturn|$ than to news flash stories, $LCoverage_{Flash}$. In addition, the results in Panel C provide evidence that the differences in marginal effects (i.e., 10th versus 50th, 50th versus 90th, and 10th versus 90th) are all significant for $LCoverage_{Full}$, but not for $LCoverage_{Flash}$, and that the difference between the 10th versus 90th percentile comparisons for $LCoverage_{Full}$ and $LCoverage_{Flash}$ are significant.

As shown in the second graph in Panel A, the marginal effect of abnormal trading volume to news stories is consistently higher for full stories; the rate of increase is much more pronounced for $LCoverage_{Full}$ as abnormal trading volume increases. Consistent with this, the marginal effects presented in Panel D for the 10th, 50th, and 90th percentiles for $LCoverage_{Full}$ are 0.000601, 0.00395, and 0.0113, respectively. In contrast, the marginal effects for the 10th, 50th, and 90th percentiles for $LCoverage_{Flash}$ are 0.00115, 0.00179, and 0.00320, respectively. With the exception of the coefficients for $LCoverage_{Full}$ at the 10th percentile and $LCoverage_{Flash}$ at the 90th percentile , the estimates are statistically significant. Panel E provides evidence that the differences in marginal effects (i.e., 10th versus 50th, 50th versus 90th, and 10th versus 90th) are all significant for both $LCoverage_{Full}$ but insignificant for $LCoverage_{Flash}$, and that the difference between the 10th versus 90th percentile comparisons for $LCoverage_{Full}$ and $LCoverage_{Flash}$ are significant. Overall, the evidence indicates that the marginal effect of return variability and abnormal trading volume to a journalist's story is larger for full stories. This evidence suggests that the larger marginal effect shown in Table 2 is attributable to articles containing more information and/or journalist created content.

4.3. Are institutional traders more sensitive to journalist stories at earnings announcements with larger information shocks?

We next provide evidence on whether journalist stories are more informative at earnings announcements with larger firm-specific information shocks by showing the marginal effects of institutional and retail trading volume to a journalist's story based on the level of information shock. We investigate this issue using the following model:

$$\begin{array}{c} AbnLargeVol_{it} \\ or \\ AbnRetailVol_{it} \end{array} = \beta_0 + \beta_1 LCoverage_{it} + \beta_2 Controls + \eta_{it} \quad (2)$$

Following Blankespoor et al. (2018) and Bonsall et al. (2020), $AbnLargeVol$ is the firm's daily average large trade percentage of shares traded during days [0, +2] relative to the earnings announcement, minus the equivalent amount over days [−41, −11], multiplied by 100. and $AbnRetailVol$ is the firm's daily average retail percentage of shares traded during days [0, +2] relative to the earnings announcement, minus the equivalent amount over days [−41, −11], multiplied by 100. We identify large and retail trades using the approach developed by Boehmer et al. (2021). The approach relies on the fact that brokers or wholesalers handle retail trades, and TAQ codes such trades with a "D" exchange code. Trades not identified as retail trades and greater than or equal to $50,000 in size are classified as non-retail trades, which are presumably trades by institutional investors. As Bushee et al. (2020) discuss, large trades should only reflect institutional investor activity. We refer to such trades as $AbnLargeVol$ to coincide with how the trades are measured.[15]

Our primary focus in Eq. (2) is on the marginal effect of $LCoverage$ across different quantiles of trading volume for institutional and retail investors, $AbnLargeVol$ and $AbnRetailVol$. If media coverage contributes more to informed trading by institutional investors when institutional investors

[15] Examining a large sample of retail trades Barber, Huang, Jorion, Odean, and Schwarz (2024) find that the Boehmer et al. (2021) approach commonly fails to identify retail trades when present. Accordingly, we caution that our classification of retail trades does not capture all retail trades. In addition, Battalio et al. (2023) finds similar evidence for retail trades but also finds that a significant number of institutional trades are classified as retail. Accordingly, similar to the inferences made by Blankespoor et al. (2018), a failure to find evidence of differences across our analyses investigating institutional and retail trading volume could be attributable to such missclassification problems; however, evidence of differences should not. Due to data unavailability, Barber et al. (2024) are unable investigate the degree to which institutional trades are also misclassified. In any event, following the arguments in Bushee et al. (2020), our $50,000 trade size cutoff for our institutional trade measure should eliminate the vast majority, if not all, retail trades from the sample.

trade more during earnings announcements, then we expect the marginal effect for $AbnLargeVol$ to be higher at higher quantiles of institutional investor trading at earnings announcements. Consistent with prior research (e.g., Blankespoor et al., 2018; Bushee et al., 2020; Bonsall et al., 2020), we presume that the marginal effect of trading on journalist stories for institutional investors is indicative of institutional trades reflecting changes in informedness and consensus, given that institutional investors are presumed not to suffer from limited attention issues (e.g., Bushee et al., 2020).

Furthermore, if media coverage of earnings announcements drives greater attention-based trading or informed trading for retail investors when earnings announcements generate greater retail trading, then we expect the marginal effect for $AbnRetailVol$ to be greater at higher quantiles of $AbnRetailVol$. For retail investors, it is difficult to separate attention-based trading from informed trading and from trading more when there are larger attention-grabbing events (i.e., the highest quantiles of idiosyncratic shocks).

Panel A of Table 4 provides the IV quantile regression marginal effects for both types of traders. As the graph illustrates, the marginal effect of institutional trading to a journalist's story is dramatically higher at higher levels of institutional trading. At the 10th percentile, the quantile regression marginal effect is 0.0102, which is much higher than that observed for retail trading. At the 90th percentile, the marginal effect is 0.0884, which is eight times higher than that for the 10th percentile but 10 percent lower than the 90th percentile coefficient for retail trading. Panel A also shows the marginal effects for retail traders. As the graph indicates, the marginal effect of retail trading to a journalist's story is also dramatically higher at higher levels of retail trading. At the 10th percentile, the IV quantile regression marginal effect is -0.000800. At the 90th percentile, the marginal effect increases dramatically to 0.1000. Both panels of the figure also show a sharp increase in the marginal effects near the 80th percentile.

For institutional trading volume, the first three columns of Panel B of Table 4 present the marginal effects of the IV quantile regression. Following the graphical evidence in Panel A, the marginal effects increase with higher levels of institutional trading; the 10th, 50th, and 90th percentile marginal effects are 0.0102, 0.0300, and 0.0884. In Panel C, the differences across the 10th versus 50th, 50th versus 90th, and 10th versus 90th percentiles are all significant. Taken together, the evidence is consistent with institutional investors responding more to journalist stories when idiosyncratic shocks are large, indicative of journalists' stories being more informative.

For retail trading volume, the last three columns of Panel B of Table 4 provide the IV quantile regression marginal effects. In general, consistent with the graph in Panel A, the slope coefficients increase with higher levels of retail trading. The marginal effects for the 10th, 50th, and 90th percentiles are -0.000800, 0.0256, and 0.1000, respectively, and accordingly are close to those for institutional trades across the different quantiles. In Panel C, the difference in marginal effects (i.e., 10th versus 10th, 50th versus 90th, and 10th versus 90th) are all significant. Overall, the evidence is consistent with retail traders responding to journalist stories more when idiosyncratic shocks are large, which may be due to greater information-based trading and/or attention-based trading during larger attention-grabbing events.

The two general types of news stories provide an opportunity to examine whether the observed differences in the marginal effects of institutional and retail trading volume to journalist stories across different levels of information shocks at earnings announcements are attributable to information-based trading or, alternatively, to attention-based trading. We explore these possibilities by including $LCoverage_{Full}$ and $LCoverage_{Flash}$ in Eq. (2) in place of $LCoverage$ as follows:

$$\begin{array}{c} AbnLargeVol_{it} \\ or \\ AbnRetailVol_{it} \end{array} = \gamma_0 + \gamma_1 LCoverage_{Full,it} + \gamma_2 LCoverage_{Flash,it} + \gamma_3 Controls + \zeta_{it} \quad (3)$$

If information-based trading is responsible for a higher marginal effect to media coverage for $AbnLargeVol$ and $AbnRetailVol$ when institutional and retail investor trading is higher at earnings announcements, then we expect a larger marginal effect for $LCoverage_{Full}$ than $LCoverage_{Flash}$ at higher quantiles of abnormal trading volume. If institutional investors are relatively more informationally efficient, we predict a higher coefficient for $LCoverage_{Full}$ relative to $LCoverage_{Flash}$ for institutional traders at higher quantiles of trading volume if detailed journalist stories provide more information to the market when there are larger information shocks at earnings announcements. If retail investors are more attention-based and full articles and news flashes grap their attention, then we should observe less of a difference for $LCoverage_{Full}$ relative to $LCoverage_{Flash}$ at higher quantiles of trading volume.

