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Front-Page News: The Effect of News Positioning on Financial Markets

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ABSTRACT

This paper estimates the effect of news positioning on the speed of price discovery, using exogenous variation in prominent ("front-page") positioning of news articles on the Bloomberg terminal. Front-page articles see 240% higher trading volume and 176% larger absolute excess returns during the first 10 minutes after publication than equally important non-front-page articles. Overall, the information in front-page articles is fully incorporated into prices within an hour of publication. The response to non-front-page information of similar importance eventually converges but takes more than two days to be fully reflected in prices.

TO WHAT EXTENT DOES THE way information is delivered by the media influence the price discovery process? In classic efficient markets, presentation and positioning of news by the media should have no effect, with information efficiently reflected in prices regardless of presentation. However, a growing body of evidence suggests that the media may play a role in how financial information is disseminated, impacting market efficiency and contributing to

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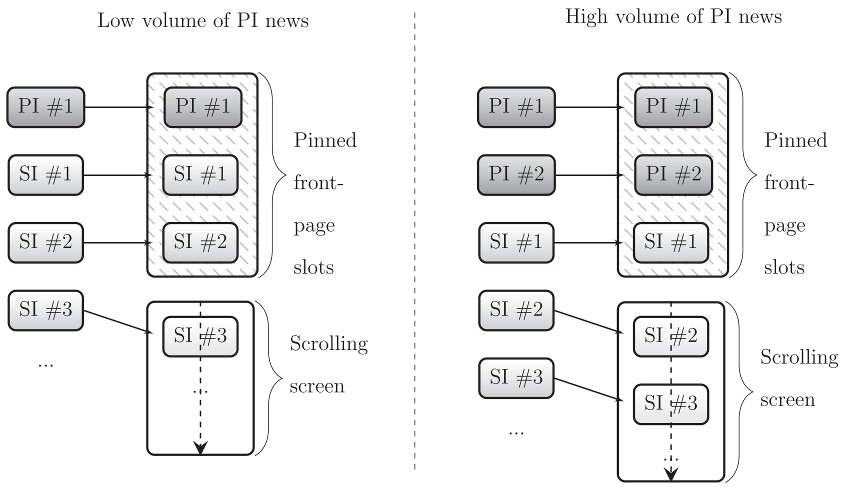

Figure 1. Illustration of how Bloomberg news articles are pinned to prominent front-page positions at the top of the news screen.

excess volatility, bubbles, and return over- and underreactions.[1] Yet cleanly identifying the causal impact of news delivery by the financial media poses an empirical challenge: news outlets are more likely to give prominence to more important events.

In this paper, I identify the causal impact of news positioning on the speed of market price discovery in the context of the Bloomberg terminal, one of the most widely used professional financial news services. I compare front-page articles with similarly important non-front-page articles by taking advantage of a space constraint on the Bloomberg terminal news screen, which has three highlighted ("front-page") slots. Because of the limited number of front-page slots, most news items are not pinned to these slots but instead appear on a scrolling screen below. To allocate front-page slots, Bloomberg designates a small subset of news articles as "primary important" (PI) and "secondary important" (SI). PI articles are always positioned on the front page. Whether a particular SI article is positioned on the front page depends on the exogenous variation in the volume of contemporaneous PI articles. I identify the causal impact of news positioning by comparing market reactions to SI articles that are pinned to the front page against market reactions to SI articles that do not make it to the front page. Given that Bloomberg marks all SI articles as equally important, this empirical design allows me to control for news importance and focus on the effect of news positioning.

Figure 1 illustrates this identification strategy. Both sides of the figure depict three slots available to pin news articles to the front page, where these articles

[1] See Busse and Green (2002), Dyck and Zingales (2003), Chan (2003), Barber and Odean (2008), Fang and Peress (2009), Ahern and Sosyura (2014), Hillert, Jacobs, and Müller (2014), Peress (2014), and Boulland, Degeorge, and Ginglinger (2017), among others.

can remain for some time. All other news articles appear on a scrolling screen below these prominent slots and scroll off the page in a matter of seconds. The number of SI articles that receive front-page slots at any point in time depends on the number of recent PI articles, which receive priority for those slots. On the left side of the figure, one PI article is pinned, leaving space for two SI articles to be displayed on the front page; on the right side, two PI articles are pinned, leaving space for only one SI article—whichever happens to be published next. Since the content of SI news is not related to whether there are front-page slots left over from contemporaneous PI news (which I confirm to be the case in several additional tests), the comparison between front-page and non-front-page SI news forms the basis for my causal analysis.

I hand-collect all PI and SI news articles (and their positions) about individual U.S. equity securities published between March 2014 and December 2015. As a benchmark against which to evaluate the effects of news positioning, I consider how the market reacts to PI news versus front-page SI news (two sets of news articles that have the same positions but differ in importance). Within the first 10 minutes, PI news articles prompt 35 basis points (bps) larger absolute excess returns (corresponding to a relative increase of 56%) and 0.11% greater share turnover (also a relative increase of 56%) than front-page SI news articles. There are no additional differences after the first 10 minutes, and the differential response to PI news remains economically similar and statistically significant even 10 days later. This evidence of a differential market response to actual news importance provides useful context against which to compare the effect of positioning.

The main analysis focuses on differences in market reactions to front-page versus non-front-page SI news. The principal finding is that news positioning has a large effect on how quickly information is reflected in prices, even controlling for news importance. Within 10 minutes of publication, front-page SI news articles lead to 37 bps higher absolute excess returns (a relative increase of 176%) and 0.12% greater share turnover (a relative increase of 240%) than non-front-page SI news articles. Compared to the effect of news importance, the immediate market reaction to news positioning is similar in absolute terms but represents a larger relative increase and is more statistically significant. Beyond the first 10 minutes, front-page SI articles are accompanied by a strong drift in the short term (for half an hour after publication) but no drift at longer horizons, whereas the incorporation of non-front-page information is much slower: only approximately one-third of the price response to non-front-page SI news occurs in the first hour, with significant drift continuing outside that window.

The response to non-front-page SI news eventually converges to the response to front-page SI news, but the gap remains statistically significant for two days and declines to zero only after 15 days. Specifically, the differential response to front-page versus non-front-page SI news is 34 bps after two days (statistically significant at the 10% level), becomes statistically insignificant at 25 bps after five days, drops to 18 bps after 10 days, and declines to a statistically indiscernible 8 bps after 15 days. By comparison, the difference between responses to PI versus front-page SI news articles, which differ in actual importance, remains stable and statistically significant at 45 bps even 10 days out. Thus, whereas the market impact of differential news importance is permanent, the effect of news positioning on institutional investors is temporary but lasts several days.

Interestingly, in the setting I consider, salient presentation of news by the media serves to speed up the price response but does not lead to overreaction. A number of studies focusing on investor attention document overreaction to salient information, especially among retail investors.[2] However, in the setting with sophisticated investors consuming news on the Bloomberg terminal, I find no evidence of overreaction to prominently positioned front-page content. Instead, reactions to front-page news events on the Bloomberg terminal illustrate efficient price formation: when information is highlighted, prices adjust completely within an hour (and largely within the first 10 minutes) of news publication, with no subsequent drift or correction. However, even in this sophisticated setting, *in*attention plays a role, manifesting as initial underreaction to non-front-page news.[3]

I also explore how other media sources may amplify the effects I document. To do so, I obtain comprehensive data on news coverage from three additional databases: (i) the Dow Jones Newswire, which is most similar to Bloomberg as a low-latency provider targeting sophisticated institutional investors, (ii) Factiva, which aggregates news from over 32,000 print and online publications, and (iii) EventRegistry, which collects news from more than 150,000 online sources. The first noteworthy result emerging from this analysis is that the Dow Jones Newswire independently gives equal coverage to Bloomberg's front-page and non-front-page SI news articles, which confirms that these two sets of articles are equally important (by contrast, PI news articles, which are marked by Bloomberg as more important, also receive more coverage in the Dow Jones Newswire).

The second noteworthy finding is that news sources that cater to less sophisticated investors, included in the Factiva and EventRegistry databases, give more coverage to front-page SI news articles than to non-front-page SI news articles only *after* their publication on Bloomberg. To explore this effect further, I separate the news sources in the Factiva database into print publications (e.g., print editions of the *New York Times* and the *Wall Street Journal*) and online content. In print publications, higher coverage of front-page (vs. non-front-page) SI news is explained by news flow: when there is less PI content to occupy the Bloomberg front page, there is also less important content to occupy the print pages, and hence contemporaneous SI news articles receive more coverage. In nonprint sources, news flow plays a smaller role, and delayed

[2] See, for example, Barber and Loeffler (1993), Huberman and Regev (2001), Da, Engelberg, and Gao (2011), and Engelberg, Sasseville, and Williams (2012). Barber, Odean, and Zhu (2008) further document that retail investor trading negatively forecasts future returns, independent of news.