As graphically depicted in Panel A of Table 5, the higher marginal effect of institutional investors is largely attributable to full stories. The marginal effect for institutional investor trades is not statistically different from zero for all quantiles of news flashes, suggesting that institutional trade occurs primarily with the release of substantive new information. This finding is indicative of higher marginal effects for institutional investors to larger shocks being concentrated in stories with more detailed and in-depth coverage rather than simply responding to the dissemination of information. In contrast, as also graphically depicted in Panel A of Table 5, the marginal effect of retail trading to journalists' stories increases with retail trading. More importantly, the evidence in the figure indicates that the marginal effect of retail trading to full articles is very similar to that in response to news flashes with the exception of the highest quantiles where full articles have a higher marginal effect.[16] This evidence suggests that the larger marginal effect for retail traders is largely (but not fully) driven by the dissemination of the earnings release rather than by the release of new information.

The results in Panel B of Table 5 provide the formal IV quantile regression results. For $AbnLargeVol$, the 10th, 50th, and 90th percentiles for $LCoverage_{Flash}$ are 0.00356, 0.000986, and -0.00656, respectively, and for $LCoverage_{Full}$ are 0.0106, 0.0261, and 0.0716, respectively. For $AbnRetailVol$, the 10th, 50th, and 90th percentiles for $LCoverage_{Flash}$ are 0.00238 , 0.0147, and 0.0492, respectively. For $AbnRetailVol$, the 10th, 50th, and 90th percentiles for $LCoverage_{Full}$ are -0.00201, 0.0183, and 0.0753, respectively. With one important exception, the results in Panel C indicate that the differences in marginal effects (i.e., 10th versus 50th, 50th versus 90th, and 10th versus 90th) are all significant for both $LCoverage_{Full}$ and $LCoverage_{Flash}$ for retail traders and institutional investors, and that the differences across the 10th versus 90th percentiles for $LCoverage_{Full}$ and $LCoverage_{Flash}$ are significant across both types of news articles. The exception is the insignificant coefficient estimates for $LCoverage_{Flash}$ for institutional investors in Panel B and the insignificant differences between quantiles for institutional investors. Again, similar marginal effects, with the exception of the highest quantiles, for news flashes and full articles for retail investors suggest that they are primarily responding to the dissemination of news, and the much larger marginal effect for full articles for institutional investors indicate that they are responding more to informative full news articles.

[16]The increase in the marginal affect for full articles may be attributable to retail investors seeking out full stories when there are greater attention-grabbing events.

4.4. *Are institutional investors more sensitive to WSJ articles at earnings announcements with larger information shocks?*

In our final analysis, similar to our analysis of news articles and full articles, we examine more closely how the differential marginal effect of abnormal trading volume for institutional and retail traders to news stories at higher volume reactions differs across *WSJ* news stories and those by the non-*WSJ*. We modify Eq. (1) to include separate explanatory variables for *WSJ* and non-*WSJ* articles:

$$\begin{array}{c} AbnLargeVol_{it} \\ or \\ AbnRetailVol_{it} \end{array} = \delta_0 + \delta_1 LCoverage_{WSJ,it} + \delta_2 LCoverage_{NonWSJ,it} + \delta_3 Controls + \nu_{it} \quad (4)$$

where $LCoverage_{WSJ}$ is the natural logarithm of one plus the number of articles published in the *WSJ* with relevance scores greater than or equal to 90 captured by RavenPack on days $[0, +1]$ relative to the quarterly earnings announcement and $LCoverage_{NonWSJ}$ is the natural logarithm of one plus the number of articles not published in the *WSJ* with relevance scores greater than or equal to 90 captured by RavenPack on days $[0, +1]$ relative to the quarterly earnings announcement. As articles by *WSJ* journalists are typically more detailed and contain a greater amount of journalist content, we predict that the coefficient for $LCoverage_{WSJ}$ will be higher than that for $LCoverage_{NonWSJ}$ at higher quantiles of $AbnLargeVol$ and $AbnRetailVol$.

We investigate differences in marginal effects for the same dependent variables used in our analysis of news flashes and full articles: $AbnLargeVol$ and $AbnRetailVol$. Our focus is the differential behavior of institutional trade for $LCoverage_{WSJ}$ relative to non-*WSJ* articles. Specifically, we expect the marginal effect for $LCoverage_{WSJ}$ to be relatively higher at higher quantiles of $AbnLargeVol$ than for non-*WSJ* articles, if institutional investors find *WSJ* articles more informative when there are larger information shocks, as institutional investors' trades should be relatively more information-based. The behavior of retail trade for $LCoverage_{WSJ}$ relative to non-*WSJ* articles is more difficult to predict. That is, we expect the marginal effect for $LCoverage_{WSJ}$ and $LCoverage_{NonWSJ}$ to be relatively higher at higher quantiles of $AbnRetailVol$, if retail investors find *WSJ* and non-*WSJ* articles more attention grabbing when there are larger idiosyncratic shocks reported by the articles. Because non-*WSJ* articles, however, may contain less incremental information (e.g., *Seeking Alpha* stories), they may be more likely to lead to greater retail trade when there are larger idiosyncratic shocks. Alternatively, given the prominence and visibility of *WSJ* articles, they may also attract retail investor attention leading to greater retail trade when there are larger idiosyncratic shocks.

The first figure in Panel A of Table 6 provides evidence of the marginal effect being higher for trading by institutional investors to *WSJ* articles at higher quantiles than for non-WSJ articles, especially past the 50th percentile. Similarly to the analysis of full articles and news flashes, the evidence is consistent with institutional investors responding to more informative news stories.

The second figure provides evidence of the marginal effect of retail trading to non-*WSJ* articles and *WSJ* articles across different quantiles of retail trade. The evidence indicates that the marginal effect of retail trading to *WSJ* articles at higher quantiles is noticeably lower than that for non-WSJ articles, especially in higher quantiles. This evidence is in sharp contrast to the trading behavior of institutional investors and may be attributable to retail investors paying greater attention to the information disseminated by news outlets that specifically target retail investors.

We present the IV quantile regression marginal effects in Panel B of Table 6. As shown in columns (1)–(3), for $AbnLargeVol$, the 10th, 50th, and 90th percentiles for $LCoverage_{NonWSJ}$ are 0.0109, 0.0244, and 0.0638, respectively, and for $LCoverage_{WSJ}$ are 0.0131, 0.047, and 0.149, respectively. In contrast, as shown in columns (4)–(6), for $AbnRetailVol$, the 10th, 50th, and 90th percentiles for $LCoverage_{NonWSJ}$ are -0.00110, 0.0240, and 0.0948, respectively, and for $LCoverage_{WSJ}$ are 0.00319, 0.0140, and 0.0446, respectively. In Panel C, the marginal effect differences are all significant for both $LCoverage_{NonWSJ}$ and $LCoverage_{WSJ}$ for both retail traders and institutional investors. In addition, the differences across the 10th and 90th percentiles for $LCoverage_{NonWSJ}$ and $LCoverage_{WSJ}$ are significant.

Taken together, the findings suggest that the higher marginal effect of trading volume to journalist articles is in part attributable to more informative *WSJ* articles. This conclusion is based primarily on evidence from institutional traders. The evidence for retail traders could be attributable non-*WSJ* articles leading to more attention-based trade because of the greater focus of these outlets on attracting retail trader attention.

The possibility exists that our results could spuriously arise if journalists produce the same news content for stories at the 10th and 90th percentiles of $|AbnReturn|$ or $AbnVol$, but institutional investors make use of the news stories differently—e.g., investors only increase their consumption at the 90th percentile due to the greater attention from the information shock. However, this possibility requires journalists and/or investors to behave irrationally, which seems unlikely. That is, why would journalists continuously produce the same level of information if they do not expect to benefit from providing the same story at the 10th percentile as the 90th percentile, as the information is not demanded? In addition, if the same information is produced by journalists at the 10th percentile, why would investors, especially sophisticated investors, continuously ignore it?

In any event, similar to the approach in Guest (2021), we investigate this possibility more directly using articles from the *WSJ* to investigate whether higher information shocks lead journalists to create more information in their articles. The stories of the *WSJ* are our focus, as opposed to those of other media outlets, since the *WSJ* is known for its high level of editorial content. Using textual analysis, we compare each *WSJ* news story to the related firm's press release for differences in content, with greater differences being consistent with journalists creating more information. Consistent with this interpretation, Guest (2021) provides evidence that the differences in textual analysis reflect differences in information creation. Specifically, the study finds evidence that the highest quantile $Word\,Diff$ articles, compared to the lowest quantile articles, are more readable, make more specific reference to entities, have more industry and economic content, have less stale news, and have more investor and expert quotes. For tractability, we construct textual analysis measures for a random sample of 1,000 firms with low shocks (i.e., 10th percentile of return variability) and compare them against a random sample of 1,000 firms with high shocks (i.e., 90th percentile of return variability).[17] The first textual analysis variable is $Word\,Diff$, which is the Jaccard (1901) similarity score between the press release text and the article text, multiplied by -1 to capture dissimilarity and then residualized with respect to the length of both the journalist's article and the press release. The second variable is $Tone\,Diff$, which is the absolute value of the difference in the percentage of negative words in the journalist's article and the press release.[18]

[17]We use return variability, rather than trading volume, as our measure of the idiosyncratic shock as it reflects the market's overall assessment of the information released.

[18]We appreciate Nick Guest providing detailed information regarding the construction of the $Word\,Diff$ and $Tone\,Diff$ variables in Guest (2021).

Panel A of Table 7 shows graphically the differences between journalist stories from low shock earnings announcements and those from high shock announcements for both $Word\,Diff$ and $Tone\,Diff$. As can be seen, *WSJ* journalists create more information for firms with large return volatility at earnings announcements. The differences across the 10th and 90th percentiles are quite stark. Panel B provides the descriptive statistics for both variables. For $Word\,Diff$, the mean and median are zero or near zero because we residualize the variable with respect to the length of the press release and journal article.[19] The interquartile range is fairly wide, ranging from -0.0277 to 0.0318. For $Tone\,Diff$, the interquartile range is also fairly wide, ranging from 0.3904 to 1.5237, relative to a mean of 1.0621 and a median of 0.8443. Panel C provides formal tests of the differences between journalist stories from low-shock earnings announcements and those from high-shock announcements. The differences for both $Word\,Diff$ and $Tone\,Diff$ are statistically significant ($p < 0.001$). Taken together, our evidence provides more refined evidence that journalists create more news content in their stories for firms experiencing greater idiosyncratic information shocks.

5. Conclusion

We investigate whether journalists produce more informative stories when large idiosyncratic information shocks occur at firms' earnings announcements. We predict that journalists will produce more informative stories when large idiosyncratic shocks occur due to investors demanding greater information to reduce the increased uncertainty caused by the shock. Following Veldkamp (2006), idiosyncratic information shocks lead to greater uncertainty as information shocks have a multiplicative effect on the persistent component of a firm's expected future payoffs. This prediction is distinct from how journalists are found to behave when other types of shocks occur—e.g., macroeconomic shocks which lead to greater demand for and dissemination of all firms' earnings information through more timely news flash stories, which crowd out the demand for detailed firm-specific full stories.

Consistent with our predictions, we find that the marginal effect of abnormal price variance and

[19] Our descriptives for $Word\,Diff$ do not align with those reported in Table 5 of Guest (2021). It appears that the numbers reported in Guest (2021) are not residualized. When we use our raw numbers for $Word\,Diff$, we find that our distribution is similar to that in Table 5 of Guest (2021).

abnormal trading volume to a journalist story at earnings announcements is considerably greater at earnings announcements with larger idiosyncratic information shocks (i.e., larger abnormal price variance and abnormal trading volume). In addition, we find that full articles, which contain greater detail and journalist-provided content, explain a much larger percentage of the larger marginal effect to earnings announcements with larger market reactions than news flashes. This evidence suggests that journalists producing more informative stories are responsible for our findings. We further support this inference by showing important differences in the marginal effect of trading to the release of a journalist story between institutional traders, whose trades are much more informationally efficient, and retail traders. We find that the larger marginal effects of news stories on trading volume when information shocks are higher are similar for institutional trading volume and retail trading volume. When separately investigating full articles and news flashes, however, we find that the marginal effects for institutional trade is much larger for full articles than for news flashes, for which the marginal effect is insignificant. We find that the marginal effects for retail trade is similar for full stories and news flashes over most quantiles, consistent with institutional investors reacting to the greater information content of a journalist's full articles and retail investors responding to the dissemination and attention-grabbing nature of larger idiosyncratic shocks. We further support the inference of journalists providing more informative stories by showing that *WSJ* articles, which typically contain more original content and synthesis from journalists, represent a much larger proportion of the larger marginal effect for institutional trading volume to larger earnings announcement information shocks than stories from other news outlets. We find, for *WSJ* articles compared to other news outlet articles, that the larger marginal effect to larger information shocks is larger for both retail traders and institutional traders, but that the larger marginal effect is more pronounced for institutional traders, again consistent with more informationally efficient traders reacting more to journalists' stories when idiosyncratic shocks become larger. To more directly confirm that journalists produce greater news content for stories during higher idiosyncratic information shocks at earnings announcements, we conduct textual analysis for word and tone differences between each *WSJ* story and the related earnings announcement press release using random samples of 1,000 firms with low information shocks and 1,000 firms with high information shocks. We find that *WSJ* journalists create more new information in their stories for firms with larger idiosyncratic information shocks.

These findings add to the accounting literature in several ways. Specifically, our evidence indicates that larger idiosyncratic information shocks lead to greater information production by journalists, consistent with journalists responding to greater investor demand for firm-specific information. This finding is in sharp contrast to prior evidence that macroeconomic shocks lead to greater demand for news flashes, which contain basic information about firms' earnings announcements but provide more timely earnings information to the market, consistent with increased demand for news flashes from investors trying to learn about the macroeconomy through other firms' earnings. Furthermore, our evidence suggests that journalists can have a more complementary relationship with financial markets when there is a large idiosyncratic information shock that moves prices or leads to elevated trading volume. In addition, our evidence suggests that information intermediaries can dramatically change their behavior when there are large idiosyncratic shocks at earnings announcements. Whether and how other information intermediaries (e.g., credit and financial analysts) respond to large shocks would be interesting to examine, given that they have different incentives and access to information.

Appendix A

The variables for each empirical analysis are described in detail below.

Variable	Description
Dependent variables	
$\lvert AbnReturn \rvert$	The absolute value of raw return minus the CRSP value-weighted index return during the earnings announcement period $[0, +1]$
$AbnVol$	The share turnover during the earnings announcement period $[0, +1]$ less the median two-day share turnover of consecutive two-day periods during the non-announcement period, which is comprised of all dates between five trading days subsequent to the release date of quarter $t-1$ earnings and five trading days prior to the release of quarter t earnings
$AbnRetailVol$	The firm's daily average retail percentage of shares traded during days [0, +2] relative to the earnings announcement, minus the equivalent amount over days [−41, −11], multiplied by 100 (from Blankespoor et al., 2018)
$AbnLargeVol$	The firm's daily average non-retail (trade size greater than or equal to $50,000) percentage of shares traded during days [0, +2] relative to the earnings announcement, minus the equivalent amount over days [−41, −11], multiplied by 100 (from Blankespoor et al., 2018)
Variables of interest	
$LCoverage$	The natural logarithm of one plus the number of news articles with relevance scores greater than or equal to 90 captured by RavenPack on days $[0, +1]$ at the quarterly earnings announcement
$LCoverage_{Full}$	The natural logarithm of one plus the number of full news stories with relevance scores greater than or equal to 90 captured by RavenPack on days $[0, +1]$ at the quarterly earnings announcement
$LCoverage_{Flash}$	The natural logarithm of one plus the number of news flashes with relevance scores greater than or equal to 90 captured by RavenPack on days $[0, +1]$ at the quarterly earnings announcement
$LCoverage_{WSJ}$	The natural logarithm of one plus the number of *Wall Street Journal* news stories with relevance scores greater than or equal to 90 captured by RavenPack on days $[0, +1]$ at the quarterly earnings announcement