[3] For a complementary perspective focusing specifically on limited attention from noise traders, see Peress and Schmidt (2020).

coverage by these sources is more strongly correlated with Bloomberg's positioning, suggesting a potential direct effect of Bloomberg on less sophisticated outlets.[4] Overall, higher delayed coverage by outside sources may amplify the direct effects of Bloomberg's positioning, allowing the gap in responses to front-page versus non-front-page news to persist for several days.

At the end of the paper, I provide several additional analyses to support a causal interpretation of my main results and to rule out the possibility that SI articles that are pinned to the front page differ systematically from those that are not. The long-term convergence of the responses to front-page and non-front-page SI articles supports the equal importance of these articles, as does the fact that the Dow Jones Newswire independently gives equal coverage to the two sets of SI articles. In addition, I show that front-page and non-front-page SI news articles do not differ along any observable characteristics, such as size and liquidity of the tagged firms. I also compare the news samples using machine learning, including (i) a comparison of the distributions of topics covered by the news using topic modeling and (ii) a deep-learning classifier of news importance based on the text of the news headlines. Neither of these methods is able to detect any differences between the content of front-page and non-front-page SI news. Finally, I conduct a direct survey of 150 active finance professionals at a broad range of financial institutions, including broker dealers such as Goldman Sachs, investment management firms such as BlackRock and PIMCO, and hedge funds such as Bridgewater Associates. Finance professionals choose front-page SI articles as more important than non-front-page SI articles 48% of the time, which is not significantly different from 50%. Importantly, all of the aforementioned analyses have enough statistical power to detect significant differences between PI and SI news.

Taken together, my results show that news positioning has a strong effect on trading volume and returns. A growing strand of research explores the effects of exogenous variation in news arrival and segmented exposure to the media across different investor groups.[5] My contribution to this literature lies in the identification of the news position effect, showing that even for equally important news, *how* news is presented impacts the speed of price discovery. I focus on a setting that represents the main source of information for sophisticated institutional investors and show that the position effect plays an important role even in this context. By focusing on a major news source that caters to

[4] This result is consistent with the evidence by Li (2018) that journalists are also subject to limited attention and salience effects.

[5] For example, Engelberg and Parsons (2011) use weather-related disruptions, Dougal et al. (2012) exploit exogenous scheduling of journalists, Peress (2014) looks at newspaper strikes, Koudijs (2016) considers disruptions to boat routes, Blankespoor, deHaan, and Zhu (2018) exploit staggered implementation of robojournalism, von Beschwitz, Keim, and Massa (2020) use variation in security relevance tags, and Lawrence et al. (2018) consider the promotion of earnings announcement news on Yahoo! Finance to a subset of website visitors. Kaniel and Parham (2017) provide complementary evidence of the impact not of news per se but of media-promoted ranking lists.

institutional investors, I am also able to explore how the effects of low latency, sophisticated news sources can be amplified by other news providers.

The remainder of the paper proceeds as follows. Section I describes the data and the natural experiment in news positioning and outlines the key empirical predictions. Section II presents the main results. Section III considers the role of other media sources. Section IV presents additional validation checks. Finally, Section V concludes.

I. Data and Empirical Strategy

To capture the causal effect of news positioning, I use quasi-random variation in the presentation of news articles on the Bloomberg terminal. Two key features of these data make them especially well suited to the current analysis. First, Bloomberg is one of the largest financial news providers and a main source of news for finance professionals, making it an ideal setting for estimating the effect of attention to news on financial markets. Second, the data allow me to take advantage of exogenous variation in positioning for a subset of news articles. The news data are merged with market data to relate news presentation to trading volume and returns.

A. *Exogenous Variation in News Positioning*

News articles on the Bloomberg terminal are aggregated from a variety of sources in real time, including key national and international news wires from a comprehensive set of news organizations, company filings, press releases, and content from web sources such as blogs and social media. The news articles are disseminated electronically to over 300,000 finance professionals through the subscription-based terminal. Overall, there are millions of articles tagged with U.S. equity securities during my sample period of March 22, 2014 to December 31, 2015.

News on the Bloomberg terminal can be consumed in two ways: through filters customized by individual subscribers and through default news screens for specific topics (e.g., company news, government news, and sports news). Most finance professionals tend to rely on the default news screens when using the Bloomberg terminal. In supplementary analysis presented in Section III.H of the Internet Appendix, I survey active finance professionals regarding their use of the Bloomberg terminal.[6] All respondents who read news on Bloomberg use default screens in at least some capacity, with the predominant majority (71%) relying *exclusively* on the default screens. These default news screens are organized as in Figure 1. At the top of the screen, three pinned slots are highlighted in yellow type (which I term the “front page”). Below is a scrolling screen of news headlines that continually move down as new articles arrive. Figure IA.2 in Section II of the Internet Appendix provides a screenshot of a default Bloomberg news screen covering company news.

[6] The Internet Appendix may be found in the online version of this article.

Whether articles get pinned to front-page slots depends on two factors: article importance and space constraints. A small subset of news articles produced by Bloomberg are classified as either PI or SI.[7] Only PI and SI news can occupy the front-page slots. Both of these categories are rare, accounting for roughly 0.1% to 0.5% of all news on the terminal. As a result, while millions of company-specific financial news articles are published on the Bloomberg terminal during the March, 2014 to December 31, 2015 sample period, the number of PI and SI news articles is only in the thousands. I hand-collect all articles that are tagged with at least one publicly traded U.S. equity security, that are published between 8 am and 5 pm EST during the sample period, and that are classified in either the PI category (1,419 unique PI articles) or the SI category (4,887 unique SI articles).[8] I exclude market-wrap articles to focus on newly released information and to limit the number of securities tagged as relevant for each article. Table IA.1 in Section II of the Internet Appendix provides a few representative examples of PI and SI articles.

PI news articles are always pinned to the front page, whereas SI news articles serve as backups for when there is an insufficient supply of PI news. Once on the front page, a news article remains there until the earlier of two events occurs: either a new PI article comes out and displaces the old article, or a predefined amount of time (on the order of 20 to 40 minutes) elapses, in which case the next SI article published is also qualified to take that spot. Once pinned, front-page SI articles are treated analogously to PI articles and are subject to the same displacement process. I hand-collect the positions of all SI articles in my sample.

Table I presents the distribution, by hour, of PI and SI news articles published between the hours of 8 am and 5 pm EST and tagged with at least one U.S. equity security. There are 2,362 PI article-ticker observations in the sample and 8,233 SI article-ticker observations, of which 1,274 receive a front-page position. PI news articles peak at the start and end of the business day, between 8 am and 10 am and especially between 4 pm and 5 pm, while SI news articles are more evenly distributed throughout the day. The correlation between the hourly volume of PI news and the hourly likelihood of SI articles receiving front-page slots is −81%, consistent with SI articles getting pinned to the front page when there are not enough PI articles. Editors are unlikely to strategically release certain SI articles ahead of others to grab front-page slots,

[7] Journalists and editors directly assign importance to novel content written by Bloomberg. For news derived from other sources, for example, press releases or filings, Bloomberg uses a complex set of rules to determine importance. Factors that can affect assigned importance include the topic, news source, tagged securities, geographic regions, time of day, specific keywords in the headline or the body of the news article, numbers, dates, and basic arithmetic (e.g., to determine whether earnings fall outside some bounds). These factors interact in highly nonlinear, branching decision rules with both inclusion and exclusion criteria.

[8] The importance tags are reflected in the article topics and can be seen by the terminal users but not immediately—one needs to click on the headline, go into the article, and expand the list of topic tags—which implies that the decision to open a particular article is made without knowing the article's importance tag.

Table I
Breakdown of News across Hours

This table tabulates the news in the sample (March 22, 2014 to December 31, 2015) by hour of publication, including hourly percentages of SI articles that are pinned to the front page. The sample is restricted to articles published between 8 am and 5 pm EST and tagged with at least one U.S. equity security.

Hour of Day	PI Articles	SI Articles	FP SI Articles	% SI Articles on FP
8 am - 9 am	370	745	134	18%
9 am - 10 am	285	1,054	135	13%
10 am - 11 am	189	1,090	174	16%
11 am - 12 pm	173	942	155	16%
12 pm - 1 pm	147	935	142	15%
1 pm - 2 pm	171	896	147	16%
2 pm - 3 pm	213	819	158	19%
3 pm - 4 pm	147	808	134	17%
4 pm - 5 pm	667	944	95	10%
Total	2,362	8,233	1,274	15%

as only 1.4%, 0.7%, and 0.2% of front-page SI articles have a non-front-page SI article released up to one minute, 30 seconds, and 10 seconds, respectively, before or after. In Figure IA.3 in Section II of the Internet Appendix, I also confirm that the editorial staff is not targeting any particular volume of high-importance content. Volumes of both PI and (all) SI news in my sample range from zero to several dozen articles per day, with a low positive correlation (25%) between the two news categories at the daily level.