Continued on next page

Appendix A continued

Variable	Description
$LCoverage_{NonWSJ}$	The natural logarithm of one plus the number of non-*Wall Street Journal* news stories with relevance scores greater than or equal to 90 captured by RavenPack on days $[0, +1]$ at the quarterly earnings announcement
Control variables	
$AbsEarnSurp$	The absolute value of the seasonally adjusted change in earnings before extraordinary items scaled by market capitalization at the beginning of the fiscal quarter
$NegSurp$	An indicator variable equal to one if the seasonally adjusted change in earnings before extraordinary items is negative and zero otherwise
$LEmployee$	The natural logarithm of the number of employees
$LOwn$	The natural logarithm of the number of shareholders
BM	Book value of stockholders' equity divided by market capitalization
$LMktCap$	The natural logarithm of market value of equity
$LFollow$	The natural logarithm of one plus the number of equity analysts following the firm during the most recent fiscal quarter
$InstHold$	Percentage of shares held by institutional investors
$IVol$	Annualized standard deviation of weekly residual returns based on the following model from Bandarchuk and Hilscher (2013): $r_{it} = a_i + b_i r_{mt} + \gamma_i r_{It} + e_{it}$
Ret	Buy-and-hold equity return during the previous twelve months
$SP500Member$	Indicator variable set equal to one if a firm is a member of the S&P 500 market index and zero otherwise
$NasdaqTraded$	Indicator variable set equal to one if a firm's common shares trade on the NASDAQ and zero otherwise
$Turnover$	Average share volume divided by shares outstanding using daily stock market data over the last six months
$MomStrength$	Absolute value of the difference between the firm's stock return over the previous six months and the median stock return over the same period (Bandarchuk and Hilscher, 2013)
$Guidance$	Indicator variable set equal to one if a firm issues management guidance during an earnings announcement
AF	Indicator variable set equal to one if an analyst issues guidance during an earnings announcement
FS	The percentage of total financial statement items disclosed with an earnings announcement

Appendix B: First-stage instrumental variables models

	(1)	(2)	(3)	(4)	(5)
	$LCoverage$	$LCoverage_{Full}$	$LCoverage_{Flash}$	$LCoverage_{WSJ}$	$LCoverage_{NonWSJ}$
$AbnNBWSJ$	-7.2283***	-10.8308***	-3.8052***	-3.1651***	-7.3498***
	(-4.95)	(-5.03)	(-3.25)	(-6.44)	(-4.97)
$AbnIndPR$	-0.0615***	-0.1091***	-0.0632***	-0.0653***	-0.0599***
	(-3.00)	(-3.17)	(-4.21)	(-7.84)	(-2.89)
$AbsEarnSurp$	0.1864**	0.1371	0.1088**	-0.0070	0.1870**
	(2.37)	(0.72)	(2.00)	(-0.23)	(2.37)
$NegSurp$	0.0296***	0.0454***	0.0083	0.0048	0.0296***
	(3.26)	(2.81)	(1.41)	(0.79)	(3.25)
$LEmployee$	0.0637***	0.0747***	0.0418***	0.0409***	0.0631***
	(8.91)	(8.76)	(7.35)	(9.25)	(8.82)
$LOwn$	-0.0308***	-0.0485***	-0.0175***	0.0171***	-0.0312***
	(-6.76)	(-7.21)	(-5.56)	(6.61)	(-6.84)
BM	0.0008	-0.0120	-0.0139	0.0087	0.0015
	(0.03)	(-0.37)	(-0.70)	(1.02)	(0.06)
$LMktCap$	0.2638***	0.4030***	0.0891***	0.0285***	0.2643***
	(12.02)	(12.79)	(7.44)	(3.51)	(12.00)
$LFollow$	0.1231***	-0.0449	0.2938***	0.0299***	0.1224***
	(4.37)	(-1.15)	(16.27)	(3.10)	(4.33)
$InstHold$	-0.0880*	-0.2538***	0.1046***	-0.1481***	-0.0889*
	(-1.76)	(-3.60)	(3.14)	(-6.03)	(-1.78)
$IVol$	0.3988***	0.2739	0.2507***	0.1062***	0.3998***
	(3.20)	(1.32)	(3.58)	(2.89)	(3.19)
Ret	-0.0605	-0.1317*	-0.0028	-0.0199	-0.0602
	(-1.42)	(-1.71)	(-0.15)	(-1.57)	(-1.40)
$S\&P500Member$	0.1160***	0.2432***	-0.0380	0.2227***	0.1133***
	(3.23)	(5.18)	(-1.66)	(7.88)	(3.16)
$NasdaqTraded$	0.1136***	0.1295***	0.0482***	0.0361***	0.1137***
	(6.30)	(5.94)	(3.48)	(3.11)	(6.32)
$Turnover$	5.9125***	17.4368***	-3.1793***	6.6575***	5.7511***
	(4.87)	(9.47)	(-3.49)	(7.75)	(4.72)
$MomStrength$	0.0650***	0.1143***	0.0365***	-0.0007	0.0649***
	(2.74)	(2.76)	(2.66)	(-0.08)	(2.72)
$Guidance$	0.1606***	0.1026***	0.2069***	-0.0194**	0.1609***
	(9.73)	(4.77)	(15.77)	(-2.30)	(9.75)
AF	0.1405***	0.1774***	0.1302***	-0.0071	0.1412***
	(8.49)	(9.02)	(7.35)	(-1.11)	(8.42)
FS	0.0030***	0.0042***	0.0020***	-0.0006***	0.0031***
	(7.22)	(8.33)	(5.85)	(-2.80)	(7.25)
Constant	1.6480***	0.3415	1.7491***	-0.1061*	1.6414***
	(9.96)	(1.40)	(16.35)	(-1.90)	(9.82)
Weak Instrument F	36.47***	35.43***	37.09***	35.74***	35.98***
Observations	129,169	129,169	129,169	129,169	129,169
Adjusted R^2	0.511	0.510	0.439	0.213	0.510

Appendix B reports the results from the estimation of the first stage model for our instrumental variables models. The dependent variables include the following: $LCoverage$, the natural logarithm of one plus the number of media articles written about a firm during days 0 through +1 relative to its earnings announcement date, $LCoverage_{Full}$, the natural logarithm of one plus the number of full articles written about a firm during days 0 through +1 relative to its earnings announcement date, $LCoverage_{Flash}$, the natural logarithm of one plus the number of news flashes written about a firm during days 0 through +1 relative to its earnings announcement date, $LCoverage_{WSJ}$, the natural logarithm of one plus the number of *Wall Street Journal* articles written about a firm during days 0 through +1 relative to its earnings announcement date, and $LCoverage_{NonWSJ}$, the natural logarithm of one plus the number of non-*Wall Street Journal* articles written about a firm during days 0 through $+1$ relative to its earnings announcement date. The instruments are $AbnNBWSJ$ and $AbnIndPR$. $AbnNBWSJ$ is defined as the abnormal proportion of stories appearing in *The Wall Street Journal* that relate to non-business news during a firm's earnings announcement window relative to the aver during the fiscal year, scaled by the average during the fiscal year. $AbnIndPR$ is the abnormal number of press releases issued by firms outside the three-digit SIC code of a firm during the earnings announcement period relative to average number during the fiscal quarter, scaled by the average number during the fiscal quarter. All control variables are defined in the Appendix. ***, **, and * denote statistical significance based on a two-sided test at the 0.01, 0.05, and 0.10 levels, respectively.

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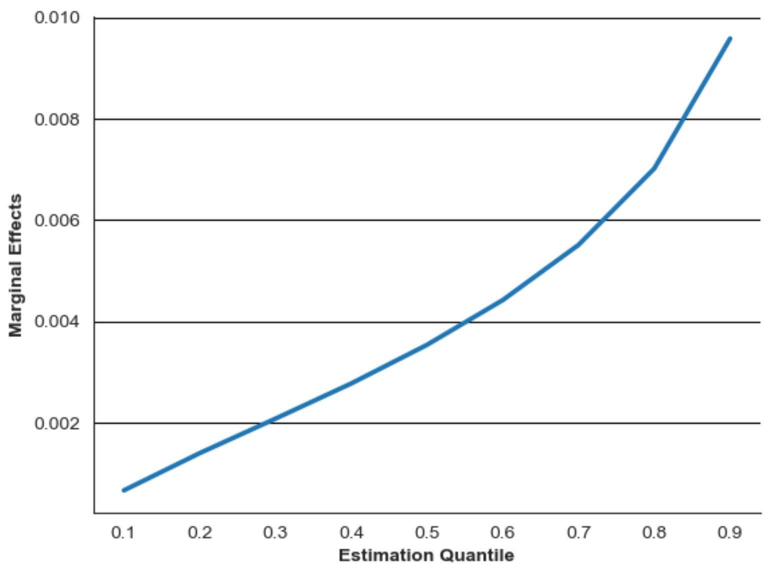
Table 1
Descriptive statistics

	Mean	Std. Dev.	Q1	Median	Q3
Dependent variables:					
$\lvert AbnReturn \rvert$	0.043	0.037	0.018	0.032	0.057
$AbnVol$	0.028	0.044	0.003	0.013	0.033
$AbnRetailVol$	0.076	0.185	0.004	0.021	0.069
$AbnLargeVol$	0.139	0.306	-0.005	0.036	0.164
Variables of interest:					
$Coverage$	109.198	142.027	36.000	67.000	120.000
$Coverage_{Full}$	72.057	124.871	12.000	31.000	73.000
$Coverage_{Flash}$	36.971	23.107	21.000	34.000	49.000
$Coverage_{WSJ}$	0.521	1.907	0.000	0.000	0.000
$Coverage_{NonWSJ}$	108.584	140.772	36.000	67.000	120.000
Control variables:					
$AbsEarnSurp$	0.004	0.067	-0.007	0.001	0.008
$NegSurp$	0.451	0.498	0.000	0.000	1.000
$LEmployee$	0.836	2.029	-0.580	0.956	2.257
$LOwn$	0.008	2.377	-1.833	-0.165	1.740
BM	0.553	0.516	0.233	0.439	0.738
$LMktCap$	7.021	2.053	5.596	7.040	8.386
$LFollow$	2.091	0.892	1.609	2.197	2.773
$InstHold$	0.676	0.296	0.501	0.772	0.912
$IVol$	0.376	0.232	0.212	0.318	0.472
Ret	0.122	0.534	-0.198	0.062	0.329
$S\&P500Member$	0.193	0.394	0.000	0.000	0.000
$NasdaqTraded$	0.517	0.500	0.000	1.000	1.000
$Turnover$	0.010	0.009	0.005	0.008	0.012
$MomStrength$	0.280	0.362	0.070	0.163	0.337
$Guidance$	0.586	0.493	0.000	1.000	1.000
AF	0.620	0.485	0.000	1.000	1.000
FS	56.724	23.991	40.260	51.948	81.818

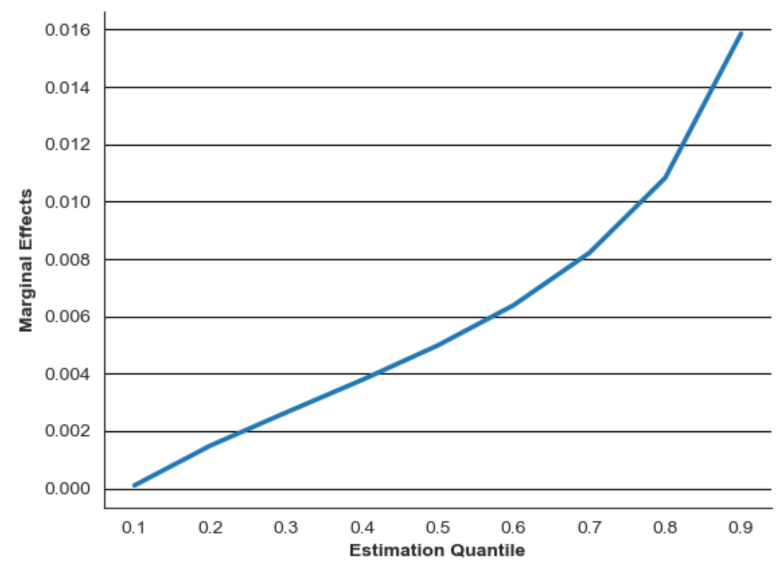
Table 1 reports descriptives statistics for the variables used in our IV quantile regression analyses. We define all variables in the Appendix.

Table 2
IV quantile regressions for return variability, $|AbnReturn|$, and abnormal trading volume, $AbnVol$

Panel A: Marginal effect of a journalist story on return variability and abnormal trading volume by quantile



Return variability



Abnormal trading volume

Panel B: IV quantile regression marginal effects

		$\|AbnReturn\|$			$AbnVol$	
	10th percentile	50th percentile	90th percentile	10th percentile	50th percentile	90th percentile
$LCoverage$	0.000674***	0.00354***	0.00958***	0.000105	0.00499***	0.0159***
	(3.06)	(11.13)	(12.02)	(0.41)	(12.87)	(13.61)
$AbsEarnSurp$	-0.00302**	-0.00769***	-0.0175***	0.00300*	0.00667***	0.0148**
	(-2.08)	(-4.52)	(-3.76)	(1.76)	(3.17)	(2.32)

	$\lvert AbnReturn \rvert$			$AbnVol$		
	10th percentile	50th percentile	90th percentile	10th percentile	50th percentile	90th percentile
$NegSurp$	-0.000172	-0.000301	-0.000571	-0.000420***	-0.000757***	-0.00151***
	(-1.10)	(-1.64)	(-1.18)	(-2.62)	(-4.32)	(-2.72)
$LEmployee$	0.000542***	0.00117***	0.00249***	0.00143***	0.00208***	0.00353***
	(7.68)	(11.41)	(9.56)	(12.51)	(11.00)	(7.44)
$LOwn$	-0.0000671	-0.000260***	-0.000665***	-0.000131**	-0.000173	-0.000268
	(-1.57)	(-3.64)	(-3.85)	(-2.22)	(-1.60)	(-0.97)
BM	0.000380*	0.000291	0.000103	-0.00169***	-0.00421***	-0.00983***
	(1.72)	(0.99)	(0.15)	(-5.31)	(-10.97)	(-10.86)
$LMktCap$	-0.000990***	-0.00361***	-0.00912***	-0.00144***	-0.00500***	-0.0129***
	(-8.69)	(-21.45)	(-20.37)	(-6.73)	(-17.50)	(-19.15)
$LFollow$	0.000857***	0.00127***	0.00215***	0.00335***	0.00340***	0.00351***
	(5.29)	(6.28)	(4.16)	(12.78)	(11.34)	(4.96)
$InstHold$	0.00178***	0.00297***	0.00547***	0.00411***	0.00532***	0.00803***
	(5.21)	(6.00)	(4.10)	(8.51)	(8.47)	(5.06)
$IVol$	0.0119***	0.0299***	0.0676***	-0.0144***	-0.0146***	-0.0149***
	(15.97)	(35.73)	(31.33)	(-14.55)	(-13.76)	(-5.56)
Ret	-0.00113***	-0.00261***	-0.00573***	0.00164***	0.00272***	0.00511***
	(-5.67)	(-11.87)	(-11.62)	(6.56)	(9.44)	(6.62)
$S\&P500Member$	-0.000688***	-0.00235***	-0.00584***	-0.00210***	-0.00465***	-0.0103***
	(-2.65)	(-6.21)	(-6.44)	(-3.72)	(-6.93)	(-6.77)
$NasdaqTraded$	0.000326*	0.00140***	0.00366***	0.000812***	0.00148***	0.00295**
	(1.68)	(5.06)	(5.31)	(2.74)	(2.97)	(2.45)
$Turnover$	0.0948***	0.194***	0.404***	0.229***	1.670***	4.882***
	(6.60)	(12.01)	(10.25)	(5.32)	(27.68)	(39.97)
$MomStrength$	0.00318***	0.00760***	0.0169***	-0.00245***	0.00155***	0.0105***
	(8.30)	(17.41)	(17.24)	(-6.70)	(3.26)	(7.55)
$Guidance$	0.00155***	0.00191***	0.00267***	0.00296***	0.00230***	0.000820
	(8.46)	(7.25)	(4.28)	(12.39)	(7.98)	(0.96)
AF	0.000877***	0.000171	-0.00131*	0.00116***	0.00224***	0.00464***
	(4.13)	(0.62)	(-1.90)	(5.23)	(6.63)	(4.73)
FS	0.0000217***	0.0000640***	0.000153***	0.0000363***	0.0000525***	0.0000888***
	(6.95)	(12.56)	(11.73)	(7.34)	(6.71)	(4.31)