As preliminary evidence of the importance of front-page positioning, in Section III.A of the Internet Appendix, I use a direct Bloomberg terminal attention measure, described in detail in Ben-Rephael, Da, and Israelsen (2017), to show that front-page news articles (whether PI or SI) are associated with significantly more attention spikes than non-front-page SI news articles. The attention measure is not directly linked to individual news stories because it reflects *daily* spikes in news readership and search volume for a given security, but even this imprecise metric picks up increases in attention to securities mentioned in front-page news.

B. Market Data

I use security tags to merge the Bloomberg news data with market data from several sources. Industry classification, market capitalization, and shares outstanding come from Compustat. Second-level price and trading data come from QuantQuote, which includes all tickers listed on NASDAQ exchanges and the NYSE and provides prices and numbers of shares traded for each second during the market open. The data are adjusted for splits, dividends, and symbol changes and include any after-hours data provided by the exchanges. Overnight returns are not included in the analysis, except in the longer-term (day-level) tests.

The high-frequency tests are conducted using all article-ticker pairs for which there are market data in QuantQuote and shares outstanding and NAICS industry codes in Compustat. The merged sample of all article-ticker pairs with at least one price data point in QuantQuote on the day of publication contains 948 front-page SI article-ticker pairs, 4,930 non-front-page SI article-ticker pairs, and 1,650 PI article-ticker pairs. Most empirical tests are run on smaller samples, depending on the time period analyzed. For example, PI news articles are more likely to come out between 4 pm and 5 pm EST than SI news articles. As a result, the PI news sample shrinks more substantially than the two SI news samples when merged to short-term market data. Similarly, due to the prevalence of PI articles immediately after market close, the vast majority of SI articles published between 4 pm and 5 pm EST do not make the front page. As a result, more non-front-page SI articles (than front-page SI articles) have no short-term market data. Reflecting these timing patterns, 79% (1,306) of PI article-ticker pairs, 91% (858) of front-page SI article-ticker pairs, and 86% (4,233) of non-front-page SI article-ticker pairs that are merged with market data have data within 10 minutes of publication.

C. Empirical Predictions

To provide intuition for the differences between front-page and non-front-page SI news articles, I first outline key aspects in the way investors are likely to pay differential attention to news articles in different positions. I then trace out the implications of these aspects for how information is incorporated into asset prices. The full conceptual framework, which follows the setups in Hirshleifer and Teoh (2003) and DellaVigna and Pollet (2009), is presented in Section I of the Internet Appendix.

The main assumptions of the conceptual framework reflect the following two frictions: (i) some investors are inattentive, and (ii) investors update their beliefs in a naïve Bayesian manner. In particular, only a fraction of investors pay attention to the news at any given point in time, and all investors update their beliefs with respect to only their own information, without taking into account the information sets and actions of others. These assumptions are standard modeling devices in models of gradual information diffusion (Hong and Stein (1999), Hirshleifer and Teoh (2003), Peng and Xiong (2006)).

I consider two key distinctions between front-page and non-front-page SI news. First, front-page news articles are more visible than non-front-page news articles from the start, inducing a higher share of immediate attention from investors. Second, front-page news articles *remain* prominently positioned for some length of time (typically 20 to 40 minutes), so that investors continue to see them at a higher rate during this time. Once a given article is removed from the front page, it becomes just as difficult to find as its non-front-page counterparts. These differences generate the following predictions for returns, trading volume, and drift after front-page versus non-front-page SI news.

Prediction 1 (Immediate Market Response): *Front-page news articles are followed by higher trading volume and absolute excess returns immediately (within minutes) after publication than equally important non-front-page news articles.*

Prediction 2 (Short-Term Return Continuation): *Front-page news articles are accompanied by higher continuation in short-term returns (while the articles are still on the front page) than equally important non-front-page news articles.*

Prediction 3 (Delayed Return Continuation): *Front-page news articles induce lower return continuation than equally important non-front-page news articles at longer horizons.*

I test these predictions by observing market dynamics following front-page and non-front-page SI news articles. For the immediate news release window, I look at 10 minutes following publication of each individual news article. As the short-term window, I consider 30 minutes following the news because front-page news articles tend to remain prominently positioned for approximately 20 to 40 minutes. I also confirm that the empirical results are robust to alternative cutoffs for the immediate and short-term windows, for example, 5 and 45 minutes, respectively. For the longer horizon, I consider windows of 90 to 120 minutes following the news release and look at long-term convergence over the course of up to 15 days.

II. News Positioning and Market Dynamics

I use the hand-collected samples of PI, front-page SI, and non-front-page SI news to estimate the causal impact of news positioning and contextualize it against the effect of actual news importance.

A. Immediate Responses to News

I begin by considering how immediate trading volume and absolute excess returns respond to news positioning, with a graphical illustration in Figure 2. Panel A displays the median trading volume from 10 minutes before to 10 minutes after the publication of front-page and non-front-page SI news. Panel B considers the average absolute excess return following front-page and non-front-page SI news, as well as the baseline price change computed 24 hours prior to each news publication. Trading volume is quoted as the percentage of shares turning over, and excess returns are computed as returns in excess of the contemporaneous value-weighted average return on all securities in the sample. Both trading volumes and absolute excess returns are substantially higher immediately following front-page SI news than following non-front-page SI news, consistent with Prediction 1.

I quantify the "position effect" in Table II. During the first 10 minutes after publication, non-front-page SI news articles are accompanied by average

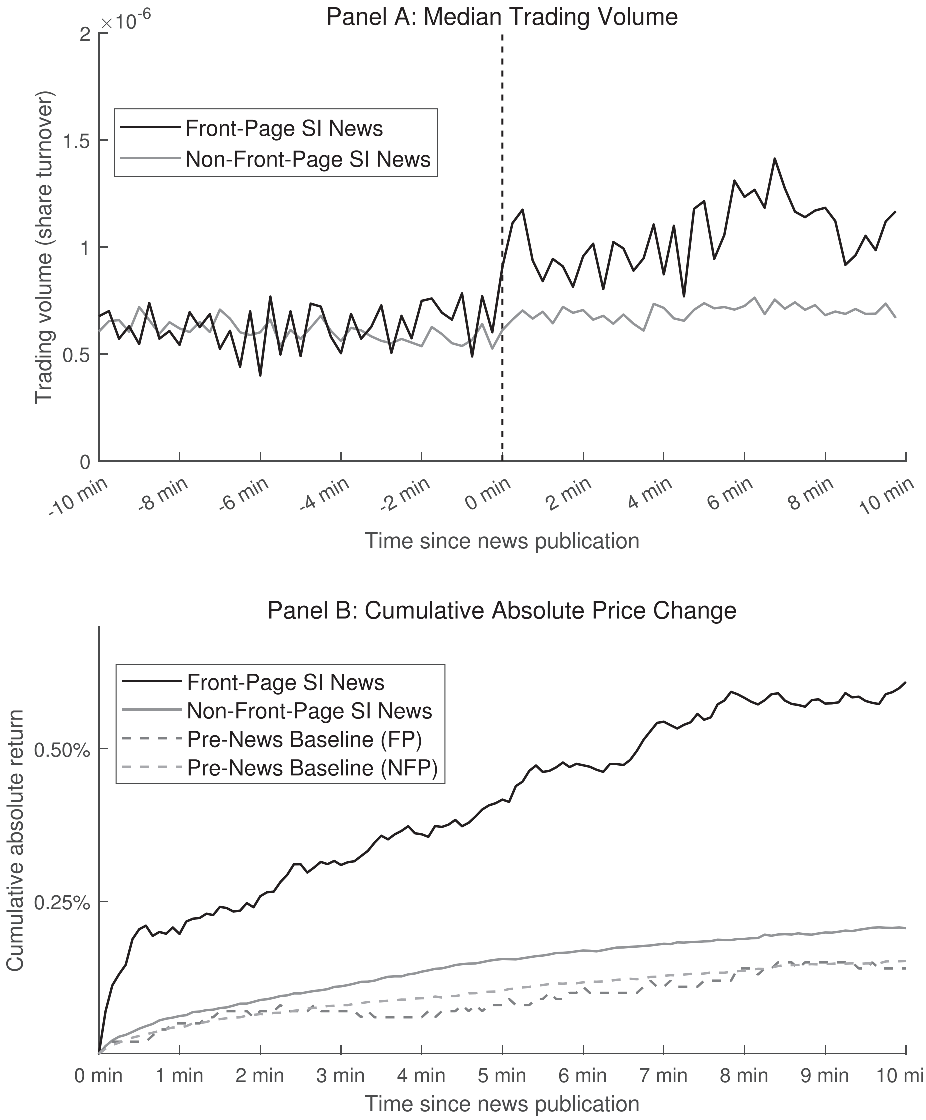

Figure 2. Absolute excess return and trading volume after news. Panel A displays the median trading volume by 15-second intervals during the 10 minutes before and the 10 minutes after news publication. Panel B presents the average absolute excess return from publication to 10 minutes later, as well as the baseline excess return in the absence of news (computed 24 hours prior to news publication). Both panels separately consider front-page and non-front-page SI news.