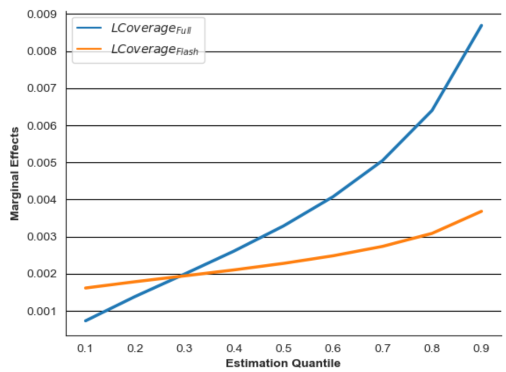
	$\|AbnReturn\|$			$AbnVol$		
	10th percentile	50th percentile	90th percentile	10th percentile	50th percentile	90th percentile
Constant	0.00299***	0.0197***	0.0550***	-0.00144	0.00633***	0.0237***
	(4.05)	(20.79)	(20.07)	(-1.20)	(3.62)	(5.56)
Observations	129,169			129,169		

Panel C: IV quantile regression marginal effect comparisons

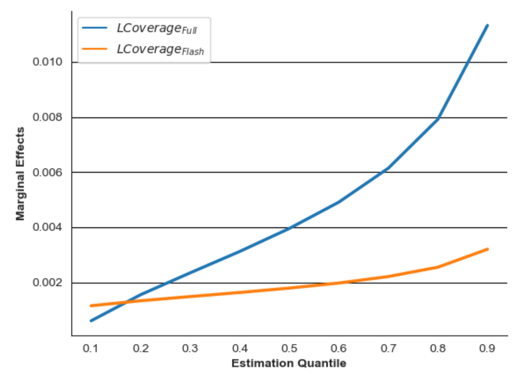
	$\|AbnReturn\|$			$AbnVol$		
	10th vs 50th	50th vs 90th	10th vs 90th	10th vs 50th	50th vs 90th	10th vs 90th
$LCoverage$	-0.00287***	-0.00604***	-0.00891***	-0.00488***	-0.0109***	-0.0158***
	(-11.33)	(-11.26)	(-11.29)	(-13.22)	(-12.95)	(-13.06)

Panel A of this table presents graphically the marginal effects of journalist coverage, $LCoverage$, on return variability, $|AbnReturn|$, and abnormal trading volume, $AbnVol$, for different quantiles of return variability and abnormal trading volume at earnings announcements based on IV quantile regression models estimated following Kaplan (2022). Using IV quantile regression, Panel B of this table provides evidence of how the marginal effects of $LCoverage$ on both return volatility ($|AbnReturn|$) and abnormal trading volume ($AbnVol$) differ across different levels of return volatility and abnormal trading volume. Panel C of the table presents formal tests of the differences in the quantile regression marginal effects. Appendix A provides the variable descriptions for the control variables. Appendix B presents the results of the first-stage estimation of instrumental variables model. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively. Reported z-statistics are based on bootstrapped standard error clustered by firm and calendar quarter using 100 bootstrap replications.

Table 3
IV quantile regressions for return variability, $|AbnReturn|$, and abnormal trading volume, $AbnVol$, by story type
Panel A: Marginal effect of a journalist story on return variability and abnormal trading volume by quantile, by story type



Return variability



Abnormal trading volume

Panel B: IV quantile regression marginal effects for return variability

		$\|AbnReturn\|$	
	10th percentile	50th percentile	90th percentile
$LCoverage_{Full}$	0.000730**	0.00329***	0.00869***
	(2.10)	(7.74)	(6.74)
$LCoverage_{Flash}$	0.00161**	0.00228***	0.00368*
	(2.25)	(3.11)	(1.79)
Controls	Yes	Yes	Yes
Intercept	Yes	Yes	Yes
Observations	129,169		

Panel C: IV quantile regression marginal effect comparisons for return variability

		$\|AbnReturn\|$	
	10th vs 50th	50th vs 90th	10th vs 90th
$LCoverage_{Full}$	-0.00256***	-0.00540***	-0.00796***
	(-5.62)	(-5.62)	(-5.62)
$LCoverage_{Flash}$	-0.000664	-0.00140	-0.00207
	(-0.89)	(-0.89)	(-0.89)
Difference			-0.0059**
			(-2.17)

Panel D: IV quantile regression marginal effects for abnormal trading volume

		$AbnVol$	
	10th percentile	50th percentile	90th percentile
$LCoverage_{Full}$	0.000601	0.00395***	0.0113***
	(1.62)	(9.37)	(8.60)
$LCoverage_{Flash}$	0.00115*	0.00179**	0.00320
	(1.79)	(2.11)	(1.28)
Controls	Yes	Yes	Yes
Intercept	Yes	Yes	Yes
Observations	129,169		

Panel E: IV quantile regression marginal effect comparisons for abnormal trading volume

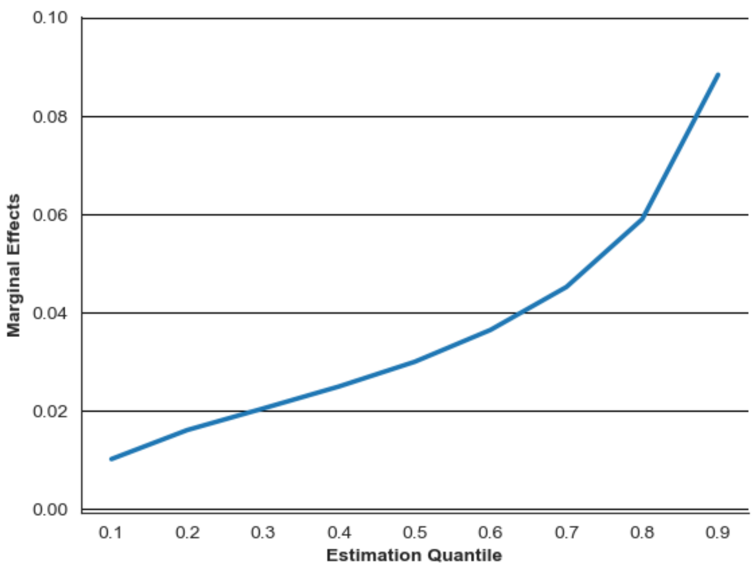
		$AbnVol$	
	10th vs 50th	50th vs 90th	10th vs 90th
$LCoverage_{Full}$	-0.00335***	-0.00737***	-0.0107***
	(-7.40)	(-7.31)	(-7.35)
$LCoverage_{Flash}$	-0.000641	-0.00141	-0.00205
	(-0.77)	(-0.77)	(-0.77)
Difference			-0.0087***
			(-2.87)

This table presents analyses of the marginal effect of a journal story on return variability and abnormal trading volume across news story type. Panel A presents graphically the marginal effects of full and news flash coverage, $LCoverage_{Full}$ and $LCoverage_{Flash}$, on return variability, $|AbnReturn|$, and abnormal trading volume, $AbnVol$, for different quantiles of return variability and abnormal trading volume at earnings announcements based on IV quantile regression models estimated following Kaplan (2022). Using IV quantile regression, Panel B of this table provides evidence of how the marginal effects of $LCoverage_{Full}$ and $LCoverage_{Flash}$ on $|AbnReturn|$ differ across different levels of $|AbnReturn|$. Panel C provides statistical comparisons of the marginal effects of each type of news story on $|AbnReturn|$ across different quantiles of $|AbnReturn|$. Using IV quantile regression, Panel D of this table provides evidence of how the marginal effects of $LCoverage_{Full}$ and $LCoverage_{Flash}$ on $AbnVol$ differ across different levels of of $AbnVol$. Panel E provides statistical comparisons of the marginal effect of each type of news story on $AbnVol$ across different quantiles of $AbnVol$. Appendix A provides the variable descriptions for the control variables. Appendix B presents the results of the first-stage denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively. Reported z-statistics are based on bootstrapped standard error clustered by firm and calendar quarter using 100 bootstrap replications.