turnover of 0.05% shares and absolute excess returns of 21 bps for the tagged securities. Front-page SI news articles see, on average, turnover of 0.19% and absolute excess returns of 60 bps over the same period. The differences are 0.12% for trading volume and 37 bps for absolute excess returns when

Table II

Trading Volume and Absolute Excess Returns after News

This table presents comparisons of trading volume and absolute excess returns immediately (within the first 10 minutes) following non-front-page (non-FP) SI news, front-page (FP) SI news, and PI news. Differences are computed controlling for firm size and industry fixed effects, as well as hour and day fixed effects. **, *, and † indicate significance at the 1%, 5%, and 10% level, respectively.

	Averages for Each News Category			Position Effect:	Importance Effect:
	Non-FP SI (1)	FP SI (2)	PI (3)	FP SI vs. Non-FP SI (4)	PI vs. FP SI (5)
Trading volume	0.05%	0.19%	0.29%	0.12%*	0.11%†
	(0.00%)	*(0.03%)*	*(0.04%)*	*(0.05%)*	*(0.07%)*
Abs. excess return	0.21%	0.60%	1.01%	0.37%**	0.35%**
	(0.01%)	*(0.07%)*	*(0.06%)*	*(0.03%)*	*(0.10%)*
# Non-FP SI Obs	4,233			4,233	
# FP SI Obs		858		858	858
# PI Obs			1,306		1,306

controlling for day and hour fixed effects, log market capitalization, and industry fixed effects, and the effect sizes are similar when controls are excluded.[9]

For comparison, the last column of Table II estimates the news "importance effect," that is, the difference in market reactions to PI news articles (which are marked as relatively more important) versus front-page SI news articles (which are relatively less important). These news articles are all equally positioned (on the front page) and vary only in importance. PI news articles induce stronger responses than front-page SI news articles, indicating that market participants are sophisticated in differentiating the more important content. The difference in the market response to PI versus front-page SI news is 35 bps in absolute excess returns and 0.11% in share turnover, which is similar to the effect of positioning in absolute terms. In relative terms and in statistical significance, the differential market reaction to news positioning (front-page

[9] I confirm the stability of these estimates to the inclusion of controls using a test introduced by Altonji, Elder, and Taber (2005) and generalized by Oster (2019), which takes into account both the movement in the coefficients and the incremental R^2 from the observed controls to estimate the extent to which unobserved controls would have to impact coefficient estimates in order to render the effect insignificant. Given how little the observed controls move the estimates, unobserved controls would need to explain 56% of the amount of variation in 10-minute absolute excess returns that is explained by all observed controls combined, even assuming that the combination of observed and unobserved controls would be able to explain *all* variation in the price response (R^2 of one, which Oster (2019) notes "may lead to overadjustment in many cases"). Full explanatory power is unrealistic given the usual level of noise in tests on high-frequency returns, where the typical R^2 ranges around 0.2 to 0.3 (Busse and Green (2002), Chuliá, Martens, and van Dijk (2010)). Assuming a maximal R^2 of 0.5, the left-out unobserved variables would need to explain noticeably more variation (by a factor of 1.3) than all included observed controls to render the estimated coefficients insignificant.

SI news vs. non-front-page SI news) is even stronger than the differential response to news importance (PI news vs. front-page SI news).

B. Short-Term Return Continuation

I now test Prediction 2, which states that price paths following front-page SI news articles should display more short-term continuation than those following non-front-page SI news articles, reflecting the more persistent attention garnered by news articles that are pinned to the top of the Bloomberg terminal screen. I estimate the following specification on the sample of SI news:

$$Ret_{s,i,[t+10,t+30]} = \alpha + \beta_1 Ret_{s,i,[t,t+10]} + \beta_2 FP_s + \beta_3 Ret_{s,i,[t,t+10]} \times FP_s + Controls + \epsilon_{s,i,[t+10,t+30]}, \quad (1)$$

where $Ret_{s,i,[t,t+10]}$ denotes the return on security i during the first 10 minutes after publication of article s, $Ret_{s,i,[t+10,t+30]}$ is the return during the remainder of the first 30 minutes, and FP_s is an indicator variable for whether article s is on the front page.

Columns (1) to (4) of Table III display results with and without controls for month or day fixed effects, hour-of-day fixed effects, log firm size, and industry fixed effects. When all controls are included, front-page SI news articles induce 22% more continuation in returns from the first 10 minutes after publication to the remainder of the first 30 minutes than do non-front-page SI news articles. This result is virtually unchanged with weaker sets of controls, and Table IA.2 in Section II of the Internet Appendix shows that this result is not sensitive to the exact choice of 10 minutes for the immediate window or 30 minutes for the short-term window. The strong short-term drift following front-page SI news articles is also reflected in the positive alpha earned by trading strategies that buy and sell securities mentioned in these news articles based on the initial price responses (see Section III.B of the Internet Appendix). Interestingly, the non-front-page SI news articles are followed by virtually zero return continuation over this time horizon. In the next subsection, I show that they instead experience considerable drift over longer horizons.

Columns (5) to (8) of Table III present analoguous results comparing PI news and front-page SI news. The results suggest that PI news articles are not accompanied by any more short-term price drift than front-page SI news articles because the coefficient on the interaction term is neither economically notable nor statistically significant. This finding provides important context for the effects of positioning that are reported in columns (1) to (4). Market participants are able to tell which news articles are more important. The greater reactions to PI news begin immediately and do not show any *differential* drift. At the same time, even sophisticated institutional investors who consume news through the Bloomberg terminal are affected by salient positioning, leading to strong short-term price drift for all front-page news (whether PI or SI) but not for non-front-page SI news. In an extension in Section III.C of the Internet Appendix, I consider how the variation in the *length* of time that front-page arti-

Table III

Short-Term Continuation in Returns after News

This table analyzes short-term continuation in returns after front-page SI, non-front-page SI, and PI news. Columns (1) to (4) estimate the following specification on the combined sample of front-page and non-front-page SI news, with controls as indicated in the columns:

$$Ret_{s,i,[t+10,t+30]} = \alpha + \beta_1 Ret_{s,i,[t,t+10]} + \beta_2 FP_s + \beta_3 Ret_{s,i,[t,t+10]} \times FP_s + Controls + \epsilon_{s,i,[t+10,t+30]},$$

where FP_s is a dummy variable equal to one if news article s is pinned to the front page, $Ret_{s,i,[t,t+10]}$ denotes the return on security i during the first 10 minutes after publication of s, and $Ret_{s,i,[t+10,t+30]}$ is the return during the remainder of the first 30 minutes. Analogously, columns (5) to (8) estimate the following specification on the combined sample of front-page SI and PI news, with PI_s denoting whether article s is from the PI category, and with controls as indicated in the columns:

$$Ret_{s,i,[t+10,t+30]} = \alpha + \beta_1 Ret_{s,i,[t,t+10]} + \beta_2 PI_s + \beta_3 Ret_{s,i,[t,t+10]} \times PI_s + Controls + \epsilon_{s,i,[t+10,t+30]}.$$

**, *, and † indicate significance at the 1%, 5%, and 10% level, respectively.

	Position Effect: FP SI vs. Non-FP SI News				Importance Effect: PI vs. FP SI News			
Coefficient on:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ret_{s,i,[t,t+10]}$	−0.011	−0.010	−0.014	−0.009	0.193**	0.194**	0.195**	0.202**
	(0.034)	*(0.034)*	*(0.034)*	*(0.036)*	*(0.036)*	*(0.037)*	*(0.038)*	*(0.040)*
$Ret_{s,i,[t,t+10]} \times FP_s$	0.208**	0.208**	0.212**	0.223**				
	(0.037)	*(0.038)*	*(0.038)*	*(0.044)*				
$Ret_{s,i,[t,t+10]} \times PI_s$					0.055	0.055	0.054	0.067
					(0.040)	*(0.040)*	*(0.041)*	*(0.044)*
# Non-FP SI obs	4,310	4,310	4,308	4,308				
# FP SI obs	892	892	890	890	892	892	890	890
# PI obs					1,322	1,322	1,315	1,315
Hour FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Month FE	No	Yes	Yes	No	No	Yes	Yes	No
Day FE	No	No	No	Yes	No	No	No	Yes
Firm size	No	No	Yes	Yes	No	No	Yes	Yes
Industry FE	No	No	Yes	Yes	No	No	Yes	Yes

cles spend on the front page ("screen time") affects the speed of price discovery. Even for articles from the same importance category (either PI or SI) and the same initial position (front page), receiving more screen time expedites incorporation of the news into prices, further confirming that being on—and staying on—the front page matters.