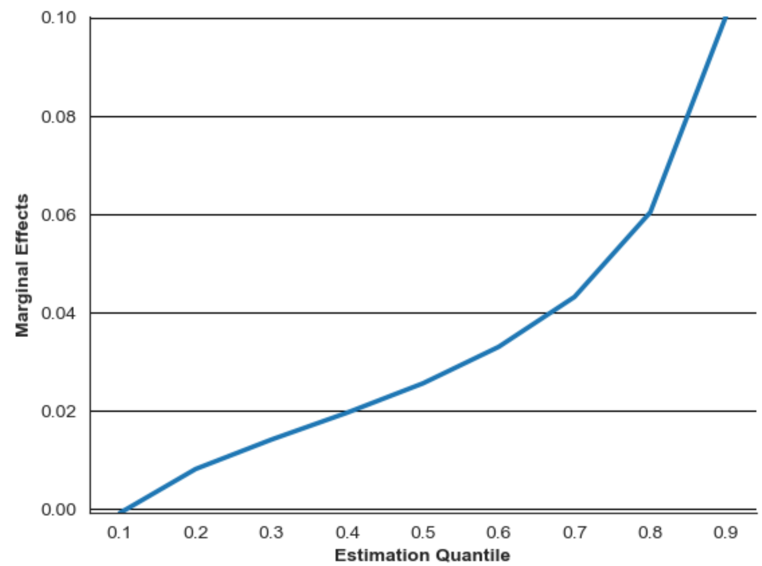
Table 4

IV quantile regressions for abnormal large trading volume, $AbnRetailVol$, and abnormal retail trading volume, $AbnLargeVol$

Panel A: Marginal effect of a journal story on large and retail trading volume by quantile



Large trade



Retail trade

Panel B: IV quantile regression marginal effects

		$AbnLargeVol$			$AbnRetailVol$	
	10th percentile	50th percentile	90th percentile	10th percentile	50th percentile	90th percentile
$LCoverage$	0.0102***	0.0300***	0.0884***	-0.000800	0.0256***	0.1000***
	(6.00)	(12.55)	(10.57)	(-0.62)	(15.81)	(18.37)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,169			129,169		

Panel C: IV quantile regression marginal effect comparisons

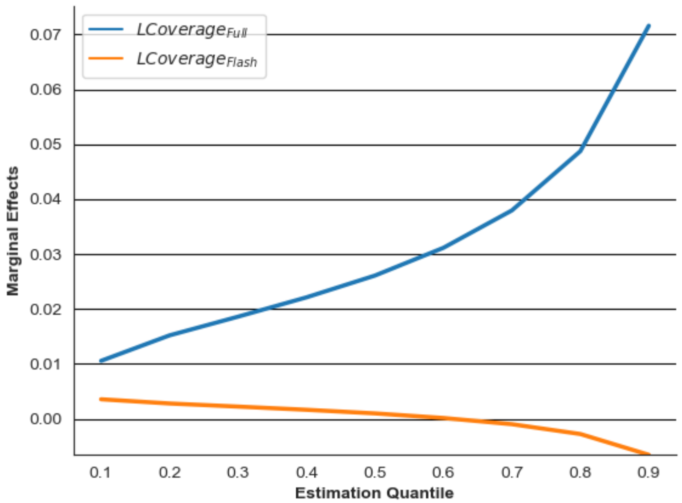
	AbnLargeVol			*AbnRetailVol*		
	10th vs 50th	50th vs 90th	10th vs 90th	10th vs 50th	50th vs 90th	10th vs 90th
LCoverage	-0.0198***	-0.0584***	-0.0782***	-0.0264***	-0.0748***	-0.1010***
	(-9.18)	(-8.97)	(-9.03)	(-19.88)	(-17.64)	(-18.33)

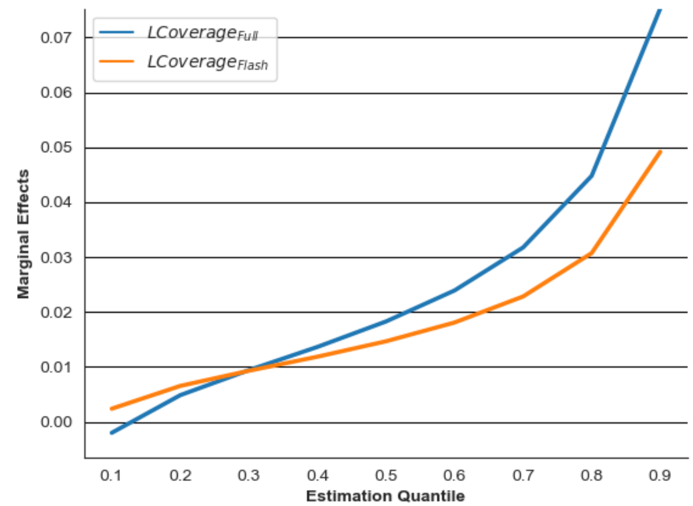
Panel A presents graphically the marginal effects of journalist coverage, *LCoverage*, on abnormal large trading volume, *AbnLargeVol*, and retail trading volume, *AbnRetailVol*, for different quantiles of non-retail and retail abnormal retail trading volume at earnings announcements based on IV quantile regression models estimated following Kaplan (2022). In Panel B, the first (last) three columns provide evidence of how the marginal effect of *LCoverage* on *AbnLargeVol* (*AbnRetailVol*) differs across different levels of *AbnLargeVol* (*AbnRetailVol*). Tests of the differences in the quantile regression marginal effects are presented in Panel C. *LCoverage* is the natural logarithm of one plus the number of news articles with relevance scores greater than or equal to 90 captured by RavenPack on days [0, +1] at the quarterly earnings announcement. *AbnLargeVol* is the firm's daily average non-retail (trade size greater than or equal to $50,000) percentage of shares traded during days [0, +2] relative to the earnings announcement, minus the equivalent amount over days [−41, −11], multiplied by 100 (from Blankespoor et al., 2018). *AbnRetailVol* is firm's daily average retail percentage of shares traded during days [0, +2] relative to the earnings announcement, minus the equivalent amount over days [−41, −11], multiplied by 100 (from Blankespoor et al., 2018). Appendix A provides the variable descriptions for the control variables. Appendix B presents the results of the first-stage estimation of instrumental variables model. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively. Reported z-statistics are based on bootstrapped standard errors clustered by firm and calendar quarter using 100 bootstrap replications.

Table 5

IV quantile regressions for abnormal large trading volume, $AbnRetailVol$, and retail trading volume, $AbnLargeVol$, by story type

Panel A: Marginal effects of full and news flash stories on abnormal large and retail trading by quantile





Large trade **Retail trade**

Panel B: IV quantile regression marginal effects

		$AbnLargeVol$			$AbnRetailVol$	
	10th percentile	50th percentile	90th percentile	10th percentile	50th percentile	90th percentile
$LCoverage_{Full}$	0.0106***	0.0261***	0.0716***	-0.00201	0.0183***	0.0753***
	(3.75)	(8.32)	(6.82)	(-1.33)	(12.26)	(10.71)
$LCoverage_{Flash}$	0.00356	0.000986	-0.00656	0.00238	0.0147***	0.0492***
	(0.81)	(0.20)	(-0.33)	(0.88)	(5.43)	(4.84)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,169			129,169		

Panel C: IV quantile regression marginal effect comparisons

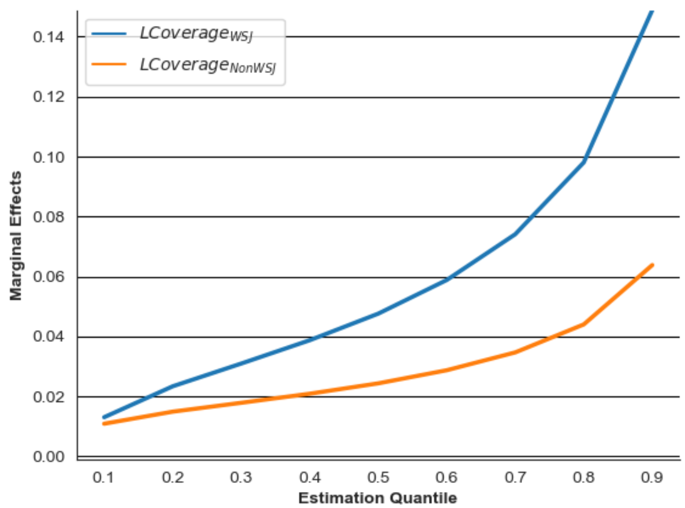
		AbnLargeVol			*AbnRetailVol*	
	10th vs 50th	50th vs 90th	10th vs 90th	10th vs 50th	50th vs 90th	10th vs 90th
$LCoverage_{Full}$	-0.0155***	-0.0455***	-0.0610***	-0.0203***	-0.0570***	-0.0773***
	(-5.44)	(-5.39)	(-5.41)	(-10.17)	(-9.65)	(-9.81)
$LCoverage_{Flash}$	0.00257	0.00754	0.0101	-0.0123***	-0.0345***	-0.0468***
	(0.46)	(0.46)	(0.46)	(-4.10)	(-4.11)	(-4.11)
Difference			-0.0712***			-0.0305**
			(-2.88)			(-2.20)

This table presents analyses of the marginal effects of different news story types on abnormal large and retail trading volume. Panel A present graphically the marginal effects of full and news flash coverage, $LCoverage_{Full}$ and $LCoverage_{Flash}$, on abnormal large trading volume, $AbnLargeVol$, and abnormal retail trading volume, $AbnRetailVol$, for different quantiles of abnormal retail and non-retail trading volume at earnings announcements based on IV quantile regression models estimated following Kaplan (2022). Using IV quantile regression, the first (last) three columns of Panel B provide evidence of how the marginal effects of $LCoverage_{Full}$ and $LCoverage_{Flash}$ on $AbnLargeVol$ ($AbnRetailVol$) differ across different levels of $AbnLargeVol$ ($AbnRetailVol$). Tests of the differences in the quantile regression marginal effects are presented in Panel C. Appendix A provides the variable descriptions for the control variables. Appendix B presents the results of the first-stage estimation of instrumental variables model. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively. Reported z-statistics are based on bootstrapped standard errors clustered by firm and calendar quarter using 100 bootstrap replications.