C. News Positioning and Longer-Term Price Dynamics

Placing a piece of news on the front page induces sizable immediate returns and short-term drift, but does the non-front-page information eventually catch up? I present evidence that at longer horizons (e.g., two hours after the news), non-front-page SI news articles prompt substantially more price drift than front-page SI news articles. The incorporation of non-front-page

Table IV

Longer-Term Continuation in Returns after News

This table presents results on continuation in returns following front-page and non-front-page SI news over longer horizons. I estimate the specification

$$Ret_{s,i,[t+30,t+t_2]} = \alpha + \beta_1 Ret_{s,i,[t,t+30]} + \beta_2 FP_s + \beta_3 Ret_{s,i,[t,t+30]} \times FP_s + Controls + \epsilon_{s,i,[t+30,t+t_2]},$$

where FP_s is an indicator for whether news article s is positioned on the front page, $Ret_{s,i,[t,t+30]}$ denotes the return on security i during the first 30 minutes after publication of s, and $Ret_{s,i,[t+30,t+t_2]}$ is the return during the delayed period, which goes out to 90 minutes in columns (1) to (4) and 120 minutes in columns (5) to (8). Controls vary across columns as indicated. **, *, and † indicate significance at the 1%, 5%, and 10% level, respectively.

	FP SI vs. Non-FP SI News: Delayed Period $t_2 = 90$ min				FP SI vs. Non-FP SI news: Delayed Period $t_2 = 120$ min			
Coefficient on:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ret_{s,i,[t,t+30]}$	0.254**	0.248**	0.249**	0.256**	0.266**	0.267**	0.255**	0.261**
	(0.029)	*(0.029)*	*(0.030)*	*(0.031)*	*(0.035)*	*(0.035)*	*(0.036)*	*(0.037)*
$Ret_{s,i,[t,t+30]} \times FP_s$	−0.143**	−0.142**	−0.145**	−0.147*	−0.185**	−0.183**	−0.188**	−0.186**
	(0.032)	*(0.032)*	*(0.032)*	*(0.034)*	*(0.032)*	*(0.032)*	*(0.033)*	*(0.035)*
# Non-FP SI obs	4,475	4,475	4,472	4,472	4,491	4,491	4,488	4,488
# FP SI obs	901	901	899	899	903	903	901	901
Hour FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Month FE	No	Yes	Yes	No	No	Yes	Yes	No
Day FE	No	No	No	Yes	No	No	No	Yes
Firm size	No	No	Yes	Yes	No	No	Yes	Yes
Industry FE	No	No	Yes	Yes	No	No	Yes	Yes

information is much slower, however, and full convergence occurs only several days after publication.

Table IV considers the continuation in returns following front-page and non-front-page SI news articles from the short-term window of 30 minutes to the remainder of the first 90 to 120 minutes, providing empirical support for Prediction 3 of the conceptual framework. Non-front-page SI news articles are followed, on average, by 25% to 27% continuation in returns over these horizons. Front-page SI news articles, however, see 14% to 19% less continuation. Together, the results in Tables III and IV demonstrate that pinning a piece of news to the front page induces stronger drift during the first half-hour, with the reactions to non-front-page articles beginning to catch up over the remainder of the first couple of hours. Theoretically, these patterns are consistent with the gradual information diffusion framework outlined in Section I.C and presented in detail in Section I of the Internet Appendix. Practically, the results indicate that for news articles consumed by sophisticated institutional investors through a subscription-based platform such as Bloomberg, market

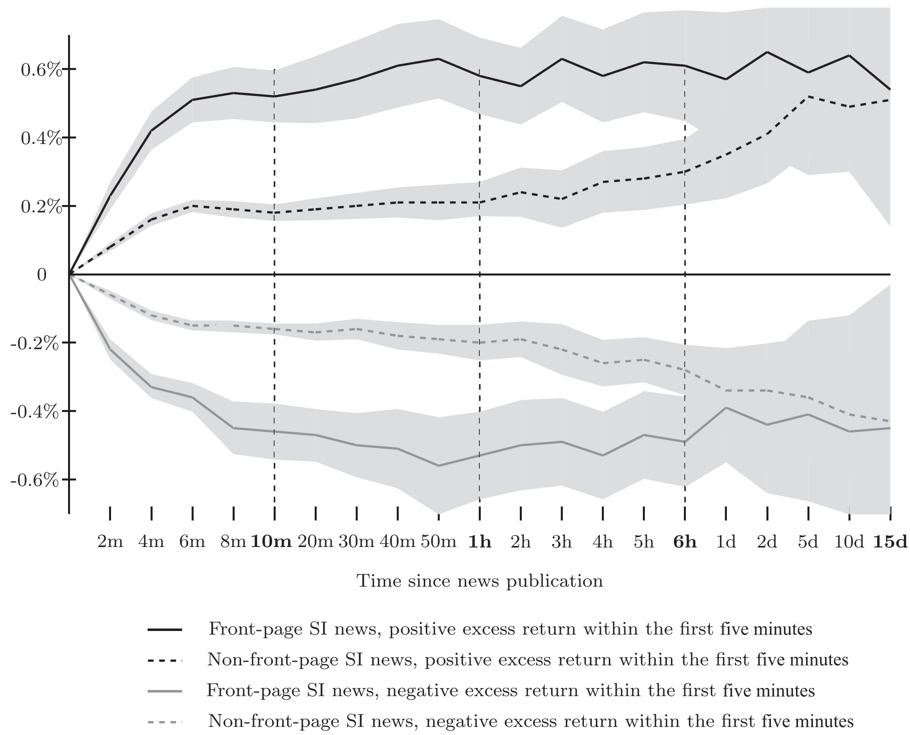

Figure 3. Cumulative excess returns after front-page and non-front-page SI news. The returns are sliced by the direction of the initial five-minute return: positive article-ticker events are displayed in black lines, negative article-ticker events are displayed in gray lines. Solid lines show returns following front-page SI news, and dashed lines indicate reactions to non-front-page SI news.

dynamics track the discretionary positioning in real time. Specifically, the duration of the drift after the publication of front-page articles mirrors the length of time (20 to 40 minutes) over which these articles tend to be prominently positioned, and reactions to non-front-page information gradually begin to catch up after that time.

The response to non-front-page SI news does eventually fully catch up. However, whereas most of the price impact of front-page information occurs within minutes of publication, non-front-page information takes several days to be fully reflected in prices. Figure 3 displays cumulative excess returns following front-page and non-front-page SI news articles grouped along two dimensions: (i) their position and (ii) the direction of the initial five-minute excess return. Immediately after publication, front-page SI news articles are accompanied by larger excess returns in both the positive and the negative directions, consistent with the absolute excess return results reported in Table II. This gap widens for about 45 minutes, corroborating the short-term drift results in Table III. After the first hour, front-page SI articles prompt no additional returns, whereas non-front-page SI information continues to be incorporated into prices, consistent with Table IV. In the last quarter of Figure 3, I show the

Table V

Differences in Absolute Excess Returns over Longer Horizons

This table examines absolute excess returns up to 15 days after news publication. Column (1) compares front-page SI news with non-front-page SI news, and column (2) compares PI news with front-page SI news. Absolute excess returns are calculated as the absolute value of the excess returns from news publication to exactly d days later. Differences are estimated controlling for firm size, industry fixed effects, and hour and day fixed effects. **, *, and † indicate significance at the 1%, 5%, and 10% level, respectively.