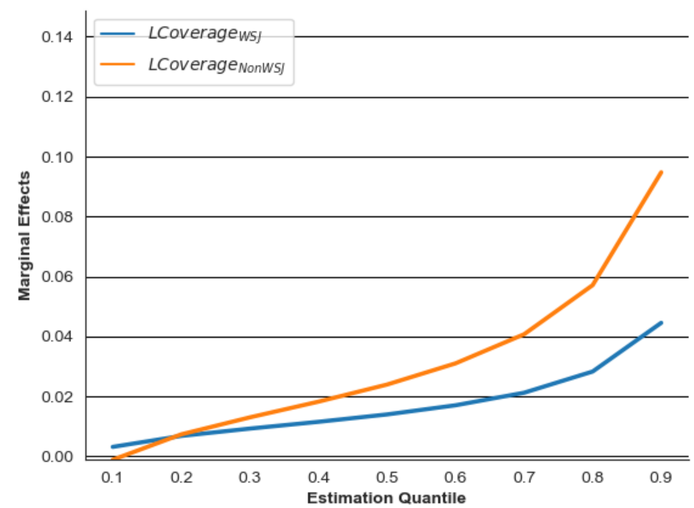
Table 6

IV quantile regressions for abnormal large trading volume, $AbnRetailVol$, and abnormal retail trading volume, $AbnLargeVol$, by journalist stories not written by and those written by *The Wall Street Journal*

Panel A: Marginal effect of a journalist story on abnormal large and retail trading volume by quantile, by news source



Large trade



Retail trade

Panel B: IV quantile regression marginal effects

		$AbnLargeVol$			$AbnRetailVol$	
	10th percentile	50th percentile	90th percentile	10th percentile	50th percentile	90th percentile
$LCoverage_{WSJ}$	0.0131***	0.0476***	0.149***	0.00319	0.0140***	0.0446***
	(3.66)	(8.34)	(7.47)	(1.28)	(5.33)	(4.26)
$LCoverage_{NonWSJ}$	0.0109***	0.0244***	0.0638***	-0.00110	0.0240***	0.0948***
	(6.61)	(9.99)	(7.67)	(-0.71)	(13.90)	(16.95)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,169			129,169		

Panel C: IV quantile regression marginal effect comparisons

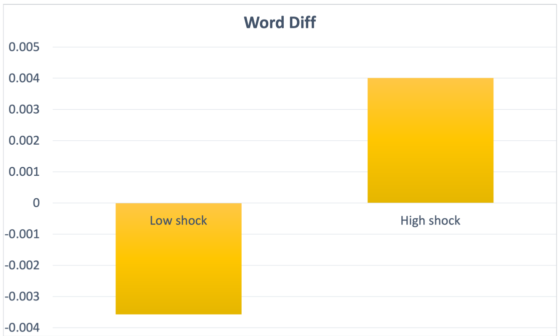
		$AbnLargeVol$			$AbnRetailVol$	
	10th vs 50th	50th vs 90th	10th vs 90th	10th vs 50th	50th vs 90th	10th vs 90th
$LCoverage_{WSJ}$	-0.0345***	-0.101***	-0.136***	-0.0108***	-0.0306***	-0.0414***
	(-6.68)	(-6.68)	(-6.68)	(-3.56)	(-3.54)	(-3.55)
$LCoverage_{NonWSJ}$	-0.0135***	-0.0395***	-0.0529***	-0.0251***	-0.0708***	-0.0959***
	(-6.19)	(-6.21)	(-6.21)	(-17.46)	(-16.14)	(-16.60)
Difference			-0.0829***			0.0545***
			(-3.76)			(4.19)

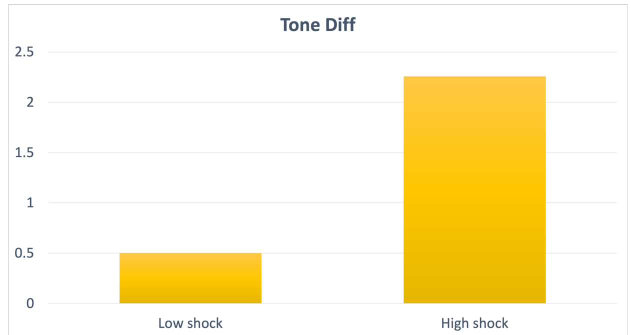
This table presents analyses of the marginal effects of stories from different news sources on abnormal large and retail trading volume. Panel A presents graphically the marginal effects of WSJ and non-WSJ coverage, $LCoverage_{WSJ}$ and $LCoverage_{NonWSJ}$, on abnormal large trading volume, $AbnRetailVol$, and abnormal retail trading volume, $AbnLargeVol$, for different quantiles of abnormal retail trading volume and abnormal large trading volume at earnings announcements based on IV quantile regression models estimated following Kaplan (2022). Using IV quantile regression, the first (last) three columns of Panel B provide evidence of how the marginal effects of $LCoverage_{WSJ}$ and $LCoverage_{NonWSJ}$ on $AbnLargeVol$ ($AbnRetailVol$) differ across different levels of $AbnLargeVol$ ($AbnRetailVol$). Tests of the differences in the quantile regression marginal effects are presented in Panel C. Appendix A provides the variable descriptions for the control variables. Appendix B presents the results of the first-stage estimation of instrumental variables model. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively. Reported z-statistics are based on bootstrapped standard errors clustered by firm and calendar quarter using 100 bootstrap replications.

Table 7

Wall Street Journal word, $Word\ Diff$, and tone, $Tone\ Diff$, content difference of stories written for a random sample of 1,000 firms in the 10th percentile and 1,000 firms in the 90th perecentile of return variability

Panel A: *Wall Street Journal* word and tone content mean differences





Panel B: Descriptive statistics

	Mean	Std. Dev.	Q1	Median	Q3
$Word\ Diff$	0.0000	0.0440	-0.0277	0.0044	0.0318
$Tone\ Diff$	1.0621	0.8635	0.3904	0.8443	1.5237

Panel C: *Wall Street Journal* word and tone content difference in stories written for firms with low and high shocks

	10th (Low shock)	90th (High shock)	Difference ($F - statistic$)
Word Diff	**-0.0035736***** **(-2.92)**	**0.0040075***** **(3.17)**	**18.52*****
Tone Diff	**0.5012468***** **(12.75)**	**2.258021***** **(43.78)**	**946.33*****

This table presents evidence of whether journalists at *The Wall Street Journal* create different levels of information in their stories for firms' experiencing high versus low idiosyncratic information shocks at their earnings announcements. Following Guest (2021), we use textual analysis to compare *WSJ* articles against the firm's press release for differences in unique word and tone content of the stories. We use two variables: $WordDiff$, which is the Jaccard (1901) similarity score between the press release text and the article text, multiplied by -1 to capture dissimilarity and then residualized with respect to the length of both journalist's article and the press release and $ToneDiff$, which is the absolute value of the difference in the percentage of negative words in the journalist's article and the press release. For tractability, we collect information for a 1,000 random earnings announcements for firms with a low shock (10th percentile) and a 1,000 random earnings announcements for firms with a high shock (90th percentile) . Information shocks are measured using return variability, as it captures the market's overall reaction to the information release. Panel A presents graphically the mean differences in $WordDiff$ and $ToneDiff$ across firms with low and high idiosyncratic information shocks. Panel B provides descriptive statistics for $WordDiff$ and $ToneDiff$. Panel C provides formal tests for the difference in means in $WordDiff$ and $ToneDiff$ across firms with low and high idiosyncratic information shocks. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.