Number of Days after News		Position Effect: FP SI vs. Non-FP SI News (1)	Importance Effect: PI vs. FP SI News (2)
$d = 1$		0.38%**	0.56%**
	Standard error	*(0.14%)*	*(0.15%)*
	# Non-FP SI obs	4,432	–
	# FP SI obs	892	892
	# PI obs	–	1,321
$d = 2$		0.34%†	0.50%*
	Standard error	*(0.19%)*	*(0.22%)*
	# Non-FP SI obs	4,415	–
	# FP SI obs	888	888
	# PI obs	–	1,250
$d = 5$		0.25%	0.44%*
	Standard error	*(0.20%)*	*(0.23%)*
	# Non-FP SI obs	4,422	–
	# FP SI obs	890	890
	# PI obs	–	1,254
$d = 10$		0.18%	0.48%*
	Standard error	*(0.22%)*	*(0.25)*
	# Non-FP SI obs	4,403	–
	# FP SI obs	878	878
	# PI obs	–	1,228
$d = 15$		0.08%	0.41%
	Standard error	*(0.25%)*	*(0.31%)*
	# Non-FP SI obs	4,411	–
	# FP SI obs	855	855
	# PI obs	–	1,234

cumulative excess returns from publication to 1, 2, 5, 10, and 15 days after the news release. Although the standard errors widen at these horizons, the economic magnitudes show no difference in the long-term reactions to front-page versus non-front-page SI news.

These findings are corroborated in column (1) of Table V, which considers differences in *absolute* excess returns after 1, 2, 5, 10, and 15 days following the publication of front-page versus non-front-page SI news, controlling for day and hour fixed effects, log market capitalization, and industry fixed effects. The results indicate that a portion of the gap in market reactions induced by positioning remains even several days after the news. The difference is highly statistically significant at 38 bps after one day, declines slightly but remains statistically significant and economically similar at 34 bps after two days, and is no longer statistically significant (although still economically visible) at 25 bps after five days. The gap narrows to a statistically insignificant 18 bps after 10 days and converges to a statistically indiscernible 8 bps after 15 days.

It is informative to again contextualize the impact of positioning against that of actual news importance. In column (2) of Table V, I compare the absolute excess returns following PI versus front-page SI news. The difference is stable at 41 to 56 bps over the course of 15 days and remains statistically significant at the 5% level even 10 days out. This is consistent with previous work documenting persistent, statistically significant price responses to individual news events multiple days or even weeks out (Barber and Loeffler (1993), Cooper, Dimitrov, and Rau (2001), Carvalho, Klagge, and Moench (2011)) and contrasts with the convergence of the price responses to front-page and non-front-page SI news. Whereas the effects of actual news importance are permanent, the price impact of differential news presentation does converge—but it takes considerable time.

III. Coverage by Other News Sources

I now consider news sources outside of Bloomberg and address the concern that my main results, which I attribute to positioning on the Bloomberg terminal, may be driven by contemporaneous coverage elsewhere. I document that (i) the Dow Jones Newswire does *not* cover Bloomberg's front-page SI news any differently than Bloomberg's non-front-page SI news, and (ii) news sources that cater to less sophisticated audiences appear to *follow* (but not lead) Bloomberg in their coverage patterns. The latter may amplify the effects of Bloomberg's initial positioning, contributing to the return drift.

I employ methods from natural language processing to identify instances of the news in my Bloomberg sample being covered in three additional data sets: (i) Dow Jones Newswire, which is a low-latency provider most comparable to Bloomberg; (ii) Factiva, which is owned by Dow Jones but features a wide range of partner publications including major print newspapers; and (iii) EventRegistry, which collects a comprehensive set of news articles from over 150,000 online sources. I preprocess all headlines to exclude stop words (e.g., "on" and "at") and stem the remaining words (e.g., "earnings" and "earned" become "earn-"). I then use the cosine similarity measure to compare each headline in the Bloomberg news sample against each headline in outside news sources covering the same ticker; articles with a cosine similarity above 0.4 are considered a match to the original headline. Despite the complexity of identifying coverage of the same event described in potentially different terms, this methodology correctly identifies most instances of matching content without capturing noise. For example, manual testing on a random subset of 50 Bloomberg news events reveals that the procedure for identifying matching events in Dow Jones has a high accuracy rate of 84%.

The results are presented in Figure 4, which plots the hourly volume of coverage in other sources from 12 hours before each article's publication on Bloomberg to 24 hours after, averaged across news articles of each type (PI, front-page SI, and non-front-page SI). Panel A considers the Dow Jones

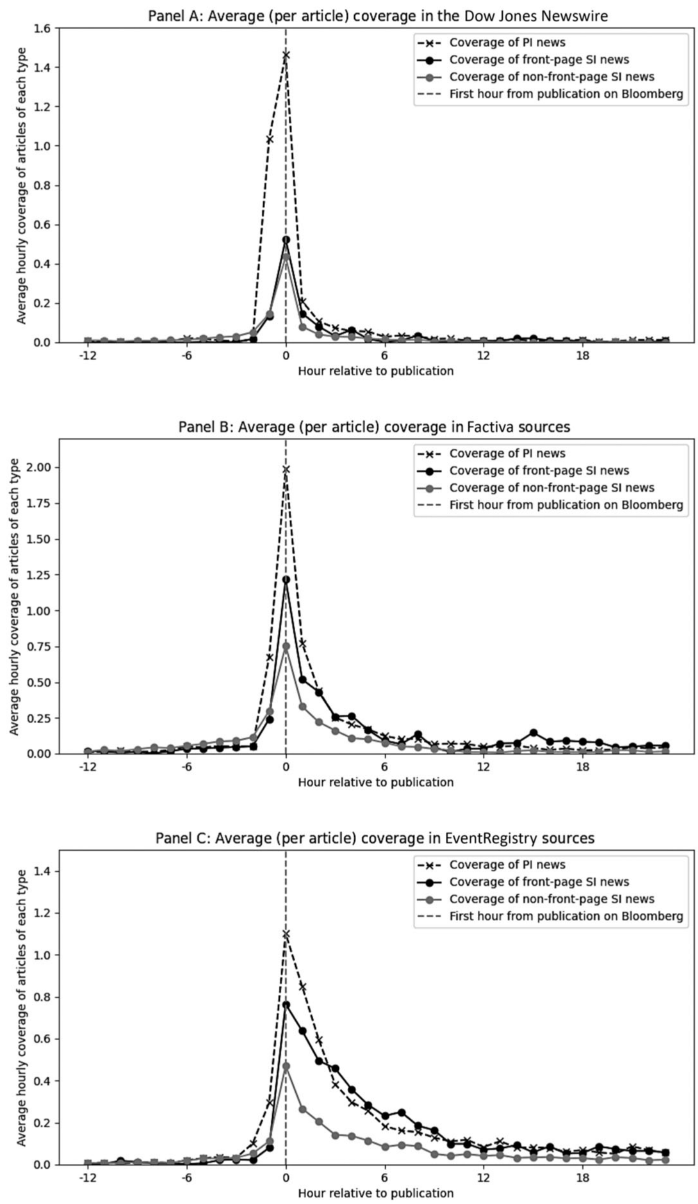

Figure 4. Coverage of Bloomberg news articles by other sources, by hour relative to publication on Bloomberg. Each hourly observation corresponds to the beginning of a 60-minute period: for example, hour 0 captures the time elapsed from the moment of publication on Bloomberg to exactly 60 minutes later. Panel A tabulates coverage in the Dow Jones Newswire, Panel B looks at coverage by sources in the Factiva database, and Panel C considers coverage in sources captured by EventRegistry. Coverage of PI news is in dashed lines, and coverage of front-page (non-front-page) SI news is in solid black (gray).

Newswire, Panel B looks at coverage in Factiva, and Panel C analyzes coverage in EventRegistry. Each hourly observation corresponds to the beginning of a 60-minute period; for example, hour 0 captures the time elapsed from the moment of publication of a given article on Bloomberg to exactly 60 minutes later.

The first noteworthy result is that the Dow Jones Newswire, which is comparable to the Bloomberg terminal in its speed and the sophistication of its target audience (institutional investors), independently gives equal coverage to Bloomberg's front-page and non-front-page SI news. This finding confirms that these two sets of articles are equally important, but some of them receive front-page slots specifically on Bloomberg. By contrast, the more important PI news articles do receive more coverage in the Dow Jones Newswire. This coverage begins even *before* publication on Bloomberg, consistent with Dow Jones competing with Bloomberg on speed and sometimes getting the news first.

The second result is that Factiva and EventRegistry also do not cover front-page SI news more than non-front-page SI news *prior* to publication on Bloomberg. However, front-page SI news articles receive more coverage in these sources *after* they are published on Bloomberg. The difference is visible starting in hour 0, which captures the first 60 minutes after Bloomberg's publication, and lasts for a few hours in Factiva and for a longer period (as long as 12 hours) in the more heterogeneous online sources in EventRegistry. I confirm that this difference is independent of the news content by training a convolutional neural network model to predict, based on the headline text, which articles receive more coverage from Factiva sources. The model does not predict higher coverage for front-page versus non-front-page SI news, despite generally having very high accuracy (71% when evaluated out of sample). 46% of front-page SI articles are predicted to receive above-median coverage in Factiva based on their headline text versus 49% of non-front-page SI articles.

Overall, the results in Figure 4 reveal differences in subsequent external coverage of Bloomberg's front-page versus non-front-page SI news, but not because front-page SI articles are more important than non-front-page SI articles. Prior work (e.g., Eisensee and Strömberg (2007)) suggests that such differences can arise from the fact that on days with high news flow, moderately important stories get pressured out of the news, which can happen concurrently across different news sources. This applies especially to print sources, which naturally face space constraints: whereas online sources can expand the number of news articles they publish when the news flow is high, print publications cannot expand the number of pages printed in response to high news flow. To explore this idea further, I take advantage of the fact that the Factiva database includes print publications (specifically, I identify 140 outlets such as the *New York Times*, *Wall Street Journal*, and *National Post* print editions) to measure coverage of different news in my sample by print versus online sources.

In Table VI, I estimate the relationship between coverage of Bloomberg SI news by print and nonprint Factiva sources and two predictors: (i) positioning on Bloomberg and (ii) a measure of high news flow—the percentage of front-page slots in my sample occupied by PI (rather than SI) news on any given

Table VI
Daily Coverage of Bloomberg SI News by Other Sources

This table presents regressions of daily coverage of Bloomberg SI news by outside sources (Factiva database) on two predictors: (i) front-page positioning on Bloomberg (FP indicator) and (ii) a measure of daily news pressure, the percentage of front-page slots taken by PI (vs. SI) news. The first column considers print sources, while the second column looks at the remaining sources in the Factiva database. ** and * indicate significance at the 1% and 5% level, respectively.

	Print Media (1)	Other Factiva Sources (2)
FP indicator	0.043	0.559*
	(0.081)	*(0.225)*
% PI on the front page	−0.632**	−0.307*
	(0.231)	*(0.124)*

day. Because print papers are published at the daily frequency (reporting news events in the next morning's paper), I aggregate coverage of each Bloomberg SI article to the daily level, looking at the day of its publication plus the next day. The dependent variable is the number of articles in Factiva's print publications that cover the same content as a given Bloomberg SI article in column (1) of Table VI and the number of other (nonprint) Factiva articles covering a given Bloomberg SI article in column (2). The results in column (1) show that in space-constrained print media, higher daily news flow is indeed associated with lower coverage of SI news, significant at the 1% level. With news flow taken into account, front-page SI articles do not receive more coverage than non-front-page SI articles. Column (2) shows that nonprint sources display a weaker impact of news flow (economically smaller and significant only at the 5% level) but show an additional effect of Bloomberg's front-page positioning (significant at the 5% level), consistent with Bloomberg's coverage having a direct delayed effect on online sources that cater to less sophisticated audiences.

IV. Validation Tests

A. Balance on Observables

I confirm that front-page and non-front-page SI news articles are balanced along firm- and article-level characteristics. First, I note that the mean (median) log market capitalization of tickers tagged in front-page SI and non-front-page SI news is 23.82 (24.62) and 23.79 (24.12), respectively. These numbers correspond to a mean firm size of approximately 20 billion dollars and a t-statistic on the difference of 0.59. Similarly, the mean (median) measure of illiquidity, computed following Amihud (2002), is 19,175 (170) bps per billion dollars of trading volume for front-page SI news and 14,019 (246) bps per billion dollars of trading volume for non-front-page SI news. The t-statistic on the difference in illiquidity is 1.04. Overall, front-page SI news articles cover marginally larger but marginally less liquid stocks, with neither difference statistically significant.

Table VII

Probit Regressions of News Categories from Observables

This table presents marginal effects from probit models predicting news categories from observable firm- and article-level characteristics. The first two columns predict article positioning (front-page vs. non-front-page) of SI news. The second two columns predict article importance (PI vs. SI news). Columns (2) and (4) include topic fixed effects, whereas columns (1) and (3) do not. **, *, and † indicate significance at the 1%, 5%, and 10% level, respectively.

	Position Effect: SI FP vs. SI Non-FP		Importance Effect: PI vs. SI	
	(1)	(2)	(3)	(4)
Market cap	−0.001	−0.002	−0.019**	−0.014**
	(0.005)	*(0.005)*	*(0.005)*	*(0.005)*
# Shares	0.005	0.004	0.007†	0.003
	(0.004)	*(0.004)*	*(0.004)*	*(0.004)*
Illiquidity	0.0004	0.0004	−0.005*	−0.004*
	(0.001)	*(0.001)*	*(0.002)*	*(0.002)*
Length	0.0003	0.001	−0.046**	−0.038**
	(0.003)	*(0.003)*	*(0.002)*	*(0.002)*
# Tags	0.005	0.005	0.018**	0.022**
	(0.004)	*(0.004)*	*(0.004)*	*(0.004)*
Topic FE	No	Yes	No	Yes
Pseudo-R^2	0.001	0.026	0.241	0.321

Second, I estimate a probit model of news positioning (front-page vs. non-front-page) from firm market capitalization, number of shares outstanding, and Amihud (2002) illiquidity, as well as article-level characteristics: the length of the headline, the number of securities tagged in each news article, and the topics covered in the news. For comparison, I also estimate a probit model of news importance (PI vs. SI) using the full set of news articles in the sample. Table VII reports the results for positioning in columns (1) to (2) and importance in columns (3) to (4). The topic dummies, classified according to the machine learning method outlined in Section IV.B, are included in columns (2) and (4). The table reports the marginal effects for the variables, along with the McFadden (1974) pseudo-R^2 for each model.

The simple probit model is able to differentiate PI articles from SI articles with high accuracy: McFadden pseudo-R^2s of 0.241 without topic fixed effects and 0.321 with topic fixed effects are both in the range of "excellent fit" based on McFadden (1977). PI articles tend to have shorter headlines and more assigned tickers, and they generally cover firms with lower market capitalization and a lower Amihud (2002) illiquidity measure. By contrast, the model is not able to differentiate front-page SI news articles from their non-front-page counterparts: the pseudo-R^2 is only 0.001 without topic fixed effects and 0.026 with topic dummies, and none of the explanatory variables is significant.[10]

[10] As an additional robustness test, in Section III.D of the Internet Appendix, I repeat the probit regression of positioning on observables for the subsample of SI news articles that are published on days with zero PI news, which correspond to times of especially high potential exposure for front-page SI news. The results are qualitatively similar despite the much smaller sample size.

B. Topic Analysis

I use machine learning to classify news articles into topics and confirm that front-page and non-front-page SI news tend to cover the same topics. In addition to confirming balance on important news characteristics, topic analysis addresses the time-series concern that certain types of news (e.g., earnings announcements) are more likely to be temporally clustered together than other types of news (e.g., merger announcements). As a result, SI articles that come out when front-page slots are left over from PI news may cover topics that are qualitatively different from those covered in SI articles that are published during periods with more PI news.

I assess potential differences in news topics as follows. I use a corpus of news articles from Reuters, which offers a data set that is substantially larger (approximately 1.8M news articles) than my hand-collected sample but has similar focus and target audience, to identify a set of broadly applicable topics.[11] I employ the latent Dirichlet allocation algorithm proposed by Blei, Ng, and Jordan (2003) to identify the topics.[12] This approach is particularly well suited to my application because it represents all documents as being generated from an underlying set of topics by a latent process and admits modeling out-of-sample documents as mixtures over the topics identified from the training data. The ability to represent out-of-sample documents in terms of the identified topics is key to my analysis. Specifically, I model out-of-sample documents (i.e., Bloomberg news articles in the PI, front-page SI, and non-front-page SI categories) as mixtures over the topics identified from the training data (i.e., the larger sample of Reuters news).

By using an unsupervised machine learning approach (latent Dirichlet allocation) to group news into topics, I contribute to the literature on textual analysis of financial news. Prior literature has studied sentiment, novelty, grammatical structure, and complexity,[13] but does not speak to thematic groupings of news articles based on topics. I bring an intuitive approach from machine learning to identify common topics in financial news and represent news articles in terms of these topics. The advantages of using unsupervised machine learning methods such as latent Dirichlet allocation to classify articles include (i) not relying on a discretionary set of topics to be prespecified ex ante and (ii) mitigating the risk of experimenter demand driving the classification, as may inadvertently occur with human taggers.

The results suggest some distinct topic patterns for PI news but no differences between the topics of front-page and non-front-page SI news. In Pearson χ-square tests of independence (Rao and Scott (1981)), the distribution of

[11] See Section IV.B of the Internet Appendix for details on the Reuters news data.

[12] For a description of the latent Dirichlet allocation methodology, please refer to Section IV.A of the Internet Appendix. In addition, Section IV.C of the Internet Appendix details the model estimation process and presents the 15 topics identified by the baseline model (Table IA.IX).

[13] See Tetlock (2007), Engelberg (2008), Li (2008), Tetlock, Saar-Tsechansky, and Macskassy (2008), Loughran and McDonald (2011), Tetlock (2011), García (2013), Loughran and McDonald (2014), and Umar (2022).

topics in PI news articles is weakly statistically significantly different (at the 10% level) from the distribution of topics covered by the front-page SI news articles, whereas the front-page and non-front-page SI articles are statistically indistinguishable in terms of their textual content, with a *p*-value of over 87%. These comparisons, presented in Table IA.III in the Internet Appendix, are robust to varying the topic model specification and considering anywhere between 10 and 25 topics. Figure IA.4 in the Internet Appendix presents a detailed breakdown of articles across the 15 topics in the baseline model. Section III.E of the Internet Appendix repeats the topic analysis using an independent human classifier instead of machine learning. This alternative analysis confirms the similarity of front-page and non-front-page SI news, while displaying an even starker difference between PI and SI news.

C. Deep Learning Model of News Importance

I train a deep learning model to identify news importance from a random subsample of PI and SI news and then test the model's ability to differentiate PI, front-page SI, and non-front-page SI news. Deep learning is especially well suited to the task of building a classifier of news importance for two reasons. First, deep learning methods do not require the researcher to prespecify a set of features, but instead uses the entirety of the news headline. Second, deep learning approaches allow for highly nonlinear interactions between various aspects of the news, thus enabling the model to capture the nuance of Bloomberg's markers of news importance, which represent highly complex hierarchies of rules.

The specific deep learning method that I use is a convolutional neural network. Within deep learning methods for natural language processing, recurrent neural networks are commonly used for longer text where sequential order matters, whereas for my sample of shorter and less word-order-dependent news headlines, convolutional neural networks offer a better fit (Yin et al. (2016)). I train a seven-layer convolutional neural network on a randomly selected subset of 650 PI and 650 SI news items, with an additional sample of 250 PI and 250 SI news items used for tuning. The remaining headlines are left out of both training and tuning, providing a fully out-of-sample set for performance evaluation.

The classifier is able to consistently distinguish PI news from SI news, with a high overall accuracy of 91%, despite the evaluation being performed on the held-out sample not seen by the model during either the training or the tuning phase. The model correctly labels 88% of PI headlines as more important and labels only 5.1% of SI headlines as more important. By contrast, when I apply the trained classifier separately to front-page and non-front-page SI news, the model does not find significant differences between them. The model misclassifies 6.6% of front-page SI headlines as PI, versus 4.7% of non-front-page SI headlines, and the difference is not statistically significant.

I confirm that the lack of distinction between front-page and non-front-page SI news is robust to the choice of machine learning method by training alternative classifiers with a structured feature selection process. Specifically, I consider all unigrams and bigrams (combinations of one and two words) in the headlines, identify the most informative 300 unigrams and the most informative 300 bigrams, and then train three models—logistic regression, random forest, and support vector machine—on these features. These models also identify no statistically significant differences between front-page SI news and non-front-page SI news.

D. Can Finance Professionals Tell the News Apart?

To directly assess the market's perception of the news in my sample, I survey the target audience of the news: active finance professionals who are likely to consume and trade on this information. Finance professionals agree with Bloomberg that PI headlines are, on average, more impactful than SI headlines, but they do not perceive front-page SI headlines to be any more impactful than non-front-page SI headlines.

I survey 150 finance professionals, recruited predominantly through the Harvard Business School alumni network and targeted based on being employed in financial firms.[14] Table IA.VIII in Section III.F of the Internet Appendix confirms that this sample is representative of the broader financial services industry. The bulk (81%) of the respondents come from large banks and broker dealers such as JPMorgan Chase and Morgan Stanley, investment management firms such as BlackRock and State Street, hedge funds such as Bridgewater Associates and AQR, and private equity firms such as the Blackstone Group and Warburg Pincus. The respondents constitute key decision makers within their respective firms. Many of the professionals from larger corporations are at the principal or managing director levels within their organizations, including heads of regional offices. The sample also includes chairmen, partners, and C-level executives. Finally, this sample is broadly reflective of the client base of the Bloomberg terminal. Approximately, 87% of the professionals in my sample report having used a Bloomberg terminal at some point, with 63% actively using the terminal on an ongoing basis.

In the survey, each respondent was asked to answer a series of 25 questions about news headlines. The respondent was told that the headlines come from a news provider that chooses how prominently to display them based in part on the importance and expected market impact of the underlying news. Each question presented two headlines and asked the respondent to specify which headline the respondent thinks is associated with a larger market impact and deserves more prominence. The participants were asked to evaluate only headlines, rather than full articles, for two reasons: (i) to keep the survey short and

[14] Survey invitations were sent to relevant alumni through the alumni messaging system; 9.2% of individuals who were contacted participated in the survey. This response rate is in line with previous academic surveys of finance professionals (e.g., Graham and Harvey (2001)), despite the lack of any follow-ups or reminders. There is no evidence of selection issues in the sample of respondents, as discussed in Section III.F of the Internet Appendix. The attrition rate was also low: among those who signed up for the study, 91% completed the entire 25-question survey.

Table VIII

Finance Professionals' Assessment of News Importance

This table presents the results from the survey of finance professionals, with and without the respondents who did not complete the survey in full (attritors). Standard errors are clustered by participant. Panel A reports the frequency with which finance professionals identified PI news articles as more impactful than front-page SI news articles. Panel B reports the frequency with which they identified front-page SI news articles as more impactful than non-front-page SI news articles. All proportions are evaluated against the null of 50%. ** indicates significance at the 1% level.

Panel A: Importance Effect (PI vs. FP SI News)

	All Participants (1)	Excluding Attritors (2)
% Choosing PI	61.16%**	61.59%**
	(2.13%)	*(2.20%)*
# Respondents	150	136

Panel B: Position Effect (FP SI vs. Non-FP SI News)

	All Participants (1)	Excluding Attritors (2)
% Choosing FP SI	48.24%	48.16%
	(1.21%)	*(1.24%)*
# Respondents	150	136

(ii) to most closely mirror the way news is delivered on the Bloomberg terminal, where a user must actively click on a headline to see the full text. A screenshot with an example question is displayed in Figure IA.5 in Section II of the Internet Appendix.

The survey questions span two sets of comparisons: (i) between front-page SI news articles and PI news articles (approximately 37.5% of the questions) and (ii) between front-page and non-front-page SI news articles (approximately 62.5% of the questions). The respondents were incentivized to identify relative news importance as accurately as they can through the survey's two-part payment system. First, each respondent received a $10 gift card for completing the five-minute survey. Second, the five respondents whose answers most closely matched actual differences in positioning by the news provider received additional prizes of $90 each, for a total payment of $100 each.

The results appear in Table VIII.[15] Panel A shows that PI news articles are chosen over front-page SI news articles 61.16% of the time, significantly higher than 50% at the 1% level. This result confirms both that the surveyed finance professionals paid attention to the survey and that Bloomberg's importance tags correctly identify content for the target audience. By contrast, Panel B

[15] Table VIII pulls responses from all participants. Section III.G of the Internet Appendix presents individual-level responses, which corroborate the results from the aggregate analysis.

shows that finance professionals identified front-page SI news as more impactful than non-front-page SI news 48.24% of the time, which is not statistically different from 50%. This result further validates that there are no differences in the content of the SI news articles that happen to be pinned to the front page and those that are not.

V. Conclusion

This paper takes advantage of exogenous variation in news positioning to directly estimate the causal effect of news presentation on a platform targeted at sophisticated institutional investors. Pinning a news article to a front-page slot on the Bloomberg terminal leads to the information being fully incorporated into prices within an hour of publication. Less prominently displayed information is also eventually incorporated into prices, but this process takes an order of magnitude longer than for front-page news.

The results in this paper highlight the importance of the way information is presented for its incorporation into asset prices. In modern informational environments, where investors face millions of news articles per day, even widely available public information may not be immediately and efficiently priced. The Bloomberg terminal is used predominantly by large, sophisticated institutional investors—precisely the demographic whose attention we would least expect to be allocated according to heuristics such as salient positioning. Yet even in this setting, presentation of information plays an important role, and the speed of incorporation depends on the method of dissemination. The effect of presentation on low-latency platforms such as Bloomberg is further amplified by delayed publications, including print papers, allowing the effect to persist for several days. These results have important implications for the role of financial media in modern financial markets. Large news providers have a disproportionate effect on investors trading on information and on firms participating in capital markets. Small variations in how the news is delivered—either from editors' discretionary choices or from logistical space constraints—can change the speed of the market response from minutes or hours to days or weeks.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